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STRATEGIE A VÝZVY OPERAČNÍHO VÝZKUMU V ODPADOVÉM HOSPODÁŘSTVÍ: INTEGRACE KOMPLEXNÍCH PŘÍSTUPŮ KE ZPRACOVÁNÍ DAT A OPTIMALIZACI SYSTÉMŮ
OPERATION RESEARCH STRATEGIES AND CHALLENGES IN WASTE MANAGEMENT: INTEGRATION OF COMPLEX DATA PROCESSING

HABILITAČNÍ PRÁCE
HABILITATION THESIS

OBOR KONSTRUKČNÍ A PROCESNÍ INŽENÝRSTVÍ
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ABSTRAKT

Habilitační práce shrnuje dosavadní výzkumné aktivity autora. Předmětem jeho výzkumu je vývoj původních přístupů a nástrojů pro podporu rozhodování a plánování v oblasti odpadového a oběhového hospodářství. Jedná se o dynamicky vyvíjející se oblasti, které v současnosti prochází řadou změn vyvolaných milníky ukotvenými v legislativě na úrovni ČR i EU. S ohledem na komplexnost problematiky je žádoucí opírat strategické a operativní rozhodování o sofistikované přístupy. Využití představených matematických modelů založených na metodách operačního výzkumu přispěje k efektivnímu a udržitelnému plánování nakládání s odpady s ohledem na celý zpracovatelský řetězec. V práci je zdůrazněn význam přípravy dat a jejich statistické zpracování pro následné využití při plánování odpadového hospodářství. Výzkumné aktivity zaměřené na práci s daty byly promítnuty do nově vzniklých metodik a dokumentů navrhujících postupy v oblastech zpracování dat a tvorby prognóz. Stěžejní výzkumnou aktivitou autora je tvorba optimalizačních modelů, které jsou následně aplikovány na jednotlivé prvky celého zpracovatelského řetězce pro různé typy odpadu. Pro zajištění širšího dopadu do komerční sféry jsou modely implementovány do softwarových nástrojů. Konkrétně se jedná o nástroj REVEDATO pro rekonstrukci a modelování dat v rámci monitoringu v odpadovém hospodářství; TIRAMISO pro tvorbu prognóz a projekcí produkce a nakládání s odpady; NERUDA pro vyhodnocení zpracovatelské infrastruktury, dostupnosti odpadu a svozových oblastí a POPELKA pro tvorbu plánu meziobecního svozu odpadu a obecní sběrné infrastruktury.

KLÍČOVÁ SLOVA

oběhové hospodářství, prognózy a projekce, matematické modely, REVEDATO, TIRAMISO, NERUDA, POPELKA

ABSTRACT

The habilitation thesis describes the author's research activities. The subject of his research is the development of original approaches and tools to support decision-making and planning in the field of waste management and circular economy. These are dynamically developing areas that are currently undergoing a series of changes triggered by milestones anchored in legislation at the level of the Czech Republic and the EU. Considering the complexity of the issue, it is desirable to base strategic and operational decision-making on sophisticated approaches. The use of presented mathematical models based on operational research methods will contribute to efficient and sustainable planning of waste management with respect to the entire treatment chain. The work emphasizes the importance of data preparation and their statistical processing for their subsequent use in waste management planning. These research activities are reflected in newly created methodologies and documents proposing procedures in the areas of data processing and forecasting. The author's core research activity is the creation of optimization models, which are subsequently applied to individual elements of the entire processing chain for different types of waste. To ensure a wider impact in the commercial sphere, the models are implemented in software tools. Specifically, it is the REVEDATO tool for the reconstruction and modelling of data as part of monitoring in waste management; TIRAMISO for creating forecasts and projections of production and waste management; NERUDA for the evaluation of the processing infrastructure, the availability of waste and collection areas and POPELKA for the creation of a plan for inter-municipal waste collection and municipal collection infrastructure.

KEYWORDS

circular economy, forecasts and projections, mathematical models, REVEDATO, TIRAMISO, NERUDA, POPELKA

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OBSAH

SEZNAM POUŽITÝCH ZKRATEK

Zkratka	**Význam**
ADMM	Alternating direction method of multipliers (český ekvivalent se nepoužívá)
ARC	Arc routing problem (český ekvivalent se nepoužívá)
ARIMA	Autoregresní integrovaný klouzavý průměr – Autoregressive integrated moving average
BAU	Základní scénář – Business-as-usual
CENIA	Česká informační agentura životního prostředí
CEP	Balíček oběhového hospodářství – Circular economy package
FSI	Fakulta strojního inženýrství
GAMS	General algebraic system (český ekvivalent se nepoužívá)
GHG	Skleníkové plyny – Greenhouse gas
GR	Obecná regrese – general regression
GWP	Potenciál globálního oteplování– Global warming potential
ISOH	Informační systém odpadového hospodářství
ISPOP	Integrovaný systém plnění ohlašovacích povinností
KO	Komunální odpad
LCA	Posuzování životního cyklu – Life cycle analysis
LR	Lineární regrese
MAE	Střední absolutní chyba – Mean absolute error
MAPE	Střední absolutní procentuální chyba – Mean absolute percentage error
MBÚ	Mechanicko-biologická úprava
MŽP	Ministerstvo životního prostředí
NO	Nebezpečný odpad
ObH	Oběhové hospodářství
ObjO	Objemný odpad
OH	Odpadové hospodářství
OO	Ostatní odpad
ORP	Obec s rozšířenou působností
PD ISOH	Pracovní databáze Informačního systému odpadového hospodářství
POH	Plán odpadového hospodářství
R^2	Koeficient determinace
RMSE	Směrodatná odchylka chyb – Root mean square error
SEP	Separovaný odpad
SKO	Směsný komunální odpad
TSA	Analýza časových řad – time-series analysis

ÚPI	Ústav procesního inženýrství
UTB	Univerzita Tomáše Bati ve Zlíně
VBA	Visual Basic for Applications (český ekvivalent se nepoužívá)
VISOH	Veřejný Informační systém odpadového hospodářství
VUT	Vysoké učení technické v Brně
ZEVO	Zařízení na energetické využití odpadu
ZÚJ	Základní územní jednotka

SEZNAM OBRÁZKŮ

SEZNAM TABULEK

SEZNAM PŘÍLOH

Příloha 1: Publikace [A1] – Predictive modelling as a tool for effective municipal waste management policy at different territorial levels.

Příloha 2: Publikace [A2] – Waste-to-energy facility planning under uncertain circumstances.

Příloha 3: Publikace [A8] – Bulky waste for energy recovery: Analysis of spatial distribution.

Příloha 4: Publikace [A11] – Comprehensive review on waste generation modeling.

Příloha 5: Publikace [A17] – Multi-level stratification of territories for waste composition analysis.

Příloha 6: Publikace [A24] – Multi-objective strategic waste transfer station planning.

Příloha 7: Publikace [A27] – Logistic model-based tool for policy-making towards sustainable waste management.

Příloha 8: Publikace [A28] – A waste-to-energy project: A complex approach towards the assessment of investment risks.

Příloha 9: Publikace [A31] – Legislation-induced planning of waste processing infrastructure: A case study of the Czech Republic.

1 CÍL PRÁCE

Cílem této habilitační práce je představení podpůrných přístupů a nástrojů pro plánování v oblasti odpadového hospodářství (OH) a oběhového hospodářství (ObH), kterým se autor věnoval v rámci své výzkumné činnosti. Uvedené přístupy jsou založeny na metodách operačního výzkumu a rozšiřují výzkumný potenciál v této oblasti. Druhotným výstupem autorovy výzkumné práce je přímý dopad na tvorbu strategických dokumentů pro efektivní nakládání s odpady v podmínkách ČR, popř. v rámci EU. Předložené výstupy jsou výsledkem činnosti týmu pod vedením autora této práce na Ústavu procesního inženýrství (ÚPI) Fakulty strojního inženýrství (FSI) Vysokého učení technického v Brně (VUT). Autor současně koordinuje mezisektorovou spolupráci s vybranými zaměstnanci a studenty Ústavu matematiky a Ústavu automatizace a informatiky FSI VUT v podobě vedení závěrečných prací všech stupňů studia, realizace výzkumných projektů a vývoje komerčních aplikací.

Tato habilitační práce je koncipována jako přehled hlavních výstupů výzkumné činnosti. Detailní popis modelů a případových studií je k dispozici v odkazované literatuře, která je rozčleněna do následujících skupin podle typu reference:

P – Strategické projekty s účastí autora a výstupy těchto projektů.
A – Reference autora citované v práci.
B – Ostatní reference citované v práci.
Z – Závěrečné práce, v nichž byl autor školitelem, školitelem specialistou nebo konzultantem.

Součástí tohoto textu jsou reprinty publikací autora publikované v předních impaktovaných časopisech (Příloha 1 až Příloha 9).

Významný je také přínos v oblasti vzdělávání, kdy je rozvíjen systém uplatnění znalostí studentů a absolventů Ústavu matematiky pro řešení praktických úloh a problémů. Výsledkem jsou prakticky použitelné výpočtové nástroje s vyšší přidanou hodnotou, které se daří aplikovat při řešení zakázek smluvního výzkumu a hospodářské činnosti.

2 ÚVOD A MOTIVACE

V oblasti OH a ObH realizuje EU kroky pro efektivnější využívání potenciálu v odpadech a tím vytvoření udržitelného systému s jejich nakládáním. Preferované způsoby nakládání s odpady jsou stanoveny v *Hierarchii nakládání s odpady* (Směrnice 2008/98/ES) [B1]. Konkrétní milníky EU jsou ukotveny v legislativě v tzv. *Balíčku oběhového hospodářství* (CEP – Circular economy package). Z pohledu komunálního odpadu (KO) jsou zásadní směrnice uvedeny v tab. 1.

Tab. 1: Milníky pro nakládání s komunálním odpadem zahrnuté v Balíčku oběhového hospodářství

	Zdroj	**Odpadový proud**	**2025**	**2030**	**2035**
Recyklace (minimum)	Směrnice EU 2018/851; [B2]	Komunální odpad	55 %	60 %	65 %
	Směrnice EU 2018/852; [B3]	Obaly	65 %	70 %	
		Obalový papír	75 %	85 %	
		Obalové plasty	50 %	55 %	
		Obalové sklo	70 %	75 %	
		Obaly ze železných kovů	70 %	80 %	
		Obalový hliník	50 %	60 %	
		Obalové dřevo	25 %	30 %	
Skládkování (maximum)	Směrnice EU 2018/850; [B4]	Komunální odpad			10 %
Omezení produkce (minimum)	Směrnice EU 2018/851; [B2]	Kuchyňský odpad	30 %	50 %	

Členské státy EU zavádějí legislativní změny vedoucí ke splnění uvedených cílů EU. Je nutné upravit stávající systémy OH tak, aby bylo možné stanovené cíle splnit. Modernizace infrastruktury pro sběr a nakládání s odpady vychází z vypracovaných strategických plánů OH. Jedná se však o velmi komplexní obor a každá úloha OH je svou povahou jedinečná, je tedy nutné běžně využívané přístupy přizpůsobit konkrétní úloze a dostupným datům. Následující text (kap. 2.1 až 2.3) rozděluje úlohy OH do tří logických bloků, kterým se autor této práce ve své výzkumné činnosti věnoval.

2.1 Plánování státní koncepce odpadového hospodářství

Stanovení adekvátních cílů v oblasti recyklace nebo předcházení vzniku odpadů vyžaduje spolehlivé dlouhodobé informace o produkci odpadu, jeho složení a způsobů zpracování. Na základě očekávaného vývoje OH je možné nastolit legislativní změny, které mají za cíl zlepšit nakládání s odpadem podle Hierarchie nakládání s odpady [B1]. Přestože národní statistické úřady nebo soukromé společnosti hodnoty o produkci a nakládání obvykle sledují, v datových sadách historických dat se vyskytuje mnoho chyb, chybějících a neúplných dat. Všechny tyto nesrovnalosti musí být vyřešeny ve fázi pre-processingu dat. Upravená historická data mohou identifikovat vazby různých socioekonomických a demografických faktorů na vývoj OH [B5]. Identifikované souvislosti pak odhalují potenciální změny tak, aby pozitivně ovlivnily trendy produkce odpadů a způsoby jeho zpracování.

Modely používané k plánování dlouhodobých záměrů lze rozdělit na predikce, prognózy a projekce (kap. 3.2). Cílem prediktivních modelů je popsat vazby mezi sociálními aspekty a parametry souvisejícími s odpady. Pro popis těchto vazeb hrají zásadní roli korelační analýzy a regresní modely, protože mají široké využití. Tyto výstupy ukazují, na jaké aspekty je vhodné cílit legislativní změny, pokud se má dosáhnout pozitivních změn současných trendů v produkci a nakládání s odpady. Nutno podotknout, že není vhodné slepě přebírat regresory ze studií, které se zaměřují na jiné země [A1]. Identifikované vazby totiž mohou být lokálního charakteru. Druhou skupinu tvoří prognózy zabývající se předpovědí produkce a nakládání s odpadem do budoucnosti na základě historických dat. CEP v EU stanovil cíle recyklace [B1] a omezení skládkování pro KO [B4] do roku 2035. V tomto ohledu jsou relevantní dlouhodobé prognózy (5–20 let), a není tedy nutné sledovat sezónnost v datech. Na úrovni států se data obvykle evidují jednou za rok. Nevýhodou takových dat je krátká časová řada. Jedinou možnou alternativou pro tvorbu dlouhodobých prognóz na základě krátkých časových řad je nalezení trendu v historických datech (viz kap. 3.2). Nejvýraznějším nedostatkem přístupů k dlouhodobějším prognózám produkce některého druhu odpadu je nezohlednění potenciálních zásahů do odpadového systému. Pokud aktuální prognóza není v souladu s cíli nebo nerespektuje vývoj ve společnosti (např. socioekonomické aspekty z predikčních modelů), je vhodné přistoupit k modelování projekcí (kap. 3.2.3). Tento přístup může odhalit potenciál dopadu možných legislativních změn v jednotlivých územních celcích na vývoj OH. Projekce obvykle upravují křivky prognózy tak, aby dosáhly konkrétních hodnot v požadovaných letech [B6].

Legislativní cíle je možné naplnit za předpokladu, že je vybudována adekvátní infrastruktura OH. Je tedy nutné zajistit sběr požadovaných frakcí odpadu, svoz odpadu s dostatečnou frekvencí a potřebnou kapacitu zpracovatelských zařízení. Tím se zabývá kap. 2.2.

2.2 Strategické plánování infrastruktury odpadového hospodářství

Strategické rozhodování v OH se zabývá plánováním a realizací dlouhodobých projektů. Patří mezi ně výstavba nebo modifikace zařízení pro nakládání s odpady, např. zařízení pro energetické využití odpadu (ZEVO) [A2], překládací stanice [A3], zařízení pro materiálové využití odpadu [B7] atd. Ve všech případech je provoz plánován na desítky let. Při hodnocení projektů je nutné vzít v úvahu několik nejistých parametrů, včetně produkce odpadu, složení odpadu, podoby stávající infrastruktury [A4], aby byla zajištěna ekonomická a technická udržitelnost. Pro umístění zařízení s dobře navrženou kapacitou je tedy nutné pro zájmové území vyhodnotit současný stav OH a jeho očekávaný budoucí výhled.

Modely pro strategické plánování infrastruktury se oproti předchozímu bodu (kap. 2.1) často zaměřují na regionální úroveň. Stejně jako data na národní úrovni, také regionální data jsou obvykle k dispozici na roční bázi, takže je možné opět odhadovat trendy z historických dat. Data a trendy nižších územních celků však mají obvykle výrazně vyšší volatilitu, prognózy jsou tedy složitější a méně přesné než na státní úrovni. Klíčovou roli hraje kvalitní pre-processing dat. Pro zajištění konzistentní prognózy mezi regiony a celou zemí je nutné zohlednit hierarchické územní členění. V tomto kontextu je vhodné aplikovat bilance trendů získané z vyrovnání dat [A5], kap. 3.2. Měly by být také zohledněny souvislosti s okolními regiony, které mohou plánovaný projekt ovlivnit [B8]. Při strategickém plánování je přínosné modelovat scénáře budoucího vývoje OH. Takové scénáře vznikají z externích zásahů do systému OH a umožňují vyhodnotit dopad na udržitelnost plánovaných projektů [B9]. Vhodné je využívat přístupy založené na stochastickém programování.

Kromě úloh týkajících se zařízení pro nakládání s odpady se ve strategickém plánování řeší problémy souvisejících s infrastrukturou sběru. Konkrétně se jedná o vhodné rozmístění sběrných míst v rámci obcí, stanovení typu, kapacity a potřebného počtu sběrných nádob s ohledem na rozvoj měst a obcí [B10]. Sběrná infrastruktura je často upravována v důsledku zavádění odděleného sběru nových frakcí, rozvoje a rozšiřování některých oblastí obcí (změna typů obydlí, výstavba nových čtvrtí atd.). Zásahy do sběrné infrastruktury nejsou na první pohled drahé (pořizovací cena sběrných nádob a kontejnerů), ale výrazně ovlivňují následný svoz odpadu. Čím více se zkracuje docházková vzdálenost občanů k nejbližšímu sběrnému místu, tím více těchto míst je v infrastruktuře a svoz pak trvá déle. Velký důraz je třeba klást na využitelnost navržených sběrných míst s ohledem na předpokládanou produkci odpadů. Sběrná infrastruktura a svoz odpadu se odvíjí zejména od očekávané produkce odpadu v dané lokalitě a od počtu odděleně sbíraných frakcí odpadu. Obvykle modely produkce pro optimalizaci svozu odpadu vycházejí z denní nebo týdenní datové sady. Tento typ dat je obvyklý pro města a obce, kde jsou data sledována podrobněji a jsou tedy k dispozici delší časové řady.

2.3 Operativní rozhodování v odpadovém hospodářství

Poslední bod v této části souvisí s plánováním denních operací. Typickým příkladem je plánování dynamického svozu, kdy se denně odhaduje množství odpadu na jednotlivých sběrných místech. Obvykle se používá analýza časových řad pro odhad produkce odpadu, např. autoregresní integrovaný klouzavý průměr (ARIMA – Autoregressive integrated moving average). Data o naplněnosti sběrných nádob se následně používají v aplikacích pro svoz odpadu, kde jsou modelovány konkrétní svozové trasy pomocí routingových modelů. Přehled routingových modelů a jejich aplikace jsou uvedeny v [B11].

Při vytváření nového plánu sběru je potřeba na základě týdenních nebo měsíčních dat o produkci odpadu naplánovat frekvenci sběru. Četnost svozu dále závisí na vlastnostech odpadu a kapacitě sběrných míst. Tato část úzce souvisí s umístěním sběrných míst a jejich kapacitou (kap. 4.2). Dalším typem úlohy je dimenzování vozového parku [B12], jedná se o strategičtější investici, kde je potřeba pracovat také s dlouhodobým plánem a zvážit třeba poruchy a údržbu vozidel. Takové aplikace by měly vzít v úvahu změny v produkci odpadu během několika let a nové frakce odpadu, které lze sbírat odděleně.

Shrnutí: Efektivní plánování a řízení provozu v OH vyžaduje vývoj komplexních výpočtových nástrojů a přístupů pro nastavení realistických cílů pro monitoring jejich plnění, a to za předpokladu minimálních ekonomických dopadů na producenty odpadu. Výše uvedené tematické okruhy 2.1 až 2.3 se často prolínají a řešené úlohy mají uplatnění ve více uvedených okruzích. Jako příklad lze uvést potřebu prognózovat produkci odpadu. Výsledky prognózy na úrovni státu je nutné zohlednit při hodnocení legislativy OH a současně je výsledek prognózy zásadní pro strategické plánování OH. Následující kapitoly obsahují oblasti využití, u kterých jsou popsány hlavní příležitosti z pohledu vývoje nových přístupů a metod pro podporu splnění vytyčených cílů v OH a ObH. Bez dopadů na obecnost jsou řešené oblasti v následujících kapitolách provázány s aktuálním stavem v ČR.

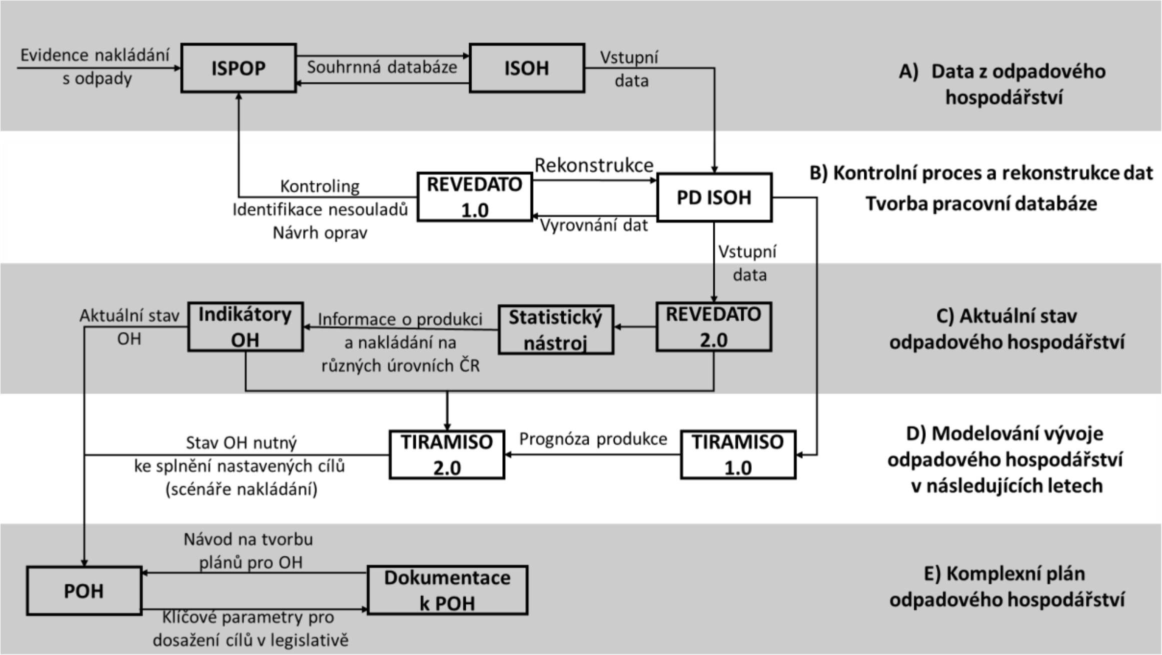
Habilitační práci pokrývá v podstatě dvě oblasti s aplikačním potenciálem, které korespondují se strukturou této práce:

- Příprava dat pro strategické plánování OH a ObH v ČR (kap. 3).
- Modely a přístupy pro plánování OH a ObH (kap. 4).

V kap. 3 bude představen přístup k přípravě dat od jejich evidence jednotlivými subjekty až po sestavení komplexního plánu OH na úrovni ČR nebo krajů. Pozornost je věnována zejména nástroji REVEDATO pro analýzu současného stavu OH (kap. 3.1) a nástroji TIRAMISO [P1] pro prognózování produkce a nakládání s odpadem (kap. 3.2). Upravená data jsou vstupy pro modely plánování OH (kap. 4), kde jsou postupně představeny modely pro odhad složení odpadu (kap. 4.1), plánování sběrné infrastruktury (kap. 4.2), logistiku odpadů (kap. 4.3), nastavení zpracovatelské infrastruktury (kap. 4.4) a dimenzování technologií zpracovatelských zařízení (kap. 4.5). V textu jsou uvedeny hlavní myšlenky jednotlivých přístupů, detailní popis modelů je k dispozici v publikovaných článcích autora, v přílohách je uvedeno deset nejvýznamnějších příspěvků na základě autorova výběru (Příloha 1 až Příloha 9). Hlavní výzkumné výstupy autora jsou sumarizovány v samostatné kap. 5.

3 PŘÍPRAVA DAT PRO STRATEGICKÉ PLÁNOVÁNÍ ODPADOVÉHO A OBĚHOVÉHO HOSPODÁŘSTVÍ V ČR

Pro plánování OH je zásadní vycházet z kvalitní datové sady. Základním zdrojem dat o produkci a nakládání s odpady v ČR je databáze ISOH (Informační systém odpadového hospodářství). ISOH vzniká z každoročního hlášení souhrnných údajů z průběžné evidence o produkci a nakládání s odpady prostřednictvím systému ISPOP (Informační systém plnění ohlašovacích povinností) podle Zákona č. 541/2020 Sb., o odpadech a Vyhlášky č. 273/2021 Sb., o podrobnostech nakládání s odpady. V rámci výzkumu autora této práce vznikají podpůrné nástroje pro zpracování dat o produkci a nakládání s odpady tak, aby byl eliminován výskyt chybných hodnot a byla doplněná chybějící data potřebná pro plánování OH. Návaznost těchto nástrojů pro podporu OH v ČR je shrnuta v obr. 1, přičemž jednotlivé fáze přípravy datové základny jsou rozděleny do částí A) až E).



Obr. 1: Datová základna pro plánování odpadového hospodářství v ČR

Níže jsou v krátkosti popsány jednotlivé moduly přípravy a zpracování dat a vazby mezi nimi. Jedná se o existující moduly, případně moduly ve vývoji na pracovišti autora této práce.

A) Data z OH

- ISPOP

  Systém zajišťuje příjem a zpracování hlášení na základě ohlašovacích povinností o produkci a nakládání s odpady. Hlášení je realizováno v elektronické podobě a s následnou distribucí příslušným institucím veřejné správy (Vyhláška č. 273/2021 Sb., o podrobnostech nakládání s odpady).

- ISOH [B13]

  Kontrolu všech doručených hlášení podle zákona o odpadech (Zákon č. 541/2020 Sb.) provádí obec s rozšířenou působností (ORP) a poté data zasílá na Ministerstvo životního prostředí (MŽP). Hlavním nástrojem pro toto ověření je křížová kontrola, tzn. porovnání množství jednotlivých druhů odpadů, které uvedli původci a partneři transakce. Na základě křížové kontroly reportovaných dat je možné požádat respondenta o jejich kontrolu. Databázi ISOH spravuje Česká informační agentura životního prostředí (CENIA). Z důvodu aktualizace systému v současnosti probíhá vývoj nové verze systému pro sběr dat z hlášení souhrnných údajů průběžné evidence (Vyhláška č. 273/2021 Sb., o podrobnostech nakládání s odpady).

B) Kontrolní proces a rekonstrukce dat, tvorba pracovní databáze
   - PD ISOH (pracovní databáze ISOH)
     Evidovaná data v ISOH jsou dále upravena podle metodiky definované v dokumentu [B14] a vzniká tak PD ISOH. I přes zmíněný systém kontrol a úprav dat jsou do PD ISOH začleněny chybné hodnoty. Chyby, které se staly součástí PD ISOH, umožňuje odhalit nástroj REVEDATO 1.0. Data z PD ISOH představují klíčový podklad pro podporu rozhodování v OH.
   - REVEDATO 1.0 (Rekonstrukce a Verifikace Dat z ISOH)
     Výpočtový nástroj REVEDATO 1.0 vyhodnocuje nesoulad dat v rámci toků odpadu mezi územními celky a zajistí tak hmotnostní bilance odpadu v územních jednotkách. Dále nástroj REVEDATO 1.0 může být zapojen do evidence hlášení nakládání s odpady, kde by umožnil identifikovat případné nesoulady již ve fázi reportingu. Detailněji bude nástroj popsán v kap. 3.1.

C) Aktuální stav OH
   - REVEDATO 2.0 (ve vývoji)
     Nástroj REVEDATO 2.0 umožňuje modelovat tok odpadu od producenta až do místa zpracování, viz 3.1. Jedná se o zásadní informaci pro vyhodnocování OH na různých úrovních územního členění (kraje, ORP, ZÚJ – základní územní jednotka).
   - Statistický nástroj (ve vývoji)
     V současnosti je velmi pracné vytvořit jakoukoli analýzu OH. Je třeba exportovat data z PD ISOH, agregovat vybrané kódy nakládání a s tímto souborem dále pokračovat ve vybraných statistických přístupech. Modul statistického nástroje umožní snadné filtrování dat s přednastavenými funkcionalitami navázanými na indikátory OH (viz níže). Bude snadné zjistit kvalitu evidence ve vybraných územních celcích, toky odpadu, předúpravu, skladování a navazující nakládání s odpadem v následujícím roce a další zaměření analýz.
   - Indikátory OH
     Pro základní monitoring vývoje OH v ČR slouží definované indikátory OH (viz metodika výpočtu [B14]). Indikátory umožňují posouzení plnění cílů v CEP. Díky nástroji REVEDATO 2.0 a na něm navazujícímu statistickému nástroji lze tyto indikátory vyhodnotit také pro nižší územní celky (kraje, ORP, ZÚJ).

D) Modelování vývoje OH v následujících letech (ve vývoji)
   - TIRAMISO 1.0 [P1]
     Jedná se o webovou aplikaci zaměřenou na prognózování produkce odpadu včetně tvorby projekcí (scénářů), viz kap 3.2. TIRAMISO 1.0 čerpá vstupní data z PD ISOH. Nástroj je spravován MŽP, které určuje detail zobrazení pro běžného uživatele. Nástroj TIRAMISO 1.0 byl vytvořen na VUT v Brně v rámci projektu TIRSMZP719 [P2]. Autor vedl tým, který vyvíjel matematický aparát použitý v nástroji a současně je hlavním autorem metodiky [P7], na které je nástroj postaven.
   - TIRAMISO 2.0
     Aplikace se zaměřuje na tvorbu prognóz a projekcí pro nakládání s odpady, viz kap 3.2. Modely zohledňují očekávanou produkci odpadu podle výsledků

TIRAMISO 1.0. Hlavní funkcionalitou modulu TIRAMISO 2.0 je tvorba projekcí vývoje nakládání s odpady s ohledem na výhled vývoje v průmyslu a službách. Díky tomu bude možné plánovat novou infrastrukturu a směřovat OH na různé úrovni územního detailu. Výstupy budou základním podkladem pro tvorbu Plánů odpadového hospodářství (POH).

E) Komplexní POH

- POH
  Jedná se o klíčový dokument udávající směřování OH s vazbou na cíle CEP, které jsou promítnuty do Zákona o odpadech 541/2020 Sb. POH se tvoří ve státní a krajských variantách. V rámci projektu CEVOOH [P3] se bude autor této práce podílet na nové podobě POH ČR, který bude platný od roku 2025.
- Dokumentace k POH
  Rešerše existujících POH (ČR, kraje) ukázala jejich značné nedostatky. Především v krajských variantách jsou texty velmi obecné bez konkrétních doporučení. Nejsou zohledněny regionální rozdíly, vazby na okolní regiony apod. Současně se státní podobou POH bude tvořena podpůrná dokumentace pro tvorbu POH všech úrovní. Tento dokument zajistí významně vyšší přínos krajských a městských POH, které budou na státní variantu POH navazovat.

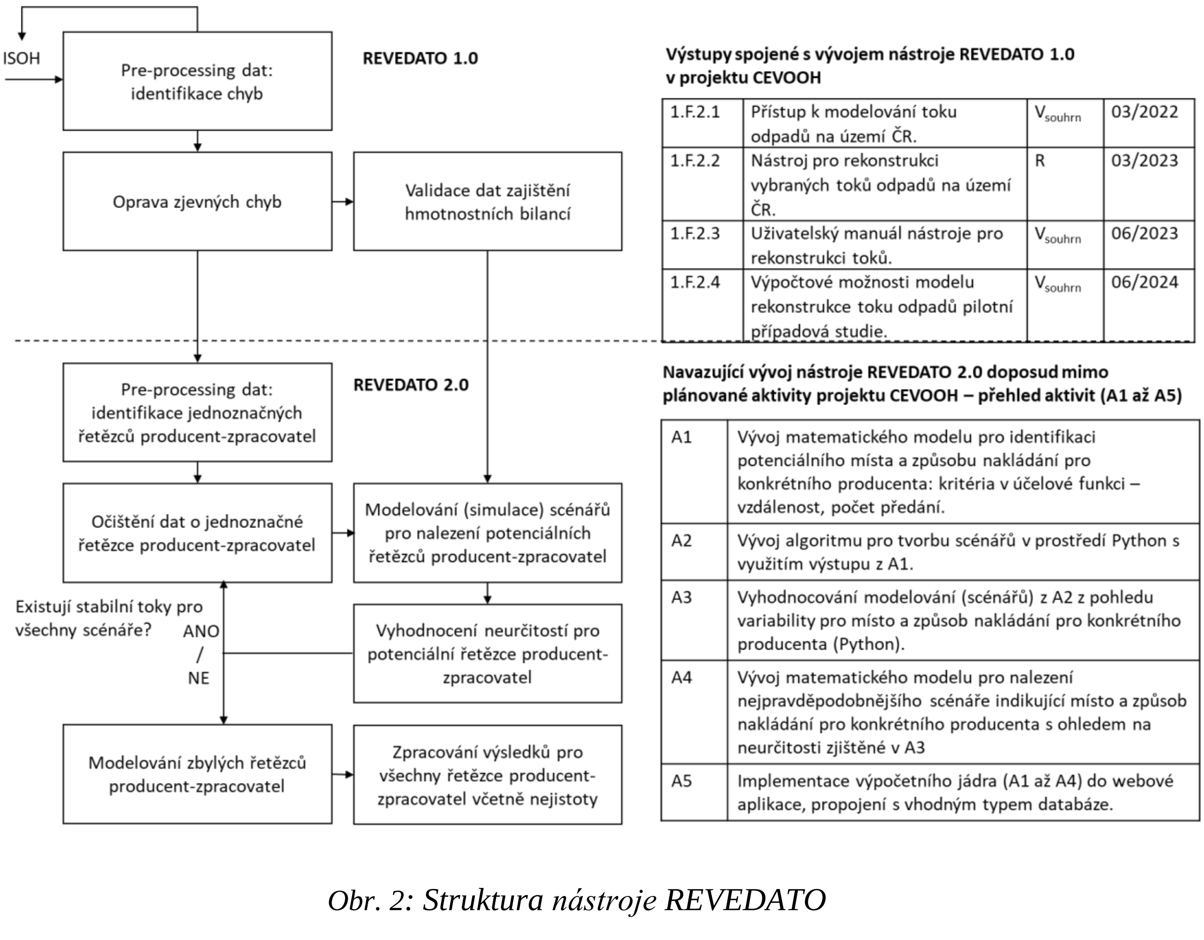
Vytvořené a připravované výpočtové nástroje pro využití v oblasti strategického plánování jsou v podstatě unikátní. V posledním období se autor zaměřil především na vývoj nástroje TIRAMISO 1.0, který již byl předán hlavnímu uživateli – MŽP. V rámci aktuálně řešeného projektu CEVOOH [P3] je nyní pozornost věnována zejména nástroji REVEDATO 1.0 a funkcionalitám, které jsou s tímto nástrojem spojeny. Dále v textu budou blíže popsány nástroje REVEDATO (analýza současného stavu OH) a TIRAMISO (prognóza produkce odpadu) ve variantách 1.0 i 2.0, které autor práce se svým týmem na ÚPI vyvíjí a již byly aplikovány na vybrané odpadové proudy.

3.1 Analýza současného nakládání s odpady

Plánování v oblasti OH se nutně musí opírat o data současné produkce a nakládání s odpady. Reportovaná data o produkci a nakládání jsou prostřednictvím systému ISPOP shromažďována v databázi ISOH [B13]. Přestože evidovaná data prochází vícekrokovou kontrolou, výsledné databáze obsahují chybné výkazy, což komplikuje využití těchto dat pro plánování OH. I za předpokladu ideálního stavu, kdy jsou všechny hodnoty v souladu, není dostupná kompletní informace o toku odpadu. V důsledku spojování (agregace) a rozpojování toků odpadu v uzlech se informace o původci odpadu ztrácejí. To znemožňuje získat informace o způsobu nakládání s odpady pro jednotlivé producenty. Chybějící informace je ale možné odhadovat pomocí bilančních výpočtů. Za účelem identifikace chybných hodnot a modelovaní toku odpadu od producenta do místa zpracování je na ÚPI vyvíjen bilanční nástroj REVEDATO.

Vývoj bilančního nástroje autor této práce založil na multioborovém zapojení studentů různého stupně studia. Prvotní modely pro vyrovnávání dat OH, následně dále vyvíjené a implementované v REVEDATO, byly řešeny v rámci prací [Z1] a [Z2]. Řešení bilančních modelů v OH může být podpořeno zohledněním ekonomických aspektů, které ovlivňují nakládání s odpadem. Ekonomický aspekt byl do modelu implementován skrze preferenci co nejkratší vzdálenosti přepravy. Důvodem je předpoklad, že odpad nebude přemisťován na velké vzdálenosti, pokud to není nutné např. z důvodu omezených kapacit zařízení.

Logistické modely pro optimalizaci toků v síti byly testovány v práci [Z3] a v rámci navazující práce byly modely rozšířeny o stochastické parametry [Z4]. Kombinace modelu pro vyrovnávání dat [A6] a logistiky [A7] zvyšuje přesnost modelu. Konkrétně jsou účelové funkce řešeny samostatně a následně se ve víceúčelové funkci zkombinují normovaná optimální řešení. Modely s různou účelovou funkcí byly analyzovány v práci [Z5]. Výpočetní hledisko této úlohy bylo rozpracování v práci [Z6]. Na zmíněném modelu byla testována účinnost řešení pomocí metody ADMM (alternating direction method of multipliers), model byl implementován v jazyce Julia. Model pro rekonstrukci toku v síti v podobě víceúčelové funkce byl prezentován v publikaci [A8] s případovou studií pro objemný odpad na krajské úrovni České republiky z roku 2015. Uvedené dílčí poznatky a aktivity, byly implementovány v uceleném výpočtovém nástroji Reflow v jazyce Julia [P4] v rámci řešení projektu SPETEP DMS [P6]. Jednalo se o bilanční model, který byl úspěšně aplikován pouze na některá katalogová čísla (kat. č). na úroveň krajů ČR. Pro větší detail územního členění nebylo možné nástroj Reflow využít z důvodu vysoké výpočetní náročnosti. Již tyto výsledky však přinášely cenné informace o transportu odpadu mezi kraji. V současnosti probíhá další vývoj bilančního nástroje, který je nyní nazýván REVEDATO, jehož struktura s rozdělením na moduly REVEDATO 1.0 a REVEDATO 2.0 je znázorněna na obr. 2.



Výstupy spojené s vývojem nástroje REVEDATO 1.0 v projektu CEVOOH

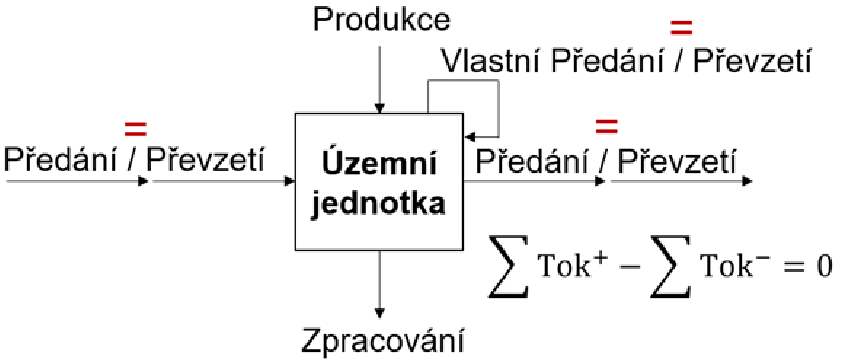
1.F.2.1	Přístup k modelování toku odpadů na území ČR.	V_{souhrn}	03/2022
1.F.2.2	Nástroj pro rekonstrukci vybraných toků odpadů na území ČR.	R	03/2023
1.F.2.3	Uživatelský manuál nástroje pro rekonstrukci toků.	V_{souhrn}	06/2023
1.F.2.4	Výpočtové možnosti modelu rekonstrukce toku odpadů pilotní případová studie.	V_{souhrn}	06/2024

Navazující vývoj nástroje REVEDATO 2.0 doposud mimo plánované aktivity projektu CEVOOH – přehled aktivit (A1 až A5)

A1	Vývoj matematického modelu pro identifikaci potenciálního místa a způsobu nakládání pro konkrétního producenta: kritéria v účelové funkci – vzdálenost, počet předání.
A2	Vývoj algoritmu pro tvorbu scénářů v prostředí Python s využitím výstupu z A1.
A3	Vyhodnocování modelování (scénářů) z A2 z pohledu variability pro místo a způsob nakládání pro konkrétního producenta (Python).
A4	Vývoj matematického modelu pro nalezení nejpravděpodobnějšího scénáře indikující místo a způsob nakládání pro konkrétního producenta s ohledem na neurčitosti zjištěné v A3
A5	Implementace výpočetního jádra (A1 až A4) do webové aplikace, propojení s vhodným typem databáze.

Obr. 2: Struktura nástroje REVEDATO

V aktuálně řešeném projektu CEVOOH [P3] vzniká verze REVEDATO 1.0, která zahrnuje tři bloky. Nejdříve probíhá algoritmus pro identifikaci chyb a následuje oprava zjevných chyb v evidenci partnerů transakce. Např. ZÚJ1 eviduje předání odpadu v rámci stejné územní jednotky. Není zde ale vykázáno, že ZÚJ1 přebírá odpad od ZÚJ1, tzn. je vykázáno předání, ale chybí převzetí. Současně jiné ZÚJ2 eviduje převzetí od ZÚJ1, které přesně odpovídá množství evidovaného ZÚJ1 jako předané. Pravděpodobně zde došlo k chybě evidence partnera transakce, která je opravena na předání uvedeného množství ze ZÚJ1 do ZÚJ2. Navazuje blok zahrnující validaci dat pro zajištění hmotnostních bilancí. Všechny bilancované toky spojené s územní jednotkou jsou zobrazeny na obr. 3. Bilance zajistí soulad množství odpadu, které je na daném území produkováno nebo sem přiváženo, s odpadem, který se odváží nebo se v tomto území zpracovává. Připouští se také možnost vlastního předání a převzetí odpadu v rámci jedné územní jednotky. Mezi územními jednotkami vzniká vazba při převozu odpadu, kdy množství předaného odpadu musí být po bilanci rovno převzatému odpadu. Pozornost v REVEDATO 1.0 je věnována nastavení vah v účelové funkci optimalizační úlohy pro vyrovnávání dat (bilance) [P5]. Bilanci v REVEDATO 1.0 je možné provádět pro libovolná katalogová čísla na úrovni ZÚJ ČR. Matematický model v základním tvaru je uveden v dokumentu [P5].



Obr. 3: Základní bilance v územní jednotce

V rámci rozšíření projektu CEVOOH [P3], nebo synergicky navázaného projektu na CEVOOH bude nástroj REVEDATO dále rozšířen o REVEDATO 2.0 (obr. 2). REVEDATO 2.0 bude umožňovat modelování toku odpadu od producenta do místa zpracování. Nejdříve jsou identifikovány jednoznačné řetězce odpadu, tzn. řetězce kde nedojde k rozdělení toku a vykazované hodnoty si odpovídají v celém řetězci. Tyto jednoznačné řetězce jsou pro další zpracování dat z analýzy vynechány. Následně se modelují scénáře možných toků odpadu tak, že se náhodně zvolí jeden producent odpadu a pro něj se modeluje pravděpodobný řetězec pomocí vícekriteriální úlohy celočíselného smíšeného programování. Tímto výpočtem se omezí možnosti pro zbylé producenty. Následně se náhodně vybírá další producent a optimalizační úloha se zopakuje. Tímto postupem dojde k vyhodnocení všech producentů pro jeden scénář. Tento postup může způsobit stav, kdy je v určitém kroku (pro vybraného producenta) úloha neřešitelná z důvodu nedostatečné dostupné zpracovatelské kapacity. V takovém případě se problém řeší fiktivním tokem odpadu s velkou penalizací. Uvedený postup se opakuje, čímž se vytvoří dostatečné množství scénářů potřebných pro další analýzy. Scénáře jsou vyhodnoceny z pohledu variability pro konkrétního producenta. Producenti se zanedbatelnou, popř. nulovou variabilitou pro nakládání s jejich odpady se považují za jednoznačné a jsou z dalších analýz vynechány. Následují opakované aplikace tvorby scénářů a jejich vyhodnocení, dokud je možné identifikovat takovéto producenty. Úpravy pro zbylé producenty spočívají v komplexnějším pohledu na problematiku, kdy není řešen pouze jeden producent, ale všichni producenti současně v jedné úloze. Okrajové podmínky úlohy jsou definovány na základě odhadnuté variability scénářů. Model je dále doplněn o vhodné váhy, které zajistí racionalitu výsledků z pohledu expertních předpokladů pro konkrétní typy odpadů (např. rozdílná penalizace pro dopravní vzdálenost u NO a OO odpadů apod.).

Vývoj REVEDATO 1.0 a identifikace jednoznačných řetězců z REVEDATO 2.0 je jedním ze zaměření práce [Z7] s plánovaným obhájením v roce 2023, kterou autor této práce vede z pozice školitele specialisty. Současně jsou tvořeny a testovány modely z REVEDATO 2.0 jako součást práce [Z8], která vzniká pod vedením autora tohoto textu.

Problematické body zjištěné v databázi PD ISOH díky bilancím nástroje REVEDATO 2.0 jsou konzultovány s CENIA. Jedním z cílů je vytvořit podporu pro evidenci nakládání s odpady a eliminovat případné chyby již ve fázi reportingu. V navazující činnosti bude do nástroje REVEDATO 2.0 implementován statistický nástroj (viz obr. 1). Tento modul umožní přehledné vyhodnocení současného stavu produkce a nakládání pro vybranou frakci odpadu a lokalitu. V současnosti je možné posoudit nakládání s odpady pouze pro agregovanou (státní) úroveň, protože data neumožňují sledování toku od producenta do místa zpracování. Není tedy známé, jakým způsobem se nakládalo s odpadem od konkrétního producenta. Díky nástroji REVEDATO 2.0 bude možné tyto toky odhadovat s rozumnou mírou neurčitosti. Statistický nástroj bude primárně vyhodnocovat plnění indikátorů OH, které budou v rámci řešení projektu CEVOOH [P3] definované.

3.2 Modelování produkce odpadu

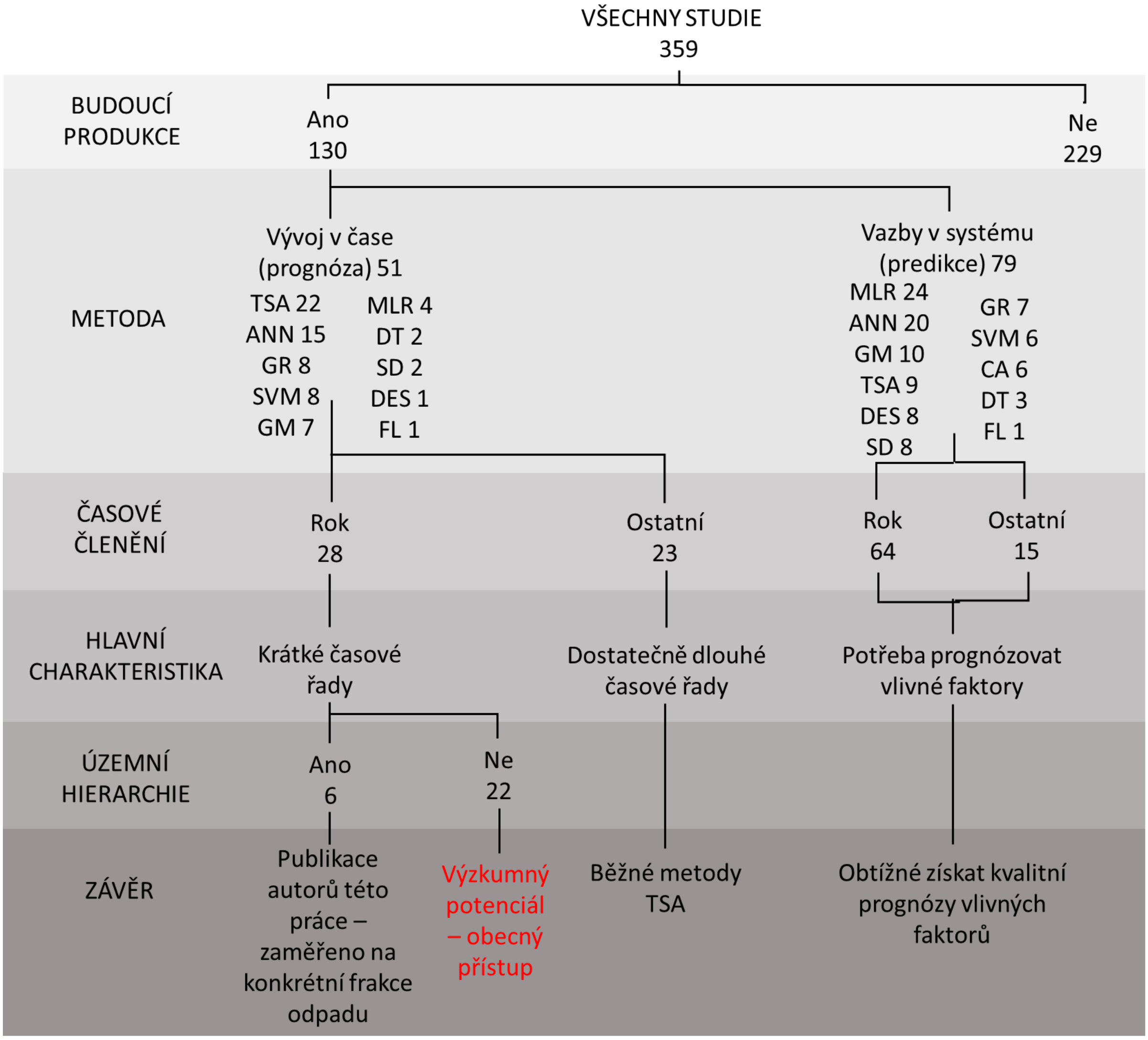
Pro řešení úloh v OH je zásadní vstupní informací očekávaná produkce odpadu (viz kap. 2.1 až 2.3). Modely produkce odpadu lze rozdělit na predikce, prognózy a projekce. Predikční modely se zabývají popisem současné nebo budoucí produkce odpadů s využitím faktorů, které ji ovlivňují [A1]. Tímto způsobem lze podle vlivných faktorů odhadnout produkci odpadu např. v lokalitě bez dostupných dat, zároveň je možné modelovat očekávaný vývoj produkce v budoucnosti. V tomto případě je však potřeba kvalitní prognóza těchto vlivných faktorů. Naproti tomu prognostické modely řeší vždy odhad produkce v budoucnu [A10]. Prognóza v pojetí této práce představuje nejpravděpodobnější scénář budoucího vývoje. Vychází z historických dat a nezahrnuje (až na nezbytné výjimky) expertní hledisko, např. změnu trendu v důsledku očekávaných změn ovlivňujících faktorů apod. Prognóza bude označována jako scénář typu „business-as-usual“ (BAU). Naproti tomu projekce vychází z nějakého definovaného scénáře budoucího vývoje. Projekce zohledňuje odborně nastavené okrajové podmínky tak, aby co nejvíce reflektovala historický průběh. Je tedy maximální možnou měrou konzistentní s prognózou (BAU). Projekce v OH vznikají, když do systému zasahují vnější vlivy a tím se historický trend mění. Tyto vlivy (legislativa, technologický pokrok atd.) nelze kvalitně prognózovat, a proto se často přistupuje k modelování projekcí, tedy scénářů budoucího vývoje ve vztahu ke konkrétním podmínkám zvolených autorem. Scénáře mohou být porovnávány se scénářem BAU za účelem simulace a hodnocení dopadu různých scénářů okrajových podmínek (vývoje).

Dostupná literatura poskytuje řadu různých přístupů k modelování produkce odpadu, jak je shrnuto v rešerši [A11]. Pro vyhodnocení přístupů využívaných k modelování produkce bylo prostudováno 359 publikací. Většina modelů (229 z 359) se zabývala predikčními modely současné produkce odpadu. Běžně užívané predikční modely pro odhalení vlivu vybraných faktorů z oblasti sociologie, ekonomiky, demografie atd. byly testovány na produkci KO v ČR v publikaci [A1]. Konkrétně byly využity modely z oblasti regresní analýzy a rozhodovacích stromů. Výsledky ukázaly, že vhodným kompromisem mezi přesností modelu a jeho interpretovatelností je lineární regresní model. Bylo prokázáno, že kvalita modelu závisí zejména na detailu územního členění, protože nižší územní celky vykazují vyšší variabilitu dat.

Modely produkce odpadu jsou nejčastěji tvořeny pro KO [A11], důvodem jsou zejména milníky EU cíleny právě na KO (viz kap. 2). Významný faktor ovlivňující produkci odpadu na osobu v ČR napříč územními úrovněmi a frakcemi KO je pouze věkové složení obyvatelstva. Pro popis produkce frakcí KO na různých územních úrovních však mají velký význam i další faktory (např. počet ekonomických subjektů, hustota obyvatelstva a úroveň vzdělání). Neexistuje však obecně platný model, který by popisoval vazby pro různý detail územního členění. Plánování OH by tedy mělo být zaměřené na konkrétní faktory ovlivňující produkci KO pro daný detail území. Pro nižší úrovně územního členění (obce a mikroregiony) je ale kvalita modelů nízká. Výsledky pro obce a mikroregiony jsou tedy nespolehlivé a mělo by se k nim přistupovat pouze jako k orientační informaci.

Rešerše [A11] zaměřená na modely produkce odpadu ukázala možnosti využití různých metod modelování. Shrnutí hlavních výstupů pro prognostické modely je na obr. 4. Číselná hodnota udává, kolik modelů z celkem 359 publikací odpovídá dané charakteristice. Je třeba poznamenat, že jedna publikace může zahrnovat více typů modelů, např. z důvodu testování různých metod nebo vývoje hybridní metody. Součet hodnot v jedné vrstvě tedy nemusí odpovídat hodnotě ve vyšší vrstvě. Prognostické modely byly představeny ve 130 publikacích z 359 a lze je rozdělit na dva základní typy. První z nich pracuje pouze s historickými daty o produkci odpadů a modeluje vývoj v čase. Obvykle tyto modely využívají běžné přístupy analýzy časových řad (TSA – time series analysis). Případně jsou aplikovány principy obecné regrese (GR – general regression), lineární regrese (LR) atd. pro modelování trendu v datech, kde nezávislou proměnnou je pouze čas. Druhý typ modeluje vazby mezi produkcí odpadů a různými faktory (ekonomickými, environmentálními, sociologickými atd.) a poté na základě očekávaného vývoje těchto faktorů je vytvořena prognóza produkce odpadů. Tato oblast zahrnuje jak konvenční metody, tak i metody strojového učení.

Pro volbu přístupu je zásadní detail časového členění, protože ovlivňuje délku časové řady. Roční data o produkci odpadu tvoří krátké časové řady, dlouhých časových řad lze dosáhnout pouze ve vyšším detailu (den, týden). Detail časových řad pro oba typy metod (vývoj v čase a vazby v systému) byl na obr. 4 rozdělen na rok a ostatní. V rešerši bylo shromážděno 28, resp. 23 modelů (rok, resp. ostatní) pro metody využívající vývoj v časových řadách a 64 resp. 15 modelů (rok, resp. ostatní) pro metody využívající vazby v systému. Celkem 92 modelů tedy využívalo data v ročním detailu a pouze 28 modelů z 92 aplikovalo metody založené na vývoji v čase. Základním nedostatkem metod využívajících vazby v systému je potřeba dosáhnout kvalitních modelů popisujících tyto vazby [A1] a navíc disponovat prognózami všech vlivných faktorů. Prognózy těchto vlivných faktorů často nejsou vůbec dostupné, nepokrývají celý predikční horizont nebo není dostupná informace o nejistotě prognózy [A13]. Z důvodu menších nároků na vstupní data je vhodnější využití metod založených na vývoji v čase, které i u krátkých časových řad umožňují modelovat trend v datech. Dále je nezbytné zabývat se otázkou územní hierarchie. Ve většině prostudovaných modelů je prognóza tvořena pouze pro jednu úroveň území (stát, kraj, obec apod.). Pro plánování OH je potřeba prognózy produkce odpadů tvořit na různých úrovních územního členění, ale tyto prognózy jsou obvykle prováděny samostatně bez zohlednění hierarchických vazeb. Rešerše zahrnuje pouze 6 modelů krátkých časových řad, které zohledňují územní hierarchii a všechny tyto modely byly již dříve prezentovány autorem této práce. Většina přístupů územní vazby neuvažuje (22 modelů pro krátké časové řady), což bylo shledáno jako jeden z výzkumných potenciálů.



Pozn: TSA – analýza časových řad (time-series analysis), GR – obecná regrese (general regression), MLR – vícenásobná lineární regrese (multiple linear regression), ANN – umělé neuronové sítě (artificial neural network), GM – gray model, SVM – metoda podpůrných vektorů (support vector machine), SD – systém dynamics, CA – korelační analýza (correlation analysis), des – popisné metody (description methods), FL – fuzzy logika, DT – rozhodovací stromy (decission trees).

Obr. 4: *Vyhodnocení rešerše, upraveno z [A11]*

Na základě rešerše byly identifikovány dva hlavní směry výzkumného potenciálu v oblasti modelování produkce odpadu, které budou diskutovány dále v textu.

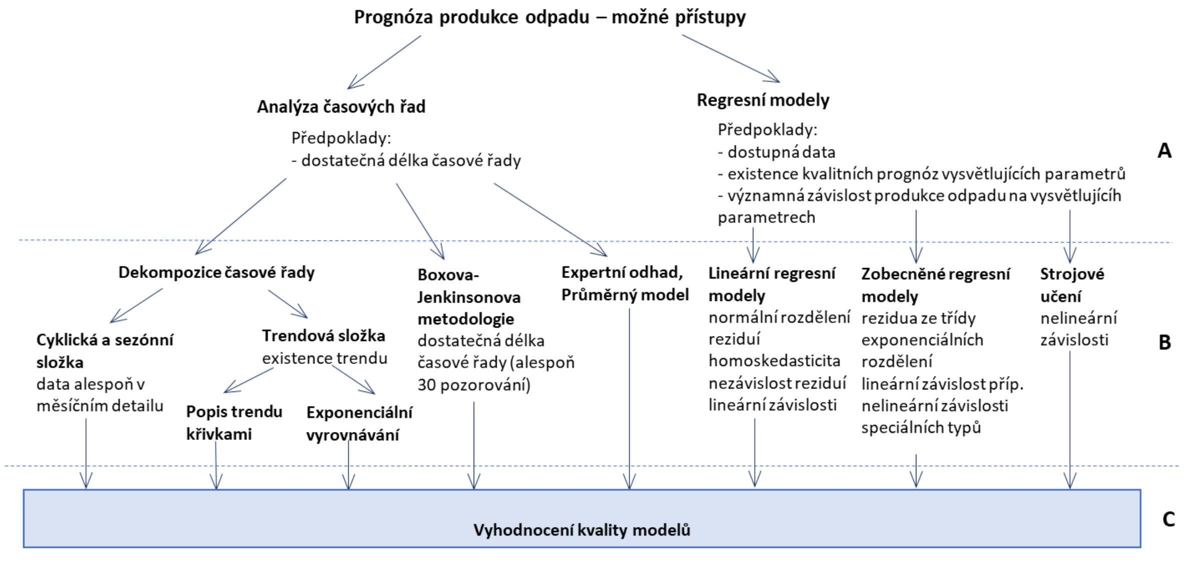
- Volba vhodné metody (kap. 3.2.1)
  Prezentované studie používají různé metody prognózování, aniž by bylo objasněno, proč byla konkrétní metoda zvolena. Na základě poznatků z provedené rešerše bylo sestaveno doporučení pro výběr vhodné metody. Primárně se zohledňuje dostupnost a vlastnosti dat. Schematické znázornění pro volbu metody je popsáno na obr. 5.
- Obecný přístup k prognózování produkce odpadů (kap. 3.2.2)
  Uvedené modely prostudované v rešerši jsou formulovány pro konkrétní frakce odpadu a jejich obecnou použitelnost nelze obvykle odvodit. Navíc jsou dřívější publikace zaměřeny na některý krok modelování. Obvykle se jedná jen o samotný model prognózy, a to bez všech nutných kroků jako je např. pre-processing dat, který

není pro krátké řady obecně popsán. V rámci této práce je uveden přístup použitelný pro libovolnou frakci odpadu se zohledněním územní hierarchie. Hlavní charakteristikou přístupu je provázanost prognózy a projekce se zahrnutí pre-processingu dat. To umožňuje modelovat budoucí produkci odpadu s přihlédnutím k reálným podmínkám.

3.2.1 VOLBA VHODNÉ MODELOVACÍ METODY

Postup výběru vhodné modelovací metody pro odhad vývoje produkce odpadu, popsán v jednotlivých krocích níže, je zobrazen na obr. 5 ve formě stromové struktury. Tento postup je obecně platný a byl navržen v rámci projektu TIRSMZP719 [P2] za použití rozsáhlé rešerše představené výše v této kapitole. Postup volby metody pro prognózování produkce odpadu se doporučuje následující:

1. Stanovení významných vysvětlujících parametrů (podmínka: dostupná data pro všechny územní celky systému).
2. Přepočet dat aktivitním členem na jednotkové množství (podmínka: aktivitní člen je významný vysvětlující parametr).
3. Úroveň A: volba obecného přístupu (podmínka: platnost předpokladů přístupů).
4. Úroveň B: volba vhodných metod a výpočet odhadu vývoje těmito metodami (podmínka: platnost předpokladů metod a zohlednění časové náročnosti výpočtu).
5. Úroveň C: vyhodnocení kvality výsledků modelů posouzením kritérií kvality, např. R^2 (koeficient determinace), $MAPE$ (střední absolutní procentuální chyba) a chyby odhadu vývoje. Následně se doporučuje využití metody s nejvyšší kvalitou modelu.



Obr. 5: Metody pro odhad vývoje produkce odpadu, TIRSMZP719 [P2]

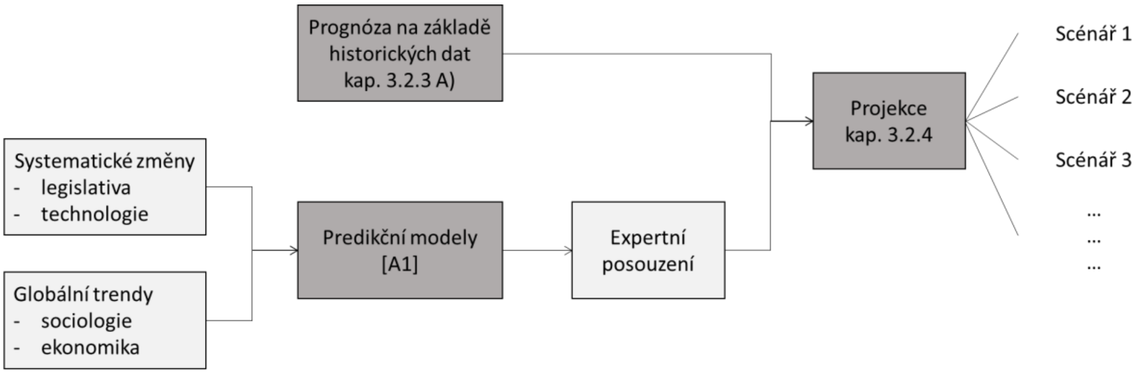
Výsledná prognóza by měla splňovat následující kritéria:

- Soulad prognóz produkce odpadů: měla by být zachována hierarchická struktura územních jednotek [A10] a frakcí odpadu [A5].
- Intervaly spolehlivosti: očekávaná nejistota je nedílnou součástí výsledků. Ve většině dříve publikovaných modelů však informace o nejistotě prognózy chybí.
- Hodnocení kvality modelu: většina modelů zahrnuje alespoň nějaké hodnocení kvality. Běžně používanými kritérii jsou R^2, $MAPE$, MAE (střední absolutní chyba)

a $RMSE$ (střední kvadratická odchylka). Rovněž se doporučuje ověřit kvalitu prognózy na základě testovacích dat. Před vytvořením prognózy je určitá část dat na konci časové řady alokována právě pro testování. Následně je intervalový odhad budoucí produkce porovnán s tímto předem alokovaným souborem dat.

3.2.2 OBECNÝ PŘÍSTUP K PROGNÓZOVÁNÍ PRODUKCE ODPADŮ

Zásadním a často opomíjeným krokem prognózování je kvalitní pre-processing dat, viz [P7]. Autor tohoto textu doporučuje k prognózování libovolné frakce odpadu využít model kombinující prognózu a následnou projekci, viz obr. 6. V prvním kroku by měla být vytvořena prognóza (BAU) produkce odpadu na základě historických dat, která zachovává historický vývoj také do budoucna, viz kap. 3.2.3 A) až C). Jedná se o základní informaci pro posouzení očekávaného vývoje. Produkci odpadů budou ale ovlivňovat systematické změny (legislativní, technologické atd.) a globální trendy (sociologie, ekonomika atd.). Pomocí predikčních modelů [A1] lze odhadnout vliv těchto faktorů na produkci odpadů, ale jejich vývoj do budoucna nelze dobře předvídat. Předpokládaný vývoj vlivných faktorů je předmětem kombinace statistických modelů (predikční modely a dlouhodobé trendy) a expertního posouzení. Tvůrce projekce má možnost nastavit okrajové podmínky modelu a tím může tvořit jednotlivé scénáře. Formou scénářů je možné odhadnout budoucí produkci odpadů, která bude co nejlépe odpovídat předpokládaným podmínkám. Doporučené přístupy k prognózování byly uplatněny pro vytvoření certifikované metodiky pro provádění dlouhodobé prognózy produkce odpadů [P7] a softwaru TIRAMISO [P1] ve verzi 1.0, které vznikly v rámci řešení projektu TIRSMZP719 [P2]. V případě modelů produkce odpadu lze přikládat značnou váhu již samotné prognóze, která odráží chování producentů a pomocí projekcí je možné zohlednit změny systému. Přínos projekcí je ale mnohem významnější v případě nakládání s odpady. Zahrnutí projekcí do modelování nakládání s odpady je téměř vždy nutné, protože závisí na nových zpracovatelských kapacitách, které nelze odhadnout z historických dat.



Obr. 6: Schematické znázornění integrace prognózy a projekce

3.2.3 CERTIFIKOVANÁ METODIKA PRO PROVÁDĚNÍ DLOUHODOBÉ PROGNÓZY PRODUKCE ODPADU

Výše uvedené obecné poznatky a doporučení pro provádění prognózy byly využity pro konkrétní výstup výzkumu – certifikovanou metodiku pro prognózování produkce odpadů [P7]. Cílem certifikované metodiky je sjednocení přístupů pro prognózování používaných v ČR. Prvotní bilanční nástroj *Justine* [A14] pro vyrovnávání dat v hierarchické struktuře byl představen v práci [Z9]. Na dosavadní výsledky navázala práce [Z10] a [Z11]. U zmíněných závěrečných prací figuroval autor této práce jako konzultant nebo školitel specialista. Výstupy nástroje Justine byly upraveny a využity pro řešení projektů [P8] a později [P9]. Certifikovaná metodika [P7] navázala na dosavadní činnost autora této práce v oblasti prognózování produkce odpadu. Metodika stanovuje obecný postup na sebe navazujících kroků, které by měla každá prognóza obsahovat. Podle metodiky [P7] má prognóza čtyři fáze: příprava dat, pre-processing, processing a post-processing. V následující části textu budou shrnuty hlavní myšlenky a doporučení pro prognózování, detaily k jednotlivým částem výpočtu jsou k dispozici ve zmíněné metodice [P7] a jejich přílohách [P10].

A) PROGNÓZA

Příprava dat

Data potřebná pro prognózování lze ve všeobecnosti rozdělit do dvou oblastí, a to data o produkci odpadů (příp. způsobů jeho nakládání) a data vlivných faktorů. Obecně je nejdříve nutno provést analýzu dostupnosti požadovaných dat [A13]. Při hledání vazeb mezi daty o produkci odpadu a vlivnými faktory se doporučuje znormovat data logickou jednotkou (počet obyvatel, rozloha atd.) a následně provést korelační a regresní analýzu. Analýza vazeb mezi produkcí odpadu a vlivnými faktory byla provedena v práci [Z12] a v navazující práci [Z13]. Z těchto prací vycházely další analýzy a výsledky. Predikční modely prezentované ve studii [A1] ukázaly, že na nižších územních celcích pokrývají tyto modely velmi malou část variability. Některé vazby mohou být výrazně ovlivněny lokálními podmínkami a lze očekávat odlišné vazby v různých skupinách územních celků. V globálním pohledu mohou tyto lokální závislosti zcela zaniknout. Pro jejich identifikaci je vhodné hledat územní celky obdobného charakteru. Doporučuje se použít shlukovou analýzu a hledat vazby pro více disjunktních souborů dat. Je velmi pravděpodobné, že se nedostaví požadovaný výsledek z důvodu nedostatku vysvětlujících proměnných.

Pro zahrnutí vlivných faktorů do prognózy produkce odpadů je navíc nutné, aby prognóza vlivných faktorů pokrývala celý predikční horizont. Pro prognózu produkce odpadů se z těchto důvodů nedoporučuje využívat jiná data než demografická. Data z ostatních oblastí (sociologie, ekonomie atd.) mají obvykle větší variabilitu než data o produkci odpadů a neexistují jejich dlouhodobé prognózy [P11]. Krátkodobé prognózy těchto faktorů obvykle vykazují příliš velkou nejistotu i na rok dopředu. Navíc zde hrozí změny v nalezených vazbách v čase, které mohou mít negativní dopad na kvalitu prognózy.

Pre-processing

Při práci s časovými řadami je nutné se vypořádat s některými vlastnostmi, které by mohly výsledný model prognózy negativně ovlivnit. V rámci pre-processingu dat je proto nutné věnovat pozornost anomáliím, jako jsou odlehlé hodnoty, skoky v datech a změny trendu. Rešerše pro přístupy k pre-processingu dat na časových řadách byla vypracována v rámci projektu TIRSMZP719, výstup V7 [P12]. Historická data o produkci odpadu mohou být ovlivněna různými vlivnými faktory (ekonomickými cykly) a jednorázovými vlivy (pandemie covid-19), jejichž důsledkem jsou zmíněné anomálie v časových řadách produkce odpadů. Jak už bylo zmíněno výše, začlenění socio-ekonomických dat do prognóz je velmi omezené. Lze ale využít vyhlazení historických dat o vliv různých faktorů. Vyhlazení je vhodné realizovat pouze na agregovaných datech za ČR, protože data vlivných faktorů nejsou často pro větší územní detail dostupná. Nicméně vyhlazení se projeví také do nižších územních celků díky vyrovnávání dat (viz níže *processing*). Hlavní myšlenka vyhlazení historických dat vychází z odhalení významných faktorů ovlivňujících produkci odpadu. Následné nalezení průměrného vývoje a cyklu v datech vlivných faktorů umožní eliminovat tento vliv z historických dat o produkci odpadu za pomocí regresního modelu.

Pro dostatečně dlouhou řadu existuje celá řada metod detekce bodových odlehlých hodnot (např. shluková analýza, statistické vyhodnocení, informačně teoretické a spektrální metody). Dostatečná délka řady nebývá specifikována, ale v jednotlivých studiích se typicky pracuje s menším množstvím delších časových řad (alespoň stovky pozorování), výjimečně se objevují metody pro časové řady obsahující pouze vyšší desítky pozorování. Pro krátké časové řady (méně než 20 pozorování, což je případ současných dat OH v ČR) však nebyly v dostupné literatuře nalezeny vhodné přístupy. Autor tohoto textu doporučuje využít přístup, který nejdříve odstraní trend z časové řady a potom analyzuje rezidua. Tento postup lze považovat za kombinaci statistických metod. Kombinuje totiž metody pro nestacionární řady (odstranění trendu) a klasické testy pro odlehlé hodnoty. Pro vyhlazení trendu se doporučuje využít Holtovu metodu a následně analyzovat rezidua s využitím Grubbsova testu. Podrobný popis přístupu je v příloze (Příloha 3, certifikované metodiky [P10]). Pro některé typy dat může být vhodné analyzovat odlehlé hodnoty v podobě logaritmické transformace dat o produkci odpadu. Množství identifikovaných odlehlých hodnot se touto transformací bude snižovat. To lze považovat za žádoucí v případě, že se očekává heteroskedasticita v datech. Úskalí nastává v časových řadách s výskytem nulových hodnot, které nelze zlogaritmovat. V případě vhodného ošetření nulových hodnot se doporučuje logaritmickou transformaci pro potřeby analýzy odlehlých hodnot zvážit. Vhodné ošetření by mělo významně redukovat nebezpečí, že se nulová hodnota stane automaticky odlehlou nebo bude mít významný vliv na podobu trendu.

V pre-processingu je vhodné pracovat na standardizovaných datech. U identifikace odlehlých hodnot standardizace není nutná, avšak v případě detekce skoků a změn trendu v datech je důrazně doporučená. Umožní totiž stanovit pouze jednu kritickou mez stejnou pro všechna území a frakci odpadu. Pokud by data nebyla standardizována, bylo by zapotřebí určit kritickou mez pro každou časovou řadu zvlášť. Navržený postup pro identifikaci odlehlých hodnot a změn trendu je detailně popsán v certifikované metodice [P7]. Přístup je založen na posouzení úhlů spojnic sousedních bodů a úhlů, které subsekvence časové řady svírají s x-ovou osou. Pokud byla produkce odpadu ovlivněna vnějším zásahem (např. legislativou), který měl za následek systematickou změnu produkce, doporučuje se skoky a změny trendu v datech neidentifikovat. U těchto časových řad se očekává systematicky vývoj v podobě S-křivky a je vhodné použít pro prognózu celou historii časové řady. Vhodný přístup byl publikován pro bio-odpad v ČR, u kterého došlo k legislativní změně v roce 2014 [A12].

Processing

V rámci úlohy řešené v projektu TIRSMZP719 [P2] (viz certifikovaná metodika [P7]) byla pro odhad vývoje produkce odpadu zvolena metoda založená na modelování trendu v historických datech pomocí vhodných funkcí. Důvodem jsou nedostupné prognózy vlivných faktorů pro dostatečně dlouhý časový horizont, takže není možné využít metody z větve regresních modelů (viz obr. 5). Krátká časová řada v ročním detailu zase omezuje využití některých přístupů pro analýzu časových řad, avšak na krátkých časových řadách lze úspěšně modelovat trend. Trend p_t v historických datech je možné modelovat vhodnou křivkou f_t, kde t je index času:

$$p_t = f_t. \tag{1}$$

Při výběru funkčního předpisu f_t pro model trendu je nutné zohlednit vlastnosti vybraných funkcí s ohledem na očekávané chování produkce odpadu. Je vhodné hledat kompromis mezi kvalitou proložení podle zvoleného kritéria (např. R^2, $MAPE$) a vlastnostmi vybraných funkcí. Jak bylo zmíněno v certifikované metodice [P7] následující vlastnosti funkce byly vyhodnoceny jako podstatné:

- Monotonie – tvar funkce pro model trendu má za úkol zajistit, že se trend v průběhu horizontu prognózy nemění z rostoucího na klesající a naopak. Trend se předpokládá za monotónní, případné oscilace okolo trendu způsobené sezónní nebo cyklickou složkou není možné na krátké časové řadě ročního detailu sledovat. Požadavkem na monotonii se také sníží riziko přeučení modelu. Autoři metodiky [P7] doporučují využít pro modelování trendu mocninnou funkci. Výhodou je její široké uplatnění pro rostoucí i klesající trend.
- Omezený růst – některé časové řady nastolily v historických datech velmi významný růst (resp. pokles), který může mít až exponenciální charakter. Takový vývoj je často zaznamenán po změně systému, např. sběrem nové frakce odpadu. Není možné očekávat, že by tak zásadní růst daná časová řada vykazovala dále po celý horizont prognózy. Trend produkce odpadu by v takovém případě rostl nad reálné meze. Pravděpodobnější scénář je takový, že až se bude produkce dané frakce blížit její maximální možné výtěžnosti, růst bude postupně zpomalovat. V takových případech se doporučuje modelovat trend pomocí křivky ve tvaru písmene S, tzv. S-křivky.

V některých případech není vhodné hledat model trendu pomocí složitého funkčního předpisu. Jedná se zejména o časové řady s vysoce variabilními daty, nebo o případy kdy model trendu nemá přínos oproti jednoduchému modelu konstantního proložení dat (průměrem dat, poslední hodnotou atd.). Pokud došlo v historických datech k systematické změně trendu např. z důvodu změny legislativy, doporučuje se pro model trendu aplikovat přístup založený na teorii kredibility [A12]. Díky začlenění kolektivní informace u takových modelů je možné modelovat reakci na zavedenou změnu také u časových řad, kde se tato změna zatím neprojevila.

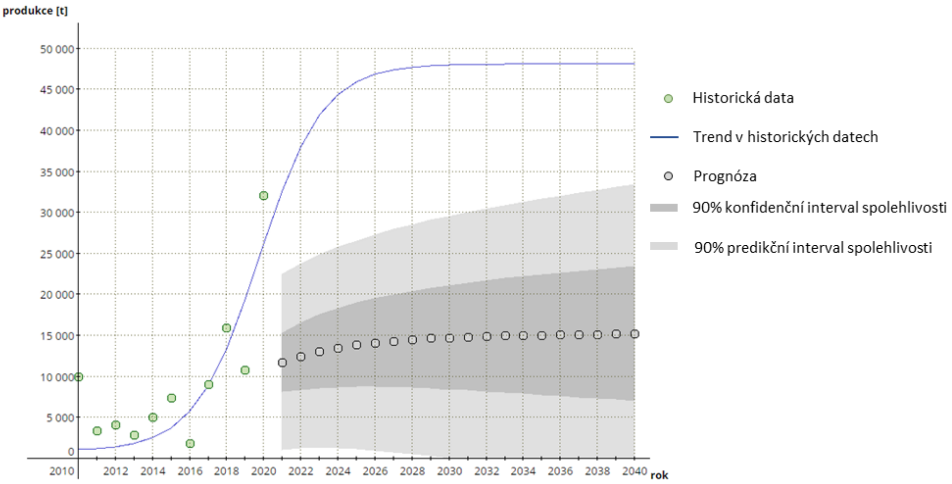
Modely trendů obecně nezachovávají hierarchické vazby, tj. součet regionálních trendů neodpovídá státnímu trendu a podobně je tomu i u vazeb frakcí odpadu. K zajištění těchto vazeb ve výsledné prognóze se doporučuje použít principy vyrovnávání dat. Model pro vyrovnávání dat lze formulovat v aditivní nebo multiplikativní podobě (viz Příloha 5 certifikované metodiky [P10]). Volba podoby modelu závisí především na vstupních datech a výpočetních možnostech zvoleného řešiče pro optimalizační úlohu. Multiplikativní podoba zápisu má významnou výhodu u odpadů s vysokou produkcí, u kterých se při testovacích výpočtech aditivního modelu vyskytovaly numerické a zaokrouhlovací chyby (např. SKO – směsný komunální odpad, v roce 2020 asi 2120 kt produkce na úrovni ČR). Na formě modelu (aditivní nebo multiplikativní) dále závisí nastavení vah v účelové funkci modelu (viz Příloha 5 certifikované metodiky [P10]). Doporučuje se zahrnout dva typy vah:

- *Váhy pro zajištění totožné významnosti vstupních dat*
  Tento typ vah by měl zajistit, aby vstupní údaje byly pro účelovou funkci stejně významné formou standardizace vstupních dat. Vzhledem k tomu, že se bilancuje hierarchická struktura, jsou přirozeně vstupní data na úrovni ČR mnohonásobně vyšší než data na nižších úrovních, např. ORP. Případně je možné do vah zahrnout preferenci dat vyšší úrovně, což může mít význam zejména pokud se součet trendů na nižší úrovni

významně odklání od trendu na vyšší úrovni (viz Příloha 5 certifikované metodiky [P10]).

- *Váhy zohledňující kvalitu proložení dat*
  Časové řady historických dat vykazují různou variabilitu. Spolehlivější model trendu mají taková data, která historicky vykazovala stabilnější vývoj. Potom je žádoucí tento trend zachovat i do budoucna. Váhovací systém umožní kvantifikovat kvalitu proložení historických dat a její zohlednění při bilanci (vyrovnání dat). Větší důvěra je přisouzena datům se stabilním trendem v historii.

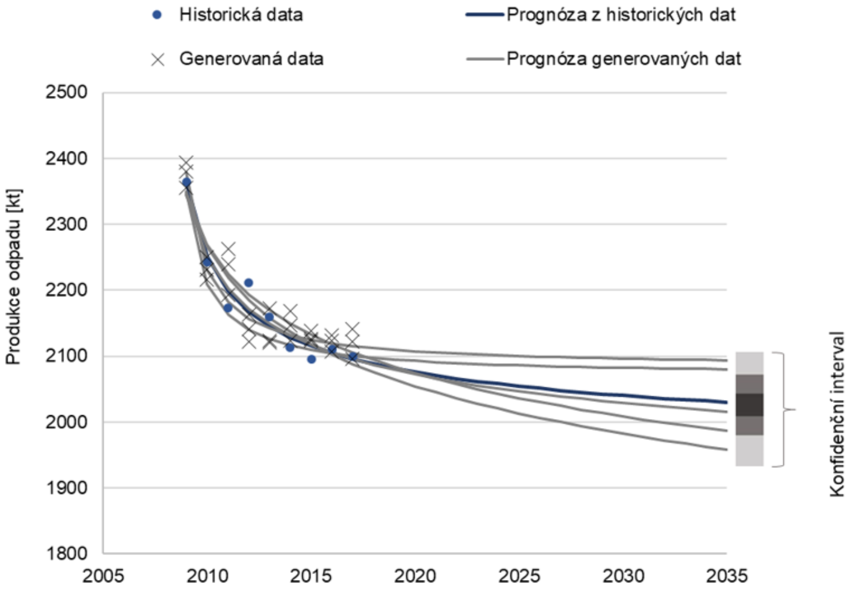
Vyrovnávání dat má navíc schopnost upravit prognózy různých časových řad, pokud z nějakého důvodu došlo ke zkreslení trendu. Ukázka je uvedena na obr. 7. Data vykazují rostoucí trend s významným nárůstem v posledním roce časové řady. Nelze jednoznačně stanovit, zda se v tomto roce jedná o odlehlou hodnotu. V pre-processingu nebyla odlehlá hodnota identifikována, proto byl modelován významný nárůst trendu pomocí S-křivky. Díky vyrovnávání dat, kdy se bilancovaly trendy z ostatních územních celků pomocí hierarchických vazeb, je výsledná prognóza významně snížena oproti původnímu trendu.



Obr. 7: Ukázka vyrovnávání dat v prognóze produkce odpadu, TIRAMISO [P1]

V rozsáhlých úlohách může dojít k situaci, kdy nebude možné najít optimální řešení. Obvykle je v takových případech k dispozici alespoň relaxované řešení, tzn. bilance nejsou splněny přesně. Pro některé tvorby prognóz to nemusí být problém. V opačných případech se doporučuje zmenšit optimalizační úlohu tak, že budou bilancovány menší množiny odpadových toků, např. pouze pro jednotlivá katalogová čísla.

Výstupem uvedených kroků prognózy jsou bodové odhady množství produkovaného odpadu. Avšak jedním ze základů teorie pravděpodobnosti je skutečnost, že pro spojitou náhodnou veličinu pravděpodobnost nabytí konktrétně stanovené hodnoty je nulová. Kvůli tomu jsou ve velké míře používány intervalové odhady, které jsou schopné se zadanou spolehlivostí stanovit meze pro výskyt bodové hodnoty prognózy. Bodové odhady prognózy jsou tedy doplněny o konfidenční a predikční intervaly. V případě konfidenčních intervalů se jedná o interval spolehlivosti pro střední hodnotu produkce odpadu, tedy bilance. Predikční intervaly udávají nejistotu pro individuální pozorování závisle proměnné (produkce odpadu). Protože konkrétní hodnoty se v jednotlivých letech mohou odklánět od trendu, predikční intervaly bývají širší než konfidenční intervaly. V rámci certifikované metodiky [P7] byla doporučena konstrukce intervalových odhadů pomocí metody známé jako parametrický bootstrap. Princip spočívá v tom, že se určí rezidua dat od trendu. Poté proběhne generování nových datových sad tak, že se z množiny reziduí vybere hodnota rezidua, která se přičte k trendu. Na nové datové sadě se provede prognóza podle přístupu uvedeného výše v této kapitole, zahrnující model trendu a vyrovnávání dat. Doporučuje se realizovat alespoň 30–50 bootsrapových opakování. Na základě nově obdržených hodnot prognóz pro generovaná data jsou konstruovány intervaly spolehlivosti pomocí Studentova rozdělení. Princip konstrukce pásů spolehlivosti je znázorněn na obr. 8 a detailní popis výpočtu je v Příloze 6 certifikované metodiky [P10].



Obr. 8: Konstrukce konfidenčního intervalu, [P10]

B) PROJEKCE

Výsledkem prognózy je scénář BAU. Nastávají však situace, kdy je do systému zasahováno zvnějšku a tím je měněn historický trend. Pomocí predikčních modelů je možné kvantifikovat dopad systematických změn a globálních trendů na produkci odpadu. Změny vlivných faktorů nelze většinou kvalitně prognózovat, proto jsou výsledkem expertního posouzení (viz obr. 6). Z tohoto důvodu se přistupuje ke konstrukci projekcí, tj. scénářů budoucího vývoje, ve vazbě na konkrétní okrajové podmínky zvolené autorem scénáře. Tyto scénáře je možné vytvářet s ohledem na cíle OH, které jsou obvykle stanoveny na národní úrovni. Následně jsou scénáře pro národní úroveň přeneseny až na úroveň obcí. Projekce má tedy dvě části – sestavení scénáře na národní úrovni a rozpad scénáře na nižší územní celky. Vstupní informací pro tvorbu projekcí jsou výsledky prognózy (BAU), která je upravena v rámci projekce tak, aby byly splněny podmínky scénáře.

Pro tvorbu projekcí byl v rámci certifikované metodiky [P7] představen přístup dle principů znázorněných na obr. 6. Detailní popis přístupu je také součástí přílohy 7 certifikované metodiky [P10]. Tvorba projekcí je představena na KO. Předpokládá se, že vnější zásahy mohou ovlivnit separaci odpadu a celkovou produkci odpadu prostřednictvím prevence před jeho vznikem. Vyšší produkce separované frakce odpadu ve scénáři je způsobena vyšší separací sledovaných frakcí (např. papír, plast, sklo) z neseparovaného odpadu (např. SKO, ObjO – objemný odpad). Autor scénáře má možnost nastavit následující hodnoty:

- prevence před vznikem odpadu [%],

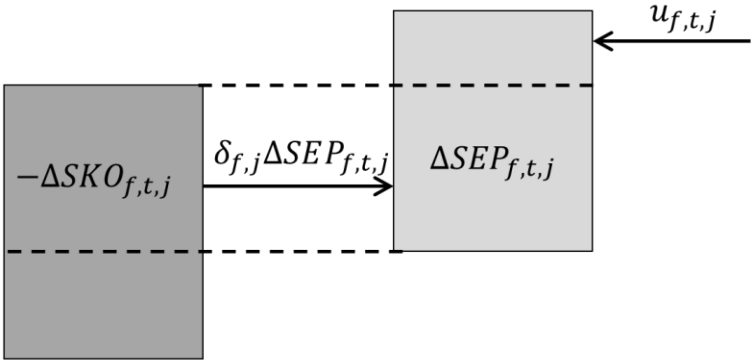
- míra separace sledovaných frakcí odpadu [%], která je vyšší než v BAU.

Výsledek scénáře pro národní úroveň je obdržen výpočtem série rovnic, které jsou detailně specifikovány v Příloze 5 certifikované metodiky [P10]. Hlavními výstupy jsou produkce a složení neseparovaného odpadu a produkce separovaného odpadu pro ČR.

V dalším kroku jsou národní cíle přeneseny do jednotlivých obcí podle jejich potenciálu pro změnu. Vyšší potenciál pro změnu mají ty obce, které jsou podle BAU dál od maximální míry separace (potenciálu). Je tedy nutné stanovit maximální míru separace, tj. poměr vyseparovaného odpadu sledované frakce a celkového množství této frakce včetně jejího zůstatku v neseparovaném odpadu. Detailní popis pro určení potenciálu obcí pro změnu je k dispozici v dokumentu (Příloha 7 certifikované metodiky [P10]). Pro scénářová řešení na úrovni obcí platí následující:

- Scénář nepřekračuje potenciál pro změnu, který byl stanoven pro konkrétní územní jednotku.
- Všechny územní jednotky vykazují posun ke splnění scénáře, pokud to potenciál dovoluje.
- Změna pro splnění scénáře na nižších celcích, než ČR probíhá tak, že se jednotlivá území v míře plnění potenciálu nepředbíhají a mají monotónní charakter. Toto pravidlo by mohlo být porušeno pro konkrétní příklady obcí, kde jsou k dispozici doplňkové informace a lze pro ně sestavit samostatný model.
- Procentuální změna míry separace v jednotlivých obcích oproti BAU je lineární. Tento vztah je dán zjednodušením modelu. V případě více dostupných informací je možné odhadnout i tvar nelineární vazby mezi potenciálem a změnou, nebo dokonce stanovit průběh změn individuálně pro každou obec.

Přínos scénářových řešení je zejména v případech, kde se vyskytují vazby v datech. Možné navýšení separace odpadu v rámci projekce je ovlivněno potenciálem v neseparovaném odpadu, převážně je řešena separace z SKO. Složky SKO v současnosti nelze prognózovat, protože není k dispozici dostatečná časová řada o složení SKO. Vztah mezi množstvím separovaného odpadu (SEP) a SKO byl nejdříve ověřen statistickou analýzou dat, avšak statisticky významné vazby byly identifikovány pouze pro bio-odpad s katalogovými čísly 20 02 01 a 20 01 08. Pro ostatní katalogová čísla statistická analýza neodhalila významnou závislost. V případě, že statistická analýza dat nepřináší významné výsledky pro popis vazby SEP a SKO, doporučuje se aplikovat bilanční model představený v Příloze 7 certifikované metodiky [P10] a publikaci [A15]. Modelované vazby mezi SKO a SEP jsou znázorněny na obr. 9. Známé vstupní hodnoty jsou meziroční změna produkce SKO ($\Delta SKO_{f,t,j}$: f – frakce odpadu, t – rok, j – území) a meziroční změna SEP ($\Delta SEP_{f,t,j}$). V modelu se minimalizuje vliv nového odpadového toku ($u_{f,t,j}$). Výstupem je odhad $\delta_{f,j}$, který udává, jaká část nově vyseparovaného odpadu pochází z SKO. Díky hodnotě $\delta_{f,j}$ je možné odhadnout potenciál pro separaci frakce f z SKO na území j a zohlednit jej v projekcích.



Obr. 9: Schematické znázornění přesunu odpadu z SKO do SEP, upraveno z [A15]

Principy prognóz a projekcí zahrnuté v certifikované metodice [P7], které byly popsány výše, byly implementovány v software TIRAMISO ve verzi 1.0 spravovaného MŽP. Software TIRAMISO 1.0 obr. 10 slouží k vytvoření prognózy a scénářů (projekcí) produkce odpadů v ČR na úrovni státu, krajů a ORP. TIRAMISO 1.0 využívá MŽP ke zpracování a hodnocení strategických dokumentů v oblasti OH ČR.

Prognóza produkce odpadů

Webová aplikace zpřístupňuje dlouhodobou prognózu odpadů na základě dat z integrovaného systému odpadového hospodářství (ISOH).

Webová aplikace je výsledkem projektu **Prognózování produkce odpadů a stanovení složení komunálního odpadu (TIRSMZP719)**, poskytovatel: Technologická agentura České republiky, program Beta 2, období řešení 2019 až 2021. Projekt byl řešen pro potřeby Ministerstva životního prostředí, Vršovická 1442/65, 100 10 Praha 10.

Přesmyčkou významných písmen v označení projektu vznikl akronym aplikace **TiramisO**.

Způsob provedení prognózy je v souladu s metodikou XXXnázev V9XXX.

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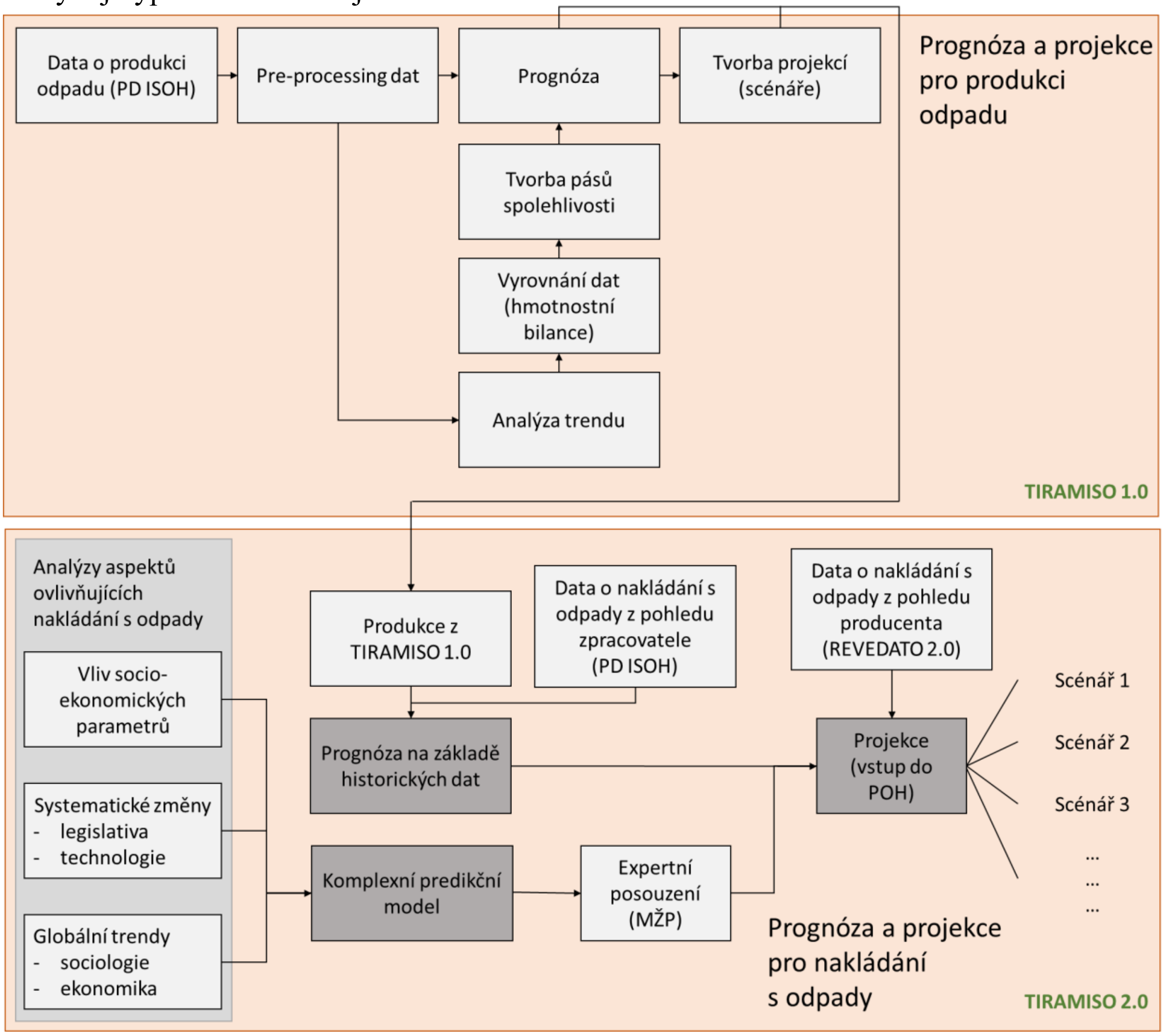
Obr. 10: Software TIRAMISO [P1], výstup projektu TIRSMZP719 [P2]

3.2.4 *PLÁNOVANÁ NAVAZUJÍCÍ ČINNOST*

TIRAMISO 1.0 [P1] je zaměřen výhradně na prognózu a projekci produkce odpadů. Na konci projektu TIRSMZP719 [P2] byl nástroj TIRAMISO 1.0 předán hlavnímu uživateli – MŽP. Nástroj TIRAMISO 1.0 disponuje uživatelským rozhraním s možností tvorby prognóz a projekcí podle stanovených kritérií. MŽP tento nástroj využívá zejména pro reportování stavu OH na státní i regionální úrovni a pro tvorbu strategických dokumentů. Přirozeným požadavkem MŽP je disponovat podobným nástrojem také pro nakládání s odpady. Navíc indikátory OH, podle kterých je posuzováno plnění milníků EU, jsou navázány na způsoby nakládání s odpady. Prognózy a projekce nakládání s odpady jsou tedy zcela zásadní pro plánování změn v OH tak, aby ČR byla schopná dosáhnout cílů EU a vyhnula se sankcím, které plynou z jejich neplnění. Nástroj TIRAMISO 2.0 pro prognózu a projekci nakládání s odpady by měl být nástavbou na již existující software TIRAMISO 1.0. Vazba mezi jednotlivými moduly je znázorněna na obr. 11. V případě TIRAMISO 2.0 se předpokládá synergická návaznost na předchozí výsledky, čímž je možné efektivně využívat prostředky na vývoj výpočetních nástrojů.



Obr. 11: Návaznost softwaru TIRAMISO 1.0 a TIRAMISO 2.0

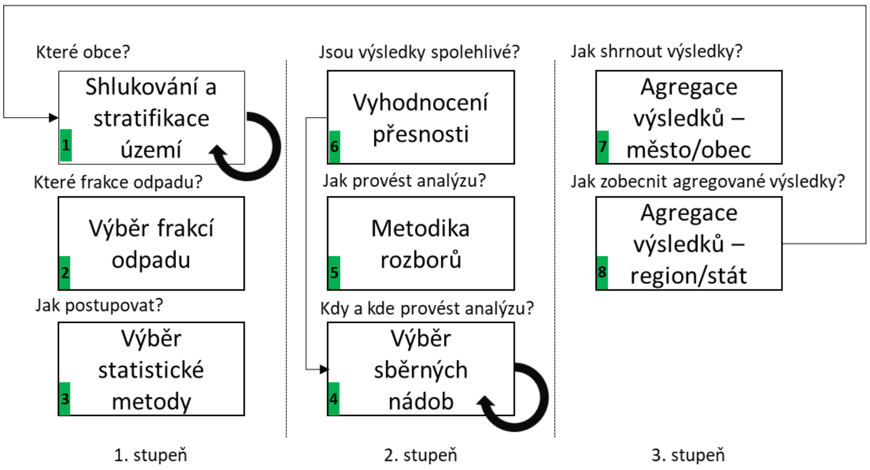
4 MODELY A PŘÍSTUPY PRO PLÁNOVÁNÍ ODPADOVÉHO A OBĚHOVÉHO HOSPODÁŘSTVÍ

Plánování v oblasti OH je velmi komplexní problematika, do které vstupuje mnoho ovlivňujících faktorů. Pro tvorbu koncepcí a strategií v OH je žádoucí využívat podpůrné nástroje. V rámci výzkumných aktivit autora vznikla celá řada těchto nástrojů pro podporu rozhodování v OH založených na optimalizačních modelech, které je snaha uvádět do praxe. V této kapitole budou postupně představeny přístupy pro odhad složení odpadu (kap. 4.1), pro optimalizaci sběrné infrastruktury (kap. 4.2), pro logistiku odpadů (kap. 4.3) a pro návrh zpracovatelské infrastruktury (kap. 4.4) a volbu technologií v ZEVO (kap. 4.5).

4.1 Složení odpadu

Podstatnou část KO tvoří SKO. V roce 2020 v ČR se jednalo asi o 49 % [B15]. Údaje o složení SKO jsou proto nezbytné pro nastavení strategií nakládání s KO. Jedná se zejména o plánování efektivního sběru odpadů, vyhodnocení potenciálu pro jeho separaci a recyklaci a možná zlepšení ostatních částí řetězce nakládání s KO. Jednotlivé metodiky pro rozbory SKO se liší především ve sledovaných frakcích, metodách vzorkování a statistickém zpracování výsledků. V EU byla snaha sjednotit přístup k rozborům SKO v podobě sady doporučení v dokumentu SWA-tool [B16]. Pro ČR vznikla jednotná metodika provádění rozborů SKO [P13] v rámci projektu TIRSMZP719 [P2]. Méně častou úlohou jsou rozbory složení separovaných frakcí odpadu. Ojedinělým případem je například publikace [B17], která se zabývá složením plastových obalů za pomocí několika skenovacích technik. Informaci o složení odpadu zpracovávaného ve zvoleném zařízení je možné odhadnout na výstupu z tohoto zařízení (energie, rezidua). Příkladem může být analýza popílku po zpracování odpadu v ZEVO, jako byla prezentována ve studii [A16].

Rozhodující vliv na analýzy složení má více faktorů, které souvisí s volbou přístupů v různých částech analýz. Souvislost a návaznost jednotlivých částí znázorňuje obr. 12. První otázkou (úloha 1 v obr. 12) je nalezení vhodných obcí, kde mají být rozbory provedeny. Hledají se podobnosti v oblasti sociálních, ekonomických, demografických a dalších faktorů. Je zásadní vybrat takové obce, které pokrývají variabilitu celé oblasti. Úloha 2 se zabývá výběrem odpadových frakcí, které budou při rozborech sledovány. Volba frakcí odpadu závisí zejména na účelu realizace rozborů (I., II., III. úroveň). Důležitým bodem je stanovení postupů v souladu se statistickými metodami (úloha 3). Druhý stupeň stratifikace zahrnuje výběr jednotlivých sběrných míst a nádob, kde budou rozbory provedeny (úloha 4). Konkrétní město, které je reprezentantem na základě stratifikace z úlohy 1, lze rozdělit podle vybraných faktorů do skupin. V těchto skupinách budou vybírány sběrné nádoby. Při výběru obcí a konkrétních sběrných míst k rozboru je žádoucí vybrat takové vzorky, aby měly co nejvyšší vypovídací hodnotu z hlediska celého území. Rovněž je nutné volit frekvenci rozborů, a to jak v rámci týdne (na základě četnosti odběru a konkrétních dnů svozu), tak v rámci celého roku s ohledem na sezónnost výskytu některých frakcí. Analýzy je také vhodné opakovat (zvyšovat četnost vzorků), dokud není dosaženo zadané absolutní nebo relativní přesnosti. Stěžejní částí je metodika analýzy složení odpadu (úloha 5), které se mohou značně lišit. Existuje několik standardizovaných metod pro provádění analýz [B16], [B18], které jsou definovány příslušnými směrnicemi. Důležitou součástí celého přístupu je zpracování výsledků pro odběrná místa. Výsledky jednotlivých analýz se často výrazně liší. Použití vhodných statistických metod může určit správnost a přesnost výsledků (úloha 6). Úloha 7 se zabývá agregací výsledku za celou obec. Poslední část tématu analýzy složení odpadu (úloha 8) by měla navrhnout metodu agregace dílčích výsledků rozborů v obcích pro odhad složení odpadu na úrovni regionů a státu.



Obr. 12: Blokové schéma úloh řešených při analýze složení odpadu, upraveno z [A17]

Podle provedené rešerše [A17] se publikace ve většině případů věnují popisu metodiky rozboru, tedy jak probíhá třídění odpadů na požadované frakce (úloha 5). Některé oblasti analýzy složení odpadu, definované na obr. 12, jsou řešeny spíše výjimečně. V dřívějších studiích byla také detailněji rozpracována témata výběru frakcí odpadu (úloha 2). V návaznosti na tyto závěry rešerše [A17] byly vyvinuty přístupy pro úlohu 1 (kap. 4.1.1) a úlohy 3, 6, 7, 8 (kap. 4.1.2). Jedná se o části analýz, které mají zásadní dopad na výsledky rozborů, ale často nejsou ve studiích zohledněny. Myšlenky navrženého obecného přístupu představeného v kap. 4.1.1 a kap. 4.1.2 byly využity u výstupu [P14] projektu TIRSMZP719.

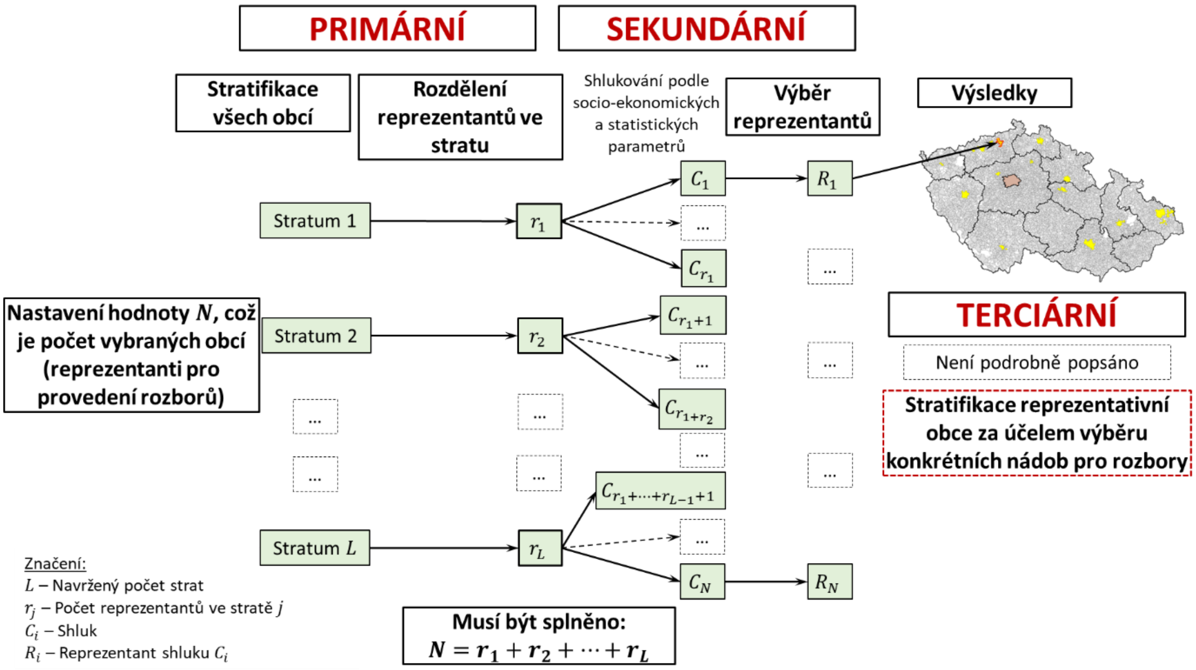
4.1.1 STRATIFIKACE ÚZEMÍ

Z důvodu omezených zdrojů (finančních i jiných) není možné provést rozbory pro všechna území. Řešením je preferovat omezený počet obcí/podoblastí. Tyto obce (reprezentanti) by měly být schopny reprezentovat složení odpadu sledovaného regionu (státu), kterou tvoří velké množství obcí. Omezený je i počet analyzovaných nádob na odpad v daném území. Pro výběr reprezentantů byla navržena víceúrovňová stratifikace, která může pomoci získat odhad složení odpadu pro celé území, viz obr. 13. Detailní popis přístupu ke stratifikaci území je k dispozici ve studii [A17].

Stratifikace je provedena ve třech úrovních – primární, sekundární a terciární stratifikace. V primární stratifikaci jsou obce rozděleny na L strat (Stratum 1 až Stratum L), přičemž platí následující vlastnosti:

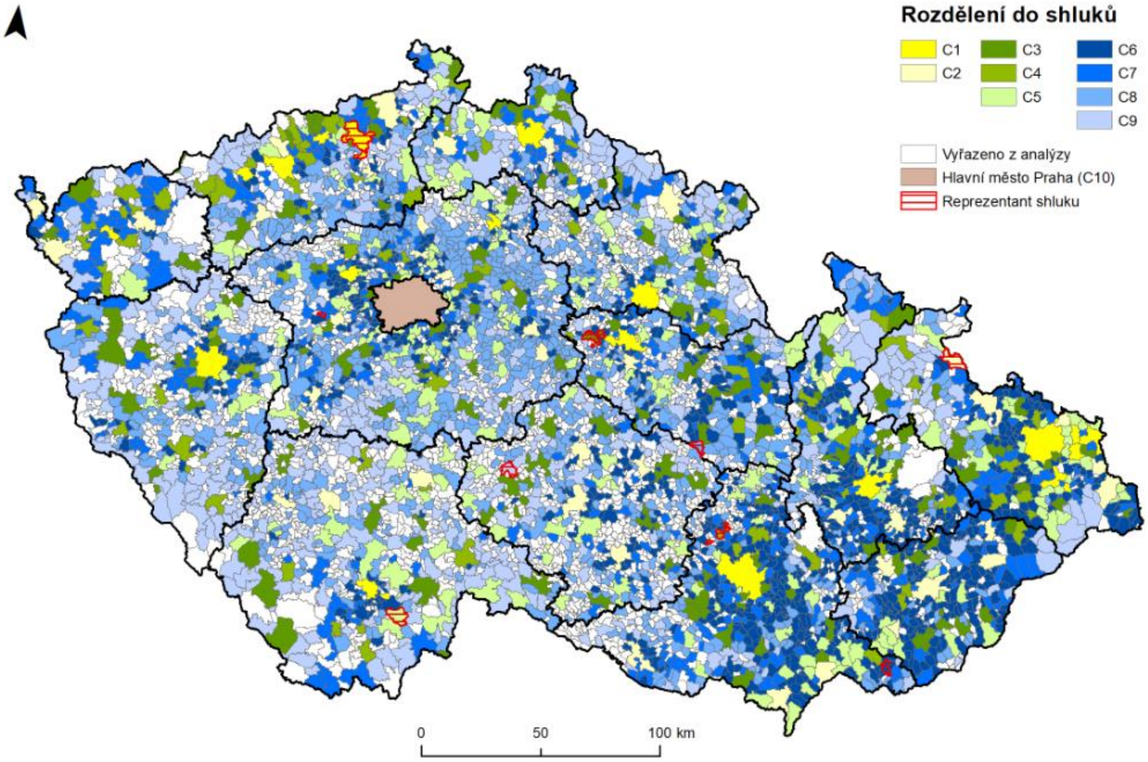
- každá obec patří právě do jednoho strata,
- obce v daných stratech mají podobnou velikost (měřeno celkovým množstvím SKO vyprodukovaného v této obci),
- strata mají podobnou velikost (měřeno celkovým množstvím SKO vyprodukovaného v daném stratu).

Každé stratum z primární stratifikace je v sekundární stratifikaci rozdělena pomocí shlukové analýzy podle socio-ekonomických a demografických charakteristik obcí, výstupem jsou tedy shluky obcí (C_1 až C_N). Dále jsou zvoleni reprezentanti (R_1 až R_N) těchto shluků (C_1 až C_N), většinou se jedná o centroidy shluků (níže v textu bude popsána také možnost volby více reprezentantů v jednom shluku). V terciární stratifikaci je vhodné rozdělit domácnosti v dané obci do více strat podobného typu (např. sídliště a rodinné domy). Pro výběr konkrétních nádob reprezentantů v terciární stratifikaci je možné využít podobné principy jako na národní úrovni. Počet nádob analyzovaných v každém stratu (Stratum 1 až Stratum L) by měl být úměrný množství vyprodukovaného SKO.



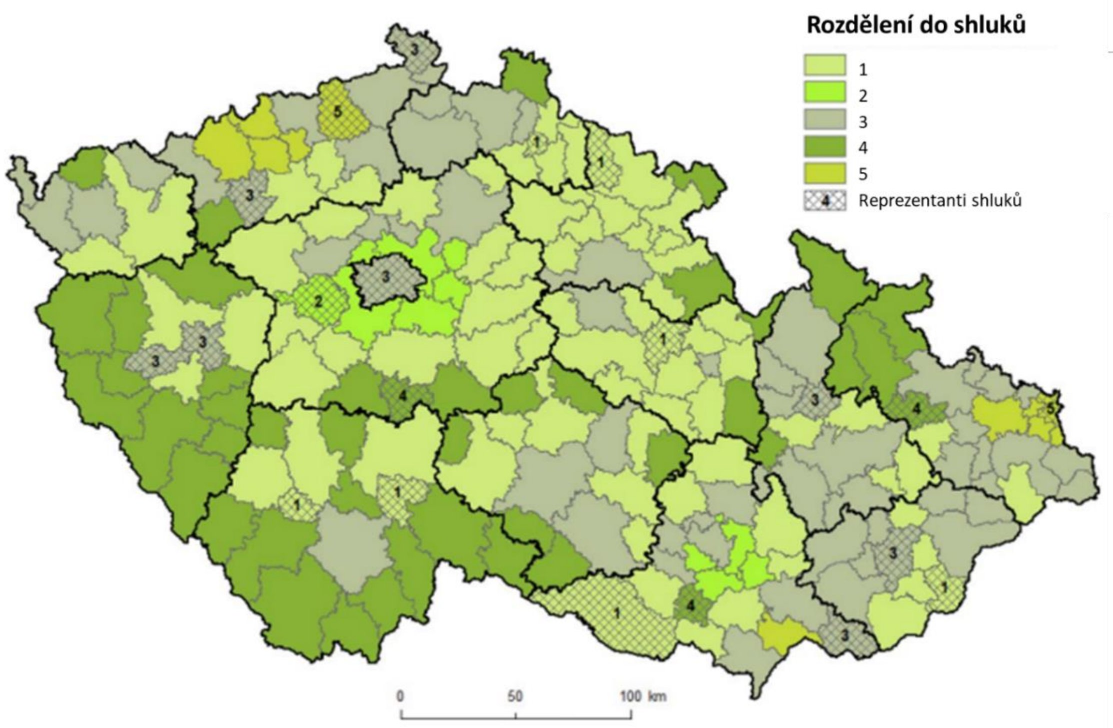
Obr. 13: Schéma víceúrovňové stratifikace a výběr reprezentantů, upraveno z [A17]

Stratifikace obcí ČR je znázorněna na obr. 14, reprezentant každého shluku je zvýrazněn červeným ohraničením. Posledním zástupcem je hlavní město Praha (C10). Z mapy je patrné, že rozdělení obcí do shluků nezávisí primárně na jejich geografické poloze, ale jsou distribuovány po celém území. Zařazení do shluků je určeno především velikostí a dalšími charakteristikami, detaily jsou k dispozici v publikaci [A17].



Obr. 14: Stratifikace obcí ČR a volba reprezentantů, upraveno z [A17]

V dosavadních přístupech pro stratifikaci je pro každý shluk vybrán jeden reprezentant, který nejlépe charakterizuje dané území. Odhad variability jednotlivých strat lze lépe stanovit, pokud bude více reprezentantů v jednom shluku. Jedná se o nový přístup k plánování analýz složení SKO prezentovaný v publikaci [A18]. Principem modelu pro volbu reprezentantů je minimalizovat vzdálenost reprezentantů od ostatních bodů a současně maximalizovat vzdálenost reprezentantů od sebe navzájem. Počet reprezentantů v určitém shluku je předem zvolený. Tímto přístupem je zaručeno, že zvolení reprezentanti co nejlépe popisují charakter shluku, kterému náleží. Výsledky případové studie pro ČR na úrovni ORP jsou znázorněny na obr. 15.



Obr. 15: Volba reprezentantů shluků, úroveň ORP ČR, upraveno z [A18]

4.1.2 STATISTICKÉ ZPRACOVÁNÍ VÝSLEDKŮ A AGREGACE ÚZEMÍ

Mezi podceňovanou úlohu v rámci analýz složení SKO podle provedené rešerše [A17] patří podrobné statistické zpracování výsledků a agregace naměřených dat z rozborů do větších územních celků s vazbou na provedenou stratifikaci. Velmi často se z naměřených dat určuje pouze průměrné složení vybraných frakcí, variabilita dat nebo intervalové odhady složení jsou uváděny pouze výjimečně. Nakonec jsou získané výsledky často zobecňovány na větší územní celky bez logických a statistických postupů (viz certifikovaná metodika [P13], výpočty byly implementovány v nástroji [P15]). To následně vede ke zkreslení výsledků, které jsou pak chybně aplikovány při plánování OH.

Všechny publikace, které byly součástí rešerše v příspěvku uvedeném v příloze 8 popisují výsledky rozborů jako poměr vybraných frakcí odpadu na celkové hmotnosti. Výpočty však předpokládají normální rozdělení dat, které obvykle není ověřeno příslušnou statistickou metodou. U frakcí, které mají v SKO významné zastoupení (např. papír, plasty), nepředstavuje tento striktní předpoklad značný problém. Avšak u frakcí, které mají malé zastoupení (např. elektroodpad, kov) by obsahoval interval spolehlivosti i záporné hodnoty, což neodpovídá skutečnosti. Další zásadní oblastí ovlivňující výsledky rozborů je stanovení počtu vzorků tak, aby byla dosažena požadovaná přesnost odhadů. Většina přístupů se zaměřuje na relativní přesnost. U frakcí s malým podílem na celkové hmotnosti vyžaduje požadovaná relativní přesnost velmi velké množství vzorků, což není časově ani ekonomicky možné provést. Tento nedostatek do určité míry eliminuje stanovená minimální absolutní přesnost. Zde je však nutné vhodnou metodikou rozlišit, které kritérium je vhodné pro danou frakci, aby byla zajištěna dostatečná přesnost a relevantní závěry z případových studií.

Přístup k odhadu složení odpadů na zkoumaném území závisí na úrovni stratifikace, která byla provedena před realizací rozborů [A17]. Doporučuje se aplikovat vícestupňovou stratifikaci (viz obr. 13) s iterativním hodnocením přesnosti pro stanovení počtu vzorků. Výsledkem je odhad procentuálního množství frakce $\hat{R}_n$ (2):

$$\hat{R}_n = \frac{\sum_{i=1}^{n} Y_i}{\sum_{i=1}^{n} T_i}, \tag{2}$$

kde Y_i je hmotnost sledované frakce odpadu (papír, plast, bio-odpad apod.) a T_i je celková hmotnost odpadu v nádobě i z celkového počtu n sběrných nádob. Získaná empirická data jsou statisticky vyhodnocena; pro každou ze sledovaných frakcí jsou stanoveny bodové a intervalové odhady. Intervalové odhady je možné konstruovat pomocí Studentova rozdělení (3):

$$(\hat{R}_n - t_{df}(1-\alpha/2)\, v_{\hat{R}_n}, \hat{R}_n + t_{df}(1-\alpha/2)\, v_{\hat{R}_n}), \tag{3}$$

kde $t_{df}(1-\alpha/2)$ je $1-\alpha/2$ kvantil Studentova t-rozdělení s df stupni volnosti. Stanovení stupňů volnosti je detailně popsáno ve studii v příloze 8. Jedná se o běžně využívaný přístup ke konstrukci intervalových odhadů. Z důvodu symetrie však může interval spolehlivosti zasahovat do záporných hodnot, což je problém u frakcí s malým procentuálním zastoupením. Asymetrické pásy spolehlivosti, které nezasahují do záporných hodnot, je možné konstruovat pomocí logitové varianty (4). Z pohledu implementace se však jedná o komplikovanější přístup než předchozí varianta.

$$\hat{\theta}_n = \log\left(\frac{\hat{R}_n}{1-\hat{R}_n}\right), \tag{4}$$

Alternativou je také využití bootstrapu, který je výpočetně jednoduchý, avšak velmi závislý na vstupních datech. Doporučuje se tedy jeho využití jako kontrolní prvek pro některou z výše uvedených variant.

Představený přístup je založen na iterativním statistickém vyhodnocování jednotlivých analýz složení odpadu, dokud není splněno kritérium relativní, nebo absolutní přesnosti v jednotlivých stratech. Relativní, nebo absolutní hodnocení přesnosti se stanoví podle frakce odpadu. Jak už bylo zmíněno výše, absolutní přesnost je vhodná u frakcí s malým podílem. Rozbory odpadů mohou být v některých lokalitách příliš nákladné nebo obtížné. Přístup tedy poskytuje doporučení pro případné přidávání nových vzorků tak, aby byl ekonomicky co nejméně zatěžující.

Navržený přístup ke zpracování výsledků z analýz složení odpadu (úloha 7 a úloha 8 na obr. 12) je součástí přílohy 4a [P15] *Metodiky pro stanovení složení směsného komunálního odpadu z obcí a komunálního odpadu* [P13]. Příloha 4a [P15] je nástroj pro vyhodnocení výsledků rozborů v podobě xlsm souboru, který přímo implementuje principy představené v kap. 4.1.2. Autor této habilitační práce se podílel na vývoji tohoto nástroje [P15], který vznikal ve spolupráci s odborníky v oblasti statistiky z Matematicko-fyzikální fakulty Univerzity Karlovy.

4.2 Sběrná infrastruktura

Jednou z možností, jak zvýšit separaci a následnou recyklaci KO, je zapojování nových frakcí odpadu do separovaného sběru. Jak ukázaly dřívější studie, vhodné umístění sběrných míst, zejména s ohledem na docházkové vzdálenosti, má významný vliv na kvalitu a míru separace [B19]. Úkolem pro samosprávy obcí je tedy zajistit vhodnou infrastrukturu sběrných míst odpadů, která by měla být navržena také s ohledem na ekonomiku daného řešení. Náklady na vybudování sběrné infrastruktury a její následnou obsluhu jsou ovlivněny především množstvím sběrných míst. Umístění sběrných míst přímo ovlivňuje také svoz odpadu, což má dopad na ekonomiku a environmentální zátěž nakládání s odpady [B21].

V rámci rozsáhlého výzkumu lokačních úloh, který se věnoval volbě vhodných míst pro umístění nějakého prvku tak, aby byla dostatečně pokryta celá oblast, byly vytvořeny nástroje, které lze použít také k optimalizaci systémů nakládání s odpady [B20]. Úloha kombinující problematiku rozmisťování sběrných nádob s následným plánem svozu byla definována ve studii [B22]. Lokalita sběrných míst, jejich kapacita, počet a svozové trasy byly ve zmíněné studii určeny kombinací exaktních a heuristických přístupů. Infrastrukturu sběrných míst lze navrhnout podle různých kritérií, která však jdou obvykle proti sobě. Např. snížení docházkové vzdálenosti nutně vede k většímu počtu sběrných míst a tím i zvýšení nákladů.

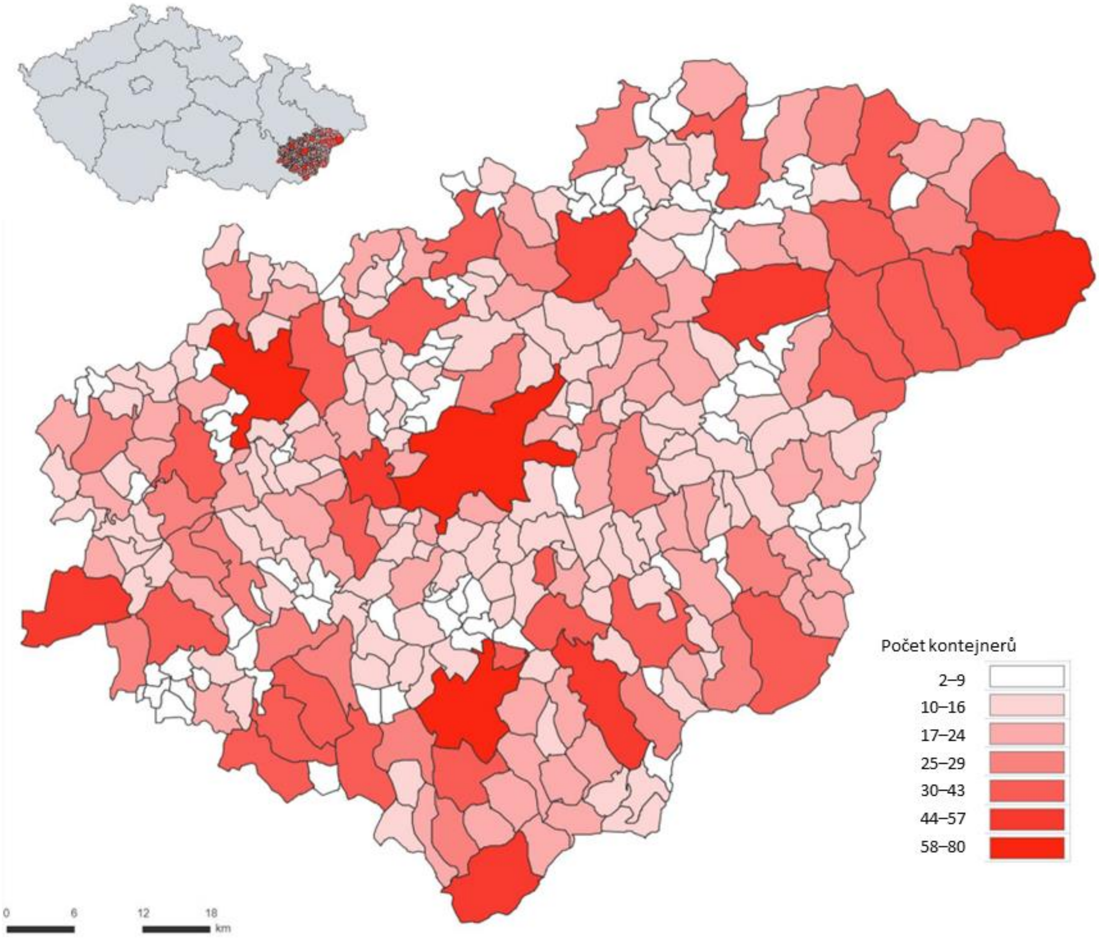
Pro řešení úloh rozmístění sběrných míst je zásadní zohlednit očekávanou produkci odpadu v dané lokalitě (viz kap. 3.2). Dále budou uvedeny modely pro optimalizaci sběrné sítě s jedno-kriteriální (kap. 4.2.1) a vícekriteriální (kap. 4.2.2) účelovou funkcí.

4.2.1 JEDNO-KRITERIÁLNÍ LINEÁRNÍ MODEL

Model je sestaven jako úloha smíšeného celočíselného programování s cílem minimalizovat celkový počet sběrných míst, přičemž je omezena průměrná docházková vzdálenost. Výsledkem je tedy optimální počet sběrných nádob a jejich lokace. Zohledněna je kapacita sběrné sítě, která musí pokrýt celkovou produkci dané frakce odpadu. Produkce odpadu se může významně lišit v různých obcích a tuto variabilitu je nutné zohlednit, aby měla navržená sběrná síť vyhovující kapacitu.

Publikace [A19] představila řešení koncepčního plánování pro analýzu potřebného rozmístění nádob na regionální úrovni. V případě chybějících hodnot se doporučuje využít shlukovou analýzu pro popis variability mezi obcemi a následně pomocí regresní analýzy modelovat požadovaný počet sběrných nádob.

Případová studie jedno-kriteriálního modelu byla prezentována pro jedlé tuky a oleje. Obce v ČR jsou od roku 2021 povinné určit místa pro jejich separovaný sběr [B23], bylo tedy nutné pro tuto novou frakci odpadu zajistit potřebnou infrastrukturu. Komplexní řešení pro celou ČR by vyžadovalo kvalitní stratifikaci a mnoho výpočtů pro reprezentativní obce. Z důvodu výpočetní náročnosti byl pro případovou studii vybrán Zlínský kraj, avšak s ohledem na podobnost regionů jsou některé výsledky aplikovatelné i na ostatní regiony [A19]. Na základě výpočtu se doporučuje přidělit 609 kontejnerů pro Zlínský kraj, což odpovídá v průměru 950 obyvatelům na jeden kontejner. Doporučený počet kontejnerů pro obce Zlínského kraje je znázorněn na obr. 16. Obecná povaha tohoto přístupu umožňuje podobně plánovat další frakce odpadu, což může být užitečné zejména pro nové frakce odpadu, jako je textil, který má být v ČR povinně separován nejpozději od roku 2025 [B23].



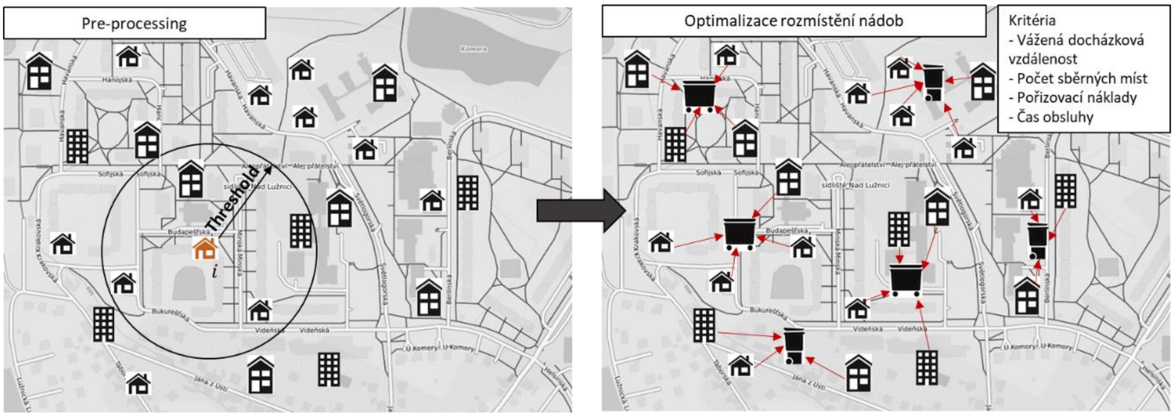
Obr. 16: Znázornění navrženého počtu sběrných nádob pro oddělený sběr jedlých tuků a olejů, Zlínský kraj, upraveno z [A19]

4.2.2 VÍCE-KRITERIÁLNÍ LINEÁRNÍ MODEL

Rozšíření modelu představeného v kap. 4.2.1 o další kritéria vedlo k formulaci více-kriteriální úlohy smíšeného celočíselné programování [A20]. Byla uvažována následující kritéria, které je cílem minimalizovat:

- docházková vzdálenost – ochota obyvatel separovat odpad;
- počet sběrných míst – náklady na svoz odpadu;
- náklady na pořízení sběrných nádob;
- doba nutná k obsloužení sběrných míst – náklady související s obsluhou sběrných míst.

Úloha je schematicky znázorněna na obr. 17.



Obr. 17: Znázornění přístupu pro optimalizaci sběrné sítě, upraveno z [A20]

V prvním kroku jsou v rámci pre-processingu vybrány kandidátské lokality pro umístění sběrného místa podle produkce odpadu a počtu obyvatel v okolí této lokality, viz obr. 17. Dále jsou definovány různé podoby jedno i více-kriteriálních modelů s různou kombinací uvedených kritérií. Jednotlivá kritéria mohou v účelové funkci jít proti sobě, kdy snížení jednoho kritéria (např. docházková vzdálenost) vede ke zvýšení jiného kritéria (např. počet sběrných míst). Výsledky jsou prezentovány na vybrané obci ČR pro separovaný plast. Nejlepších výsledků dosahuje vícekriteriální model, který minimalizuje zhoršení od optimálních hodnot všech jednokritériálních úloh. Byly posouzeny pořizovací náklady pro zřízení infrastruktury sběru plastového odpadu při využití různých typů účelové funkce. Tyto náklady jsou v testované obci o 23 % nižší (pro model minimalizující zhoršení od optimálních hodnot všech jednokriteriálních úloh) než ve srovnání s dalším testovaným vícekriteriálním modelem na principu min-max. Tato nižší pořizovací cena je na úkor docházkové vzdálenosti, která je pro model „min-max" o 12 % nižší než pro druhý posuzovaný model. Navržená metoda slouží zainteresovaným subjektům a samosprávám obcí k rozhodování o počtu kontejnerů k nákupu a jejich rozmístění na analyzovaném území. Přidanou hodnotou představeného přístupu v [A20] je i omezení související s minimální naplněností nádob a průměrná naplněnost za všechny nádoby.

Podobu modelu pro optimalizaci sběrné infrastruktury na daném území je vhodné volit v závislosti na cílech a rozsahu konkrétní úlohy. Vždy se však doporučuje zohlednit očekávanou produkci odpadu (kap. 3.2) a vhodně tak dimenzovat kapacitu sběrné sítě. V případě, že se jedná o zcela novou frakci odpadu, může zásadní informaci přinést potenciál separace tohoto odpadu odhadnutý na základě složení neseparovaného odpadu (kap. 4.1). Následně je nutné přizpůsobit svoz odpadu v rámci obce (kap. 4.3).

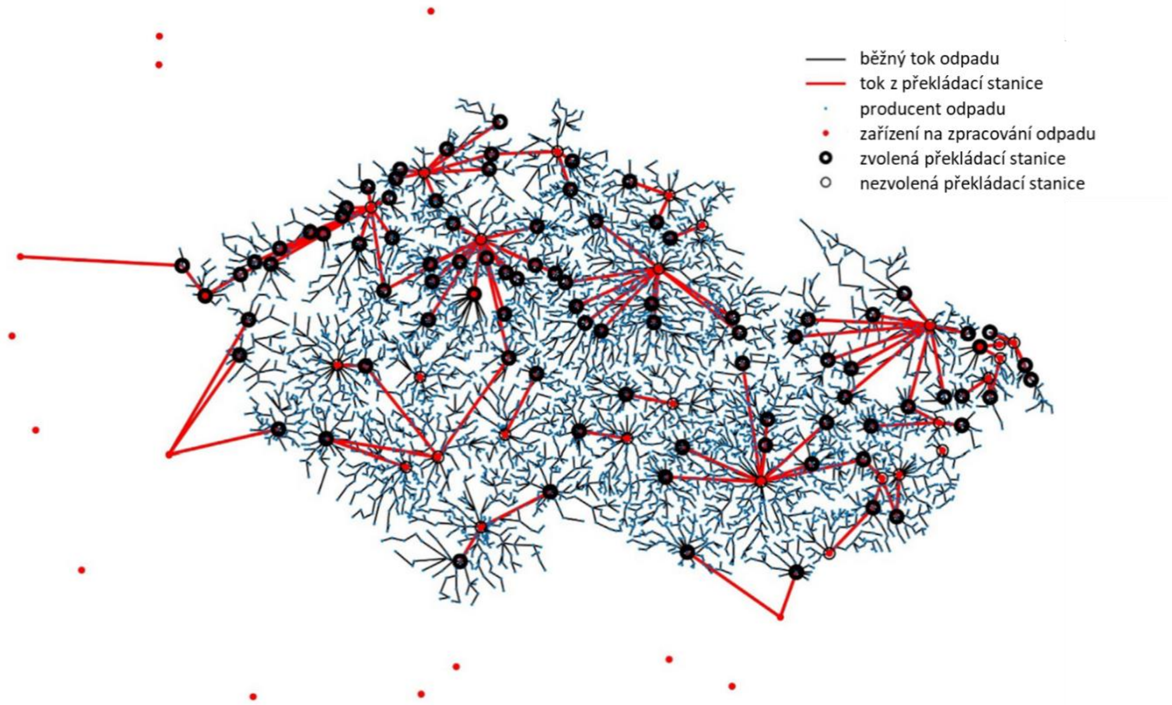
4.3 Logistika odpadů

Ze sběrných míst je odpad svážen v rámci obce a následuje meziměstská přeprava až do zařízení ke zpracování odpadu. Optimalizací svozových tras je možné dosáhnout snížení nákladů a dopadů na životní prostředí [B24]. Přehled existujících a nově vyvíjených variant řešení problémů svozu odpadu byl představen v rešerši [B25]. Z důvodu řešitelnosti rozsáhlých úloh jsou často aplikovány heuristické přístupy. Jak bylo zmíněno, nové modely by měly brát v úvahu různý účel řešených úloh a metriky pro vyhodnocení vhodnosti daného řešení. Rešerše [B25] shrnuje současné nedostatky, poslední směřování vývoje, a hlavně nové výzvy při návrhu a vyhodnocování svozových úloh. Většina dosavadních modelů využívá routingové algoritmy pro minimalizaci ceny za svoz odpadu nebo případně v kombinaci se zohledněním ekologického hlediska [B25].

Pro plánování nejvhodnějších svozových tras v rámci obce byl na principu ARC (Arc Routing Problem) vytvořen nástroj *NERUDA Street* [A21], který je jedním z modulů nástroje *NERUDA* (viz kap. 4.4) a byl vyvíjen v rámci práce [Z18]. NERUDA Street je možné využít pro optimalizaci svozových tras a také pro hodnocení dopadu změn v systému (nové sběrné místo, další separované komodity atd.). Doprava je modelována na mapových podkladech *OpenStreetMap*. K zajištění efektivnějšího a úspornějšího systému sběru se začíná využívat koncept *smart city collection*. Hlavním prvkem toho přístupu je zavedení snímačů do sběrných nádob. Jejich reálné využití je možné hlavně díky snižující se pořizovací ceně, což otevírá prostor pro efektivnější plánování svozu odpadu. Posouzení rozdílů statického plánování oproti dynamickému bylo provedeno v [B26] na reálných datech ze Švédska pro KO. Byla zde provedena simulace, která analyzovala nákladovost a další indikátory pro navržení optimálního systému, přičemž dynamické plánování vykázalo lepší výsledky. Implementace sítě bezdrátových senzorů ve sběrných nádobách byla analyzována v [B27]. Zde byla představena monitorovací aplikace pro zjištění aktuálního stavu naplněnosti. Dále byla zkoumána životnost těchto senzorů a jejich použitelnost v oblasti KO. Na základě výsledků lze konstatovat, že využití dat ze senzorů ve sběrných nádobách může významně snížit provozní náklady celého systému. Z NERUDA Street vychází nástroj POPELKA (Modul 1), viz kap. 5.3.4.

Při optimalizaci meziměstského svozu odpadu je rozhodující místo a způsob zpracování, což má vliv na celkovou cenu za nakládání s odpadem a ekologickou zátěž pro konkrétního producenta. Na základě této myšlenky byl sestaven matematický model [A22], který zohledňuje různou cenu za zpracování odpadu v jednotlivých zařízeních a produkci skleníkových plynů prostřednictvím potenciálu globálního oteplování (GWP – global warming potential). Jedná se o vícekriteriální optimalizaci zohledňující náklady a ekologickou zátěž. Z důvodu slučování a rozdělování toků není z výsledku modelu [A22] známá informace o tom, kam byl převezen odpad od konkrétního producenta a výsledkem je víceznačné řešení. Publikace [A22] navrhuje řešení pro odhad nákladů a ekologické zátěže pro jednotlivé producenty prostřednictvím modelu toku v síti, kdy se sestaví pořadí výběru pro producenty metodou Monte Carlo. Úlohy optimalizující dopravu odpadu většinou zahrnují ekonomická a globální environmentální kritéria, nicméně důležitou roli hrají také přímé místní důsledky, které by měly být zohledněny. V příspěvku [A23] je navrženo hodnocení OH s ohledem na dopad emisí na místní obyvatele žijící v blízkosti cest a zpracovatelských zařízení. Výpočet emisí produkovaných při přepravě odpadů zohledňuje výškové profily tras, zatížení kontejnery a konkrétní typy vozidel. Následný odhadovaný dopad na obyvatelstvo počítá se vzdálenostmi mezi dopravními trasami resp. zpracovatelskými zařízeními a obcemi a současně zohledňuje velikost obcí z hlediska počtu obyvatel. Pro toto vyhodnocení jsou dopravní trasy rozděleny na menší segmenty. Tento přístup aplikovaný na celou síť pak poskytuje vstupní data potřebná pro budoucí výzkum nových strategií při problémech s výběrem umístění zařízení.

Meziměstská doprava odpadu může být zefektivněna překládkou odpadu z běžných svozových automobilů („kuka vozů“) na velkokapacitní vozy. Za tímto účelem jsou budovány překládací stanice. Lze očekávat, že význam překládacích stanic v ČR v následujících letech poroste v souvislosti s omezováním skládkování odpadu (Zákon 541/2020 Sb., o odpadech). Dopravní technicko-ekonomické modely pro posouzení dopravní ceny pro různé scénáře byly představeny v práci [B29]. Pro navržení sítě překládacích stanic byl sestaven dvoustupňový stochastický model [A24]. Návrh překládacích stanic tvoří kompromis mezi ekonomikou (očekávané náklady) a environmentálním aspektem (vzdálenost přepravy). V aplikaci pro ČR bylo generováno 10 000 scénářů vyjadřujících nejistotu vstupních parametrů, výsledkem je robustní síť překládacích stanic zohledňující také přeshraniční přepravu odpadu. Ukázka výsledků preferujících environmentální aspekt v účelové funkci je zobrazena na obr. 18.

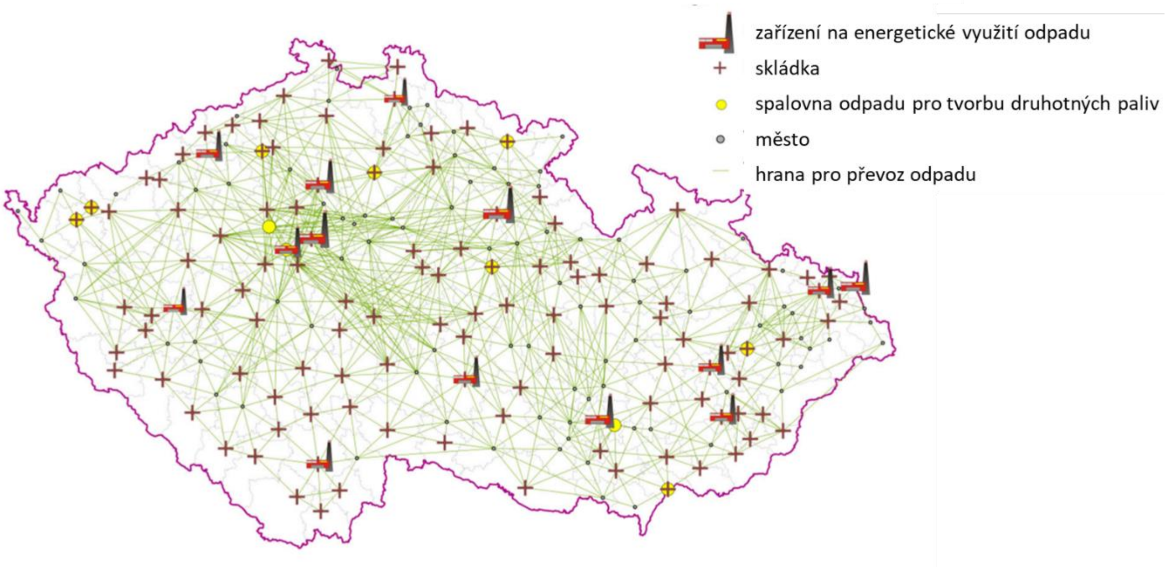


Obr. 18: Ukázka výstupu pro plánování přepravy odpadu, upraveno z [A24]

4.4 Zpracovatelská infrastruktura

Preference způsobů nakládání s odpady je definována Hierarchií nakládání s odpady [B1], která podporuje přechod na ObH. Tato hierarchie upřednostňuje prevenci před vznikem odpadů, následuje opětovné využití, materiálové a energetické využití a poslední je odstranění odpadů [B28]. Jiný pohled nabízí porovnání různého způsobu nakládání s odpady podle produkce skleníkových plynů (viz publikace [A25] pro SKO). Jedná se o frakci odpadu, která je stále významnou měrou skládkována (asi 77 % v ČR v roce 2020 [B15]) a má potenciál pro vhodnější využití. Konkrétně bylo posouzeno energetické využití odpadu v ZEVO, skládkování a mechanicko-biologická úprava (MBÚ) s následným využitím paliva získaného z odpadu. Protože energetické využití je preferovaný způsob nakládání s SKO byl také kvantifikován vliv různého složení SKO na produkci GHG (greenhouse gas). Výsledky ukázaly, že zvýšený obsah plastů v odpadu zpracovávaném v ZEVO zhoršuje produkci GHG. Dále bylo prokázáno, že pokud je poptávka po teple, jedná se o výhodnější způsob zpracování odpadu než výroba elektřiny z pohledu produkce GHG produkovaného ZEVO a GHG v případě jiných zdrojů energie.

Přechod na ObH vyžaduje vytvoření nezbytné infrastruktury pro zpracování, která pokrývá všechny stupně hierarchie nakládání s odpady, vhodné umístění zpracovatelských kapacit a návrh dopravní infrastruktury včetně překládacích stanic. Pro podporu plánování investic v OH byl vytvořen nástroj NERUDA [A26]. Tento nástroj optimalizuje logistiku odpadu a zohledňuje různé situace budoucích podmínek, zejména možné umístění nových zpracovatelských zařízení. Modely implementované v NERUDA prošly postupným vývojem v rámci výzkumných aktivit a závěrečných prací. Prvotním výstupem, prezentujícím modely, které byly později implementovány v nástroji NERUDA, byla práce [Z14], na níž navázala práce [Z15]. Výpočet na reálné síti s ohledem na výpočtovou náročnost byl analyzován [Z16]. Deterministické a heuristické přístupy byly následně implementovány v práci [Z17] s důrazem na přiblížení modelu reálné úloze v OH. Komplexní přístup k plánování svozu odpadů zahrnující přípravu dat, tvorbu dopravní infrastruktury, alokaci sběrných nádob atd. byl představen v práci [Z18]. Nástroj NERUDA pro plánování nových kapacit ZEVO implementuje mimo jiné poznatky z uvedených závěrečných prací a byl prezentován v publikaci [A27]. Princip je založen na minimalizaci ceny za dopravu odpadu a jeho zpracování. Případová studie v [A27] byla provedena pro infrastrukturu OH v ČR, stochastické parametry vstupující do výpočtu byly modelovány pomocí Monte Carlo simulace. Klíčovými prvky pro tuto případovou studii byla zpracovatelská zařízení (ZEVO, skládky, MBÚ, zařízení pro zpracování paliva získaného z odpadu) a ORP jako producenti odpadu. Znázornění dopravní infrastruktury pro modelovanou situaci v [A27] je na obr. 19. V příspěvku [A28] byla provedena analýza rizik spojených s omezenými zdroji odpadu jako paliva pro ZEVO. Výpočet byl proveden v nástroji NERUDA, nalezené vazby je vhodné zohlednit při plánování nových zpracovatelských kapacit.



Obr. 19: Dopravní infrastruktura ČR modelu s klíčovými prvky, upraveno z [A27]

Rešerše [B30] poskytuje přehledovou studii pro plánování v systémech dodavatelského řetězce, včetně nakládání s odpady. Příspěvky diskutované ve zmíněné rešerši pojednávají o různých typech udržitelnosti systému, kterým se věnoval i autor této práce. Specifická rozhodovací kritéria se týkají následujících aspektů:

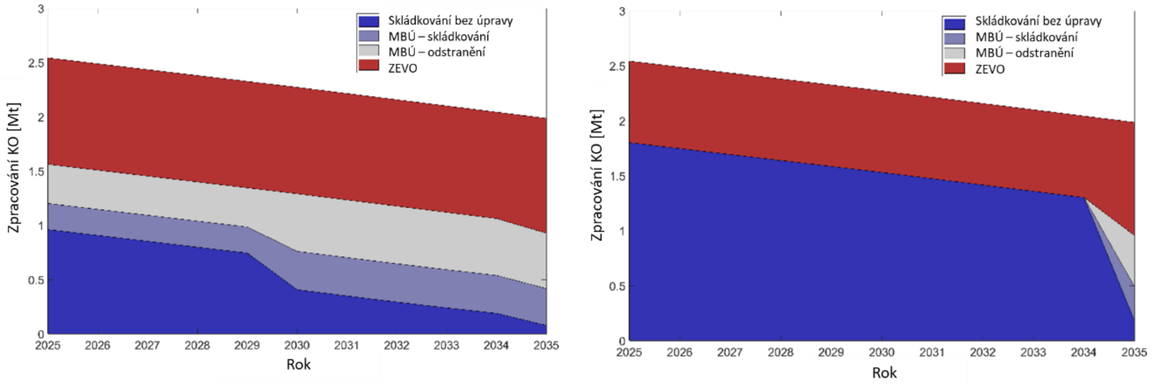
Ekonomické aspekty

Minimalizace celkových nákladů je základním a nejčastěji používaným ukazatelem ekonomicky orientovaných výpočtů udržitelného řetězce [B31]. Náklady se zdají být dostatečným ukazatelem, zvláště pokud je podoba infrastruktury stabilní a jsou přijímána pouze taktická rozhodnutí; navíc se jedná o nejjednodušší kvantifikaci ekonomiky projektu. Čistá současná hodnota nebo vnitřní výnosové procento se posuzují méně často [B32], a to zejména v případě strategických rozhodnutí, např. výstavby nového zařízení. Pro vyhodnocení ekonomiky výstavby nových zařízení bylo na ÚPI sestaveno více modelů a vhodnost jejich aplikace závisí na typu úlohy. Investiční riziko výstavby ZEVO bylo kvantifikováno v publikaci [A28]. V tomto příspěvku byly představeny základní vlastnosti nástroje NERUDA (viz výše) zejména pro alokaci zpracovatelské kapacity. Optimální svozové oblasti byly porovnávány s kapacitou nového projektu, dostupnost odpadu jako paliva pro ZEVO byla simulována v různých scénářích. Hlavním rizikem ve výstavbě nového ZEVO v provedené studii byla nejistá dostupnost odpadu. Pro kvantifikaci tohoto rizika byl definován pojem faktor dostupnosti odpadu [A28].

Práce [Z19] se věnovala výstavbě nových ZEVO v lokalitě, kde je již provozováno stávající energetické zařízení – teplárna. Byl vytvořen matematický model pro posouzení ekonomické efektivity spolupráce s použitím společné technologie. Pro vyhodnocení dlouhodobé ekonomické udržitelnosti ZEVO v závislosti na umístění zařízení byl sestaven model [A29]. Ekonomika projektu byla optimalizována prostřednictvím minimalizace nákladů na přepravu odpadu od producenta do tohoto zařízení a maximalizace výnosů z poplatků za zpracování odpadu a prodej tepla a elektřiny. Z důvodu problematické řešitelnosti úlohy byl sestaven meta-heuristický algoritmus.

Provoz ZEVO je významně ovlivněn složením odpadu, který je v daném zařízení zpracováván. Kromě očekávaného množství odpadu určeného ke zpracování v plánovaném zařízení by mělo být zohledněno také jeho složení. Publikace [A30] představuje model pro plánování vhodné lokality a kapacity ZEVO zavedením stochastického lineárního modelu, který zachycuje nejistotu složení odpadu prostřednictvím scénářů možného budoucího vývoje. Model je formulován s cílem minimalizovat počáteční investici i náklady na chod zařízení. Výsledky modelu poskytují vhled do ekonomiky provozu a identifikují důležité faktory udržitelnosti systému nakládání s odpady.

Pro vyhodnocení ekonomických aspektů OH při plnění cílů EU byl navržen model vícestupňového stochastického programování [A31]. Nejistá produkce odpadu je v modelu začleněna v podobě více scénářů, konkrétně byla studie v příspěvku [A31] provedena pro tři různé scénáře produkce odpadu. Současně je zohledněna aktuální míra materiálového využití. Tento přístup byl aplikován na OH v ČR s daty z roku 2017. Jedním z hlavních přínosů je srovnání modelů s progresivními cíli a bez těchto cílů. Model s progresivními cíli, zohledňuje postupně cíle CEP v letech 2025, 2030 a 2035. Model bez progresivních cílů pracuje pouze s finálním cílem v roce 2035. V modelu s progresivními cíli byla doporučena kapacita ZEVO 981 kt již v roce 2020 oproti 741 kt stávajících kapacit v roce 2017. Druhý model bez progresivních cílů navrhuje zcela opačnou strategii a navrhuje počkat se změnami ve zpracovatelské infrastruktuře do poslední chvíle, kdy mají být plněny cíle EU. Zmíněné scénáře jsou znázorněny na obr. 20. Výhodou modelu je možnost jeho využití pro plánování „rolling-horizon“, je tedy možné výsledky po několika letech znovu přepočítat s nově dostupnými daty a aktualizovat nadcházející rozhodnutí o nově dostupné informace.



a) Model s progresivními cíli *b) Model bez progresivních cílů*

Obr. 20: Zpracování komunálního odpadu v ČR, upraveno z [A31]

Environmentální aspekty

Z hlediska environmentálního hodnocení systému je významný rozdíl mezi používanými ukazateli. Velká pozornost je věnována emisím oxidu uhličitého, a to přímým hodnocením uhlíkové stopy [B33] nebo výpočtem skleníkových plynů prostřednictvím GHG, viz [B34]. Dále se běžně používá GWP pro srovnání vlivu jednotlivých polutantů na změny životního prostředí, viz [B35]. Dalším běžně používaným indikátorem je změna klimatu, viz [B36]. Všechny tyto indikátory pomáhají vyhodnotit dopad systémů na životní prostředí ve vztahu ke globálnímu oteplování. Další důležitou kategorií dopadů na životní prostředí je redukce a recyklace odpadu, viz [B37]. Výše uvedené publikace se zaměřují výhradně na jeden z ukazatelů; to však může výrazně zkreslit konečné výsledky. Přístup tzv. hodnocení životního cyklu (LCA – life cycle assessment) obvykle zahrnuje více než jeden environmentální aspekt, viz [B38].

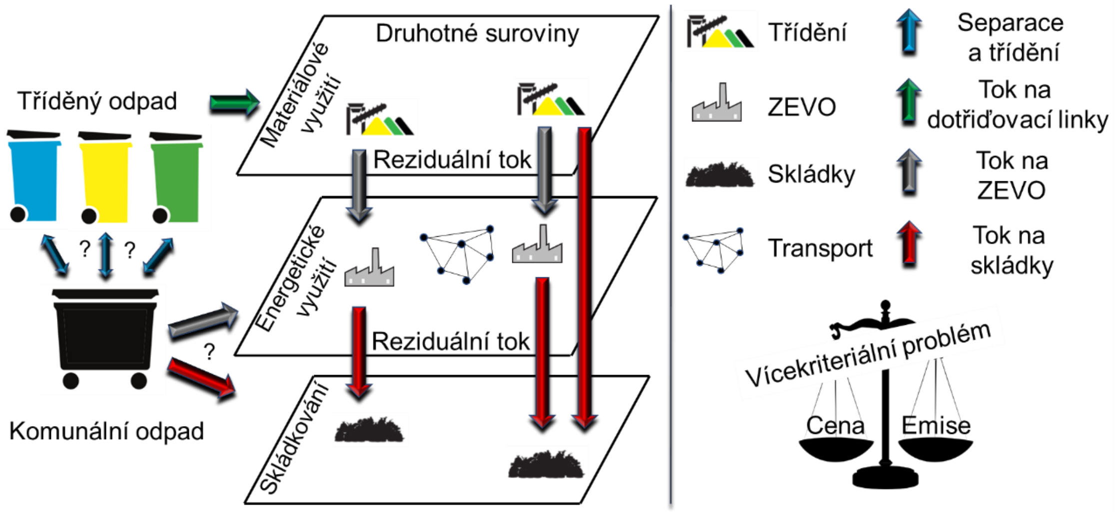
Nástroj NERUDA přizpůsobený pro variantu NO byl aplikován v případové studii [A9]. Model byl sestaven na vícekomoditní síti toku odpadu včetně proudů popisujících výmět odpadu ze zpracovatelských zařízení, aby co nejlépe simuloval reálnou situaci OH. Zohledněna je současná produkce odpadu a taky výhled produkce do roku 2030 a poté je posouzena kapacita infrastruktury zařízení na zpracování NO. Výsledky studie ukázaly na nedostatečnost možností tepelného zpracování a stabilizace NO. Navrhuje se rozšíření kapacity spalování, protože to ovlivňuje stabilizační jednotky, které musí zpracovávat zbývající odpad. Doporučené navýšení kapacit je až o 100 % s různým podílem v jednotlivých krajích.

Sociální aspekty

Mezi nejčastěji hodnocené indikátory kategorie sociálních aspektů patří tvorba pracovních míst, bezpečnost, zdraví a další, viz [B39]. Kromě toho se při plánování v OH významně projevuje tzv. efekt NIMBY (Not-In-My-BackYard), jak uvádí [B42]. NIMBY charakterizuje postoj lidí, kteří odmítají, aby obecně prospěšný projekt (např. výstavba zpracovatelského zařízení) byl realizován v blízkosti jejich domova.

Vícekriteriální přístupy

Komplexní pohled na systém nakládání s odpady by měl brát v úvahu více než jen jeden aspekt diskutovaný výše. Posouzení ekonomického a environmentální hlediska je nejčastější přístup při hodnocení výstavby nového zařízení. Jak bylo zmíněno v příspěvku [A32] vhodným způsobem zpracování SKO je v ZEVO, které z pohledu ekologické zátěže nahrazuje skládky a současně výrobu energie z fosilních paliv. Pro vyhodnocení ekonomické stability ZEVO je nutné zohlednit odběr tepla a elektřiny. Dokument [A32] analyzuje vztah mezi emisemi skleníkových plynů a náklady na zpracování SKO a posuzuje dopad různých možností zpracování na životní prostředí. Model je sestaven jako úloha reverzní logistiky s nelineárními vazbami ve vztahu nákladů na zpracování SKO. Studie je provedena pro zpracování SKO v ČR na úrovni ORP a vychází ze skutečné infrastruktury v roce 2016. Navržený koncept pro rok 2016 umožňuje snížit produkci skleníkových plynů o 150 % (efekt snížení produkce energií z primárních zdrojů) při navýšení nákladů na nakládání s SKO asi o 2,5 EUR/t. Komplexní pohled na síť infrastruktury pro nakládání s odpady byl zpracován v práci [Z21], na kterou navázal příspěvek [A33]. Cílem modelu je navrhnout vhodný počet a umístění zařízení na zpracování a předúpravu KO, jedná se o třídicí a dotřiďovací linky, ZEVO a skládky. Je zohledněna separace odpadu a jeho doprava. Důležitým bodem je zahrnutí výmětů z dotřiďování KO do výpočtu. Infrastruktura je i v tomto modelu navržena s ohledem na ekonomiku a environmentální zátěž (viz obr. 21).



Obr. 21: Koncept toku komunálního odpadu, upraveno z [A33]

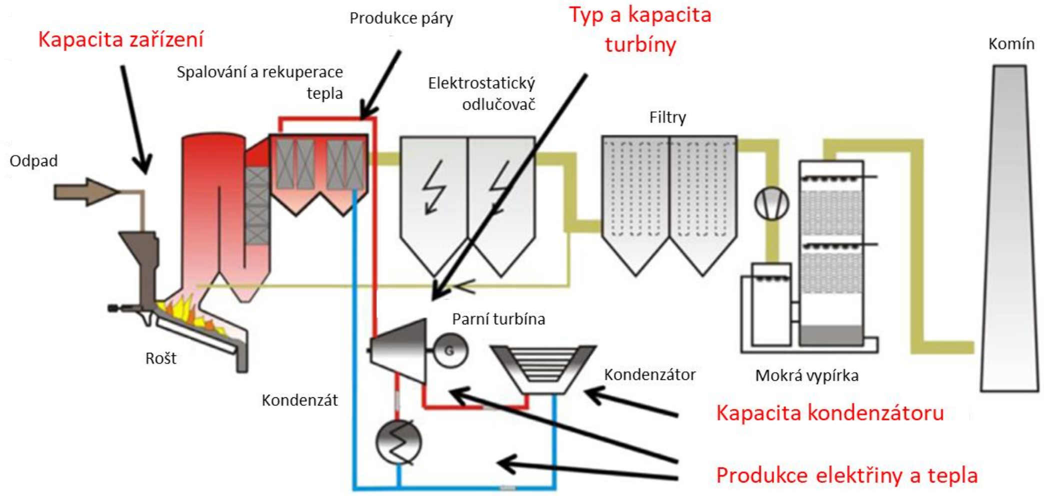
Model pro návrh optimální sítě nakládání s odpady zohledňující ekologický, environmentální i sociální aspekt, byl představen ve studii [A34]. Produkce odpadu v tomto modelu je ovlivněna postojem producentů k předcházení vzniku odpadu, přičemž prevenci je v modelu možné podpořit investicí do propagace. Produkce odpadů a jejich dostupnost se promítá do ceny za zpracování. Navrženy byly nelineární závislosti popisující vliv jednotlivých faktorů na cenu nakládání s OH. Z důvodu řešitelnosti byly tyto vazby nahrazeny po částech lineární aproximací. Model kombinuje čtyři účelové funkce. Výsledky modelu pro ČR odhalily potenciál pro prevenci vzniku odpadu v obcích ČR, na druhou stranu zvyšování recyklace odpadu je limitováno z ekonomického hlediska. V případě upřednostnění environmentálního aspektu model doporučuje realizovat investici pro podporu recyklace odpadu.

Přístupy založené na teorii her

Změny v OH související zejména s CEP (kap. 2) vyžadují spolehlivé strategické plánování od všech zúčastněných stran: vláda, investoři projektů, provozovatelé zařízení, svozové společnosti, obce apod. Obce mohou snížit své náklady na OH spoluprací mezi obcemi prostřednictvím vytváření koalic (svazků obcí). Meziobecní spolupráce umožňuje optimalizovat materiálové (odpadové) a finanční toky, sdílet fixní náklady obecních a regionálních systémů, realizovat úspory díky většímu rozsahu zakázky, snižovat transakční náklady na řízení apod. Pro seskupování obcí do svazků byl formulován model založený na subaditivní teorii her s mnoha hráči [A35]. Subaditivnost potenciálně vede k vytvoření velké koalice, což pro řadu hráčů není reálné, protože udržení takové struktury vyžaduje další investice. Aby bylo možné rozumně implementovat pravidla sloučení a rozdělení do uvažované hry, byl zaveden model nákladů na spolupráci. Tato úprava umožňuje manipulovat s procesem tvorby koalice pomocí penalizace. Náklady pro jednotlivé obce byly rozděleny pomocí Shapleyho hodnoty [B43]. Přístup byl ověřen na případové studii pro 47 ORP v ČR. Po aplikaci uvedené metody byla asi polovina ORP zapojena do nějaké koalice pod výslednou koaliční strukturou a jejich úspory se pohybovaly od cca 2 % do 8 % oproti variantě bez vzájemné spolupráce. Prezentovaný přístup má potenciál sloužit jako podklad pro volbu místa zpracování odpadu s ohledem na vznik svazků obcí.

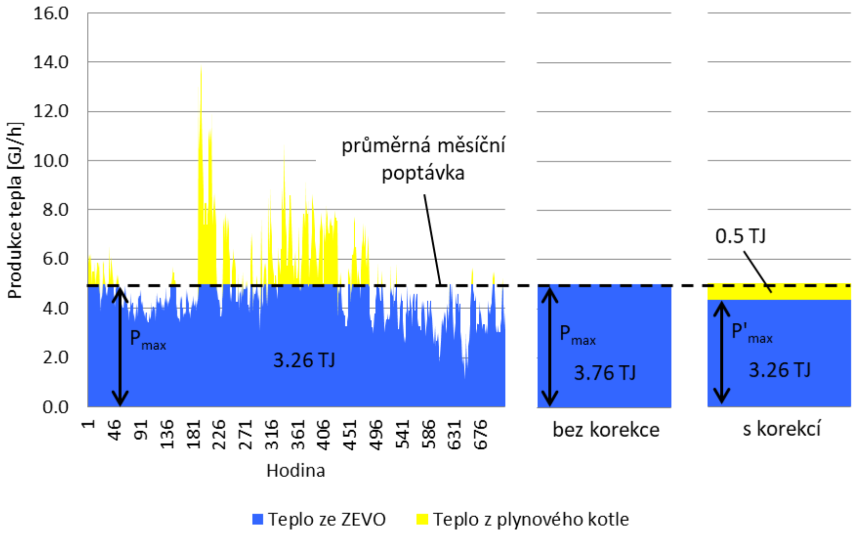
4.5 Technologie v zařízení pro energetické využití odpadu

Každé zařízení na zpracování odpadu je velmi komplexní systém zahrnující řadu na sebe navazujících procesů. Autor této práce se ve svém výzkumu věnoval některým otázkám spojených s technologií ZEVO. Již v rané fázi každého projektu výstavby ZEVO představuje zásadní rozhodnutí určení vhodné kapacity zařízení a dimenzování produkce tepla a elektřiny. Zároveň by měla být zaručena ekonomická udržitelnost projektu, která je ve studii [A2] hodnocena vnitřním výnosovým procentem. Pro dimenzování parametrů ZEVO byl představen dvoustupňový stochastický optimalizační model. Na obr. 22 je znázorněn systém ZEVO a červeně jsou vyznačeny jeho prvky, které jsou součástí optimalizace v představeném modelu. Je nutné zohlednit, že výstavba nového ZEVO od prvotních úvah až po jeho plný provoz je dlouhodobý proces s dobou trvání odhadovanou minimálně na 5 až 7 let. Po montáži pak následuje provozní fáze přesahující 20 let. Z tohoto důvodu byly výpočty opakovány a hodnoceny pro několik scénářů s různým nastavením klíčových vstupních parametrů.



Obr. 22: Schéma technologie zařízení pro energetické využití odpadu, upraveno z [A2]

Technické i ekonomické modely ZEVO, které byly detailně popsány v práci [B40], jsou značnou měrou ovlivňovány nejistými parametry (např. poptávka po teple). Tyto parametry se v průběhu času mění a obvykle je nelze kvalitně předvídat v době dimenzování a výstavby zařízení. Podrobnosti problematiky kolísání poptávky po teple jsou k dispozici v práci [B41]. Řešením této problematiky při plánování investic v oblasti energetického využití odpadů se zabývala publikace [A4]. Jak bylo zmíněno výše, životnost ZEVO se většinou plánuje alespoň na 20 let a jejich výstavba je také časově i investičně náročná. Je tedy zapotřebí dimenzovat robustní zařízení s nízkou citlivostí na budoucí změny klíčových parametrů. Publikace [A4] tedy analyzuje vliv kolísání poptávky po teple na přesnost technicko-ekonomických modelů a variabilitu jejich výstupů. Citlivost dvou různých modelů byla porovnána na jednoduchém modelu ZEVO s plynovým kotlem a komplexním modelu ZEVO s kombinovanou výrobou tepla a elektřiny. Optimalizační modely, běžně používané k návrhu těchto zařízení, provádějí výpočty v určitých časových krocích (např. týden, den, hodina). Výpočty ale musí být často zjednodušeny obvykle na roční nebo měsíční bázi, protože pro krátký časový krok může být řešení výpočetně příliš obtížné. Toto zjednodušení však vede k nepřesnostem modelu. Publikace [A4] nabízí alternativní řešení k běžně užívaným metodám modelování ZEVO pomocí tzv. korekčních koeficientů, které pomáhají zvýšit přesnost modelů při zachování přijatelné doby výpočtu. Princip začlenění korekčních koeficientů je znázorněn na obr. 23. Hodnota P_{max} je měsíční průměr poptávky, který byl určen z dat v detailu hodin. Tato poptávka po teple P_{max} je korigována koeficientem, aby nebyl nadhodnocen zisk z prodeje tepla z důvodu hodinových výkyvů. Podle metodiky představené v [A4] je původní poptávka P_{max} uvedená v příkladu na obr. 23 korigována snížením o 0,5 TJ na hodnotu označenou jako P'_{max}. Autoři doporučují pro modelování ZEVO využívat hodnotu P'_{max} z důvodu robustního řešení. Detaily spolupráce ZEVO s teplárnou jsou detailně rozebrány v práci [B41]. Autor tohoto textu spolupracoval na vytváření matematického modelu pro optimalizaci celého systému, viz práce [Z20].



Obr. 23: Princip korekčních koeficientů pro poptávku po teple, upraveno z [A4]

Návrhu parametrů konkrétní technologie ZEVO se věnovala práce [Z22]. Jednalo se o optimalizaci výhřevnosti a maximální kapacitu spalovacího roštu. Klíčovým neurčitým parametrem tohoto modelu je výhřevnost odpadu, která byla modelována na základě analýzy dat z reálného provozu. Vývoj složení odpadu, které výrazně ovlivňuje jeho výhřevnost, byl modelován prostřednictvím scénářů. Na tuto závěrečnou práci se navázalo při vývoji softwaru [P16] pro ZEVO Malešice, který optimalizuje chod zařízení. Tento software na základě matematických modelů v kombinaci s provozními daty předpovídá výrobu energie na následujících 40 hodin. Zásadním krokem bylo i v této úloze vhodné zpracování dat z provozu. Výsledkem je zefektivnění plánování produkce energie, což umožňuje v maximální možné míře pokrýt poptávku po teple a vyrobit co nejvíce elektřiny. Tím se minimalizuje produkce energie z primárních zdrojů.

Často řešenou otázkou při dimenzování ZEVO je čištění spalin, které podléhá řadě legislativních omezení. Systém na čištění spalin je nutné modernizovat tak, aby bylo možné plnit přísné limity. Ve spolupráci s Ústavem chemických procesů Akademie věd ČR byla vypracována studie na odstraňování SO_2 a HCl ze spalin. Experimentální výzkum kladl důraz na přenos výsledků do praxe, probíhal tedy ve velkém měřítku a se skutečnými spalinami. Regresní modely aplikované pro kvantifikaci vlivu koncentrace HCl na koncentraci SO_2 byly ve shodě s experimentálními daty, lze je tedy využít pro predikci chování systému čištění spalin nebo jeho optimalizaci. Další aktivitou v této oblasti bylo využití membrán pro čištění spalin v ZEVO. Publikace [A36] představila model a sérii simulačních výpočtů pro vyhodnocení základních parametrů membrán s ohledem na energetickou náročnost systému.

5 NEJVÝZNAMNĚJŠÍ VÝSLEDKY

V této kapitole jsou shrnuty hlavní výsledky dosavadní výzkumné činnosti autora. Jedná se o sumarizaci výstupů, které byly již představeny výše v kap. 3 a kap. 4.

5.1 Interdisciplinární charakter činnosti

Výsledky činnosti autora jsou založeny na koordinaci mezioborové spolupráce, která probíhá především v rámci závěrečných prací nebo výzkumných aktivit studentů doktorského studia. Konkrétně se jedná o propojení oborů procesního inženýrství, aplikované matematiky a aplikované informatiky. Díky těmto aktivitám je reálné řešit výzkumné výzvy v tak širokém rozsahu. Autor byl vedoucím, popř. konzultantem následujících prací (z toho je uveden v závorce počet aktuálně řešených prací):

- Bakalářské práce na Ústavu matematiky (FSI VUT): 15(1) závěrečných prací.
- Bakalářské práce na Ústavu procesního inženýrství (FSI VUT): 8.
- Bakalářská práce na Fakultě aplikované informatiky (Univerzita Tomáše Bati ve Zlíně – UTB): 3.
- Diplomové práce na Ústavu matematiky (FSI VUT): 14(1).
- Diplomové práce na Ústavu procesního inženýrství (FSI VUT): 4.
- Diplomové práce na Ústavu soudního inženýrství (VUT): 3.
- Diplomové práce na Ústavu automatizace a informatiky (FSI VUT): 2(1).
- Disertační práce na Ústavu procesního inženýrství (FSI, VUT): 7(3).
- Disertační práce na Ústavu matematiky (FSI VUT): 3(3).

Až na výjimky byly všech závěrečné práce navázány na výzkumné aktivity v řešených projektech na pracovišti autora tohoto textu.

5.2 Vyvinuté metodiky

5.2.1 *CERTIFIKOVANÁ METODIKA PRO PROVÁDĚNÍ DLOUHODOBÉ PROGNÓZY PRODUKCE ODPADŮ V ČR VČETNĚ REVIZE PROGNÓZY*

Certifikovaná metodika [P7] vznikla pro hodnocení současného stavu OH v ČR a pro podporu jeho plánování. Dokument stanovuje přístup k prognóze produkce všech odpadových frakcí a jejich vybraných agregací. Využití certifikované metodiky zajistí adekvátní prognózování u všech aktérů v OH na různých úrovních (národní, regionální apod.) při tvorbě dlouhodobých prognóz produkce odpadů. Využití metodiky je považováno za záruku, že informace získané při prognózování mají relevantní a dostatečnou úroveň. Certifikovaná metodika je obecné povahy a stanovuje obecný postup prognózování formou na sebe navazujících kroků. Součástí metodiky jsou přílohy k textu [P10], které se zabývají konkrétní aplikací metodiky dle požadavků zadavatele – MŽP. Metodika byla využita při tvorbě software TIRAMISO [P1] spravovaného MŽP (viz kap. 5.3.2).

5.2.2 CERTIFIKOVANÁ METODIKA PRO STANOVENÍ SLOŽENÍ SMĚSNÉHO KOMUNÁLNÍHO ODPADU Z OBCÍ A KOMUNÁLNÍHO ODPADU (PŘÍLOHA 4A: VYHODNOCENÍ VÝSLEDKŮ ROZBORU)

Certifikovaná metodika [P13] stanovuje postupy, které umožňují srovnatelnost a opakovatelnost výsledků terénních průzkumů zaměřených na stanovení složení SKO. Součástí jsou přístupy pro realizaci rozborů a také pro statistické zpracování výsledků tak, aby bylo možné odhadnout složení SKO za agregované území.

Autor tohoto textu se podílel na tvorbě nástroje pro vyhodnocení výsledků z rozborů [P15], který je k dispozici v MS Excel a kód výpočtů je implementován ve Visual Basic for Applications (VBA). Nástroj je připraven pro zaznamenání základních informací o jednotlivých rozborech a jejich výsledků. Implementovaný statistický výpočet poté umožní výpis agregovaných výsledků pro I., II. a III. úroveň rozborů včetně grafických výstupů.

5.2.3 TVORBA **PD ISOH**

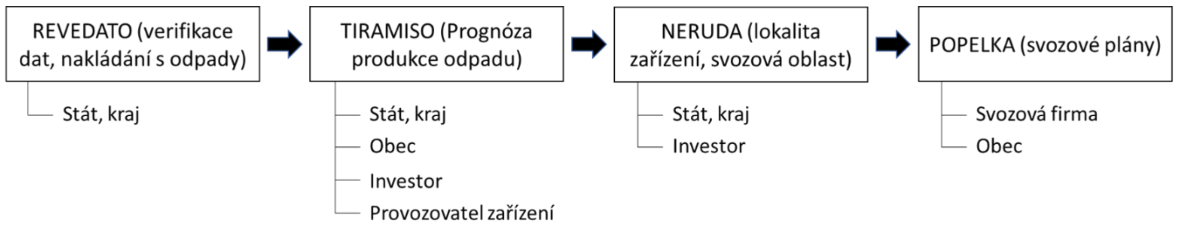
PD ISOH vzniká zpracováním a dílčími úpravami databáze ISOH (viz kap. 3.1). V souvislosti s tvorbou nového ISOH je nutné revidovat postup tvorby PD ISOH do jeho nové podoby. Z požadavků na PD ISOH lze zmínit: zohlednění legislativních změn v souvislosti se Zákonem 541/2020 Sb. o odpadech a Vyhlášky č. 273/2021 Sb. o podrobnostech nakládání s odpady; odstranění zjevných chyb v ISOH (viz kap. 3.1); odstranění duplicitních záznamů a další kroky uvedené v dokumentech V1.F.1.1 – V63 projektu CEVOOH [P3].

Navržené přístupy pro tvorbu PD ISOH2 vznikají v rámci projektu CEVOOH [P3], bod 1.F.1.1: Datová základna pro komplexní modelování stavu OH a ObH v ČR, ve spolupráci řešitelů z VUT a CENIA – konzultováno s MŽP. Vstupní data pocházejí z hlášení souhrnných údajů z průběžné evidence podle Vyhlášky č. 273/2021 Sb., o podrobnostech nakládání s odpady. Výstupem jsou podpůrné dokumenty vztahující se k V1.F.1.1 – V63, které vznikly z důvodu aktualizace ISOH podle nové legislativy (Zákon 541/2020 Sb., o odpadech a příslušné směrnice).

Autor tohoto textu navrhl řadu dílčích úprav, které vycházejí z jeho dosavadního praktického využívaní PD ISOH. Konkrétně lze zmínit nové agregace dat na úroveň obcí (doposud byla k dispozici pouze úroveň ZÚJ), propsání změn v PD ISOH do starších záznamů pro zajištění konzistentnosti časové řady (např. od roku 2021 se již komunální obaly nevykazuji pod katalogovými čísly podskupiny 15 01, ale pod podskupinu 20 01) a další.

5.3 Software

Přístupy ke zpracování dat v OH (kap. 3) a výpočtové modely (kap. 4) jsou postupně implementovány do software. Tím je umožněno jejich využití k řešení praktických úloh v OH. Jednotlivé software na sebe navazují a dohromady nabízejí komplexní řešení OH na úrovni státu, místních samospráv, zainteresovaných firem apod, viz obr. 24. Představení jednotlivých software je dále v kap. 5.3.1 až kap. 5.3.4



Obr. 24: Propojení vyvinutého software

5.3.1 REVEDATO

Nástroj REVEDATO se zabývá identifikací chyb v hlášení souhrnných údajů z průběžné evidence, opravami těchto chyb a zajištění platnosti všech hmotnostních bilancí v systému. Dále tento nástroj umožňuje modelovat kompletní řetězec toku odpadu od producenta přes předání/převzetí až k finálnímu zpracování pomocí bilančních, hierarchických a korekčních vztahů. Díky tomu je známo nakládání s odpady i na regionální úrovni až po ZÚJ. Vývoj nástroje je spojen s modely:

- Reflow [P4]
  Jedná se o úvodní model pro identifikaci chyb v PD ISOH založený na více-kriteriálním matematickém programování. Model minimalizuje celkovou odchylku od původních dat a současně zahrnuje logistiku a tím simuluje ekonomické chování subjektů v síti. Implementace algoritmu a přidružených výpočtů je v programovacím jazyce Julia. Funkčnost modelu byla ověřena na datech databáze VISOH (Veřejný informační systém odpadového hospodářství [B15]) na úrovni krajů ČR.
- Modul 1.0
  Vývoj uvedeného modulu je součástí projektu CEVOOH [P3] a současně je spojen s prací [Z7], kde je autor v pozici školitele specialisty. Tento modul je zaměřen na identifikaci chyb v databázi PD ISOH. Data jsou upravena pomocí jejich vyrovnání tak, aby byly splněny všechny hmotnostní bilance. Software byl testován pro vybraná katalogová čísla na úrovni ZÚJ. V současnosti je výpočet probíhá v prostředí GAMS (General algebraic modelling system) s načítáním dat a výpisem do MS Excel. Předpokládá se implementace v programovacím jazyce Julia a vytvoření uživatelského rozhraní.
- Modul 2.0
  V tomto modulu budou rekonstruovány (modelovány) odpadové toky od producenta do místa zpracování. Cílem je odhadnout lokalitu a způsob nakládání pro jednotlivá ZÚJ. Model je v současnosti ve fázi vývoje a postupně je implementován v programovacím jazyce Julia. Vývoj tohoto modulu je spojen s prací [Z8].

5.3.2 TIRAMISO

Nástroj TIRAMISO je určen k prognózování produkce a nakládání s odpady pro všechna katalogová čísla na úrovni ORP. Současně nástroj umožňuje tvořit projekce a modelovat tak scénáře budoucího vývoje podle zadaných okrajových podmínek. Výpočet nástroje TIRAMISO se řídí certifikovanou metodikou [P7]. Vývoj nástroje TIRAMISO zahrnuje více modulů:

- Justine [A14]
  Justine představuje prvotní model vyvíjený na ÚPI pro prognózování produkce odpadu. Trend je modelován mocninnou funkcí a následně je vyrovnán pro zachování vazeb systému. Prognóza byla provedena jen pro vybraná katalogová čísla

v závislosti na požadavcích prováděných studií. Výpočet Justine probíhá v prostředí GAMS s načítáním dat a výpisem v MS Excel.

- Modul 1.0 [P1]
  Uvedený modul zahrnuje prognózu produkce všech katalogových čísel dle Katalogu odpadů a vybraných agregovaných toků včetně pre-processingu dat, viz certifikovaná metodika [P7]. Nejistota prognózy je vyjádřena prostřednictvím konfidenčních a predikčních intervalů. Dále Modul 1.0 umožňuje modelovat scénáře produkce odpadu. Jedná se o webovou aplikaci, kdy výpočty jsou implementovány v programovacím jazyce Julia. Hlavním uživatelem TIRAMISO 1.0 je MŽP.
- Modul 2.0
  Modul 2.0 je rozšíření podoby TIRAMISO 1.0 o prognózy a projekce nakládání s odpady. Výpočet se opět řídí certifikovanou metodikou [P7], která byla vytvořena primárně pro prognózy produkce odpadu. Modely nakládání s odpady jsou tvořeny v souladu s očekávanou produkcí. V projekcích pro modelování scénářů jsou implementovány identifikované vazby nakládání se socio-ekonomickými parametry, systematickými změnami a globálními trendy.

5.3.3 NERUDA

Nástroj NERUDA [A26] byl vytvořen pro optimalizaci nakládání s odpady v konkrétním regionu z pohledu ekonomiky a dopadu na životní prostředí. Možnosti nakládání s odpady jsou v nástroji posouzeny také s ohledem na transport odpadu od producentů do místa zpracování. Jedním ze zásadních výstupů nástroje je návrh lokality pro výstavbu nových zpracovatelských kapacit. Nástroj NERUDA zahrnuje dílčí moduly, které byly vykázány samostatně.

- Výpočtový nástroj na bázi logistické úlohy pro simulaci konkurenčního prostředí v oblasti OH na regionální úrovni [P18]:
  Jedná se o výpočtové jádro nástroje NERUDA, které bylo představeno v práci autora tohoto textu [A37]. Součástí nástroje je také interface pro načítání vstupních dat získaných na základě dílčích výsledků řešení projektu WtECC [P17]. Model je dimenzován pro tři typy primárních a dva typy reziduálních odpadů. Modul je implementován v prostředí GAMS.
- Softwarová implementace redukčních technik pro wait and see přístup [P19]:
  Uvedený modul slouží jako podpora pro výpočty v prostředí GAMS. Jedna část uvedeného softwaru umožňuje vytvářet stromové struktury optimalizačních výpočtů včetně pre-processingu a post-processingu a celý proces tak zautomatizovat a zjednodušit. Druhá část slouží ke vhodnému rozmístění nezávislých výpočetních úloh na jednotlivá jádra procesoru. Primárně je určen pro řešení scénářových optimalizačních úloh přístupu wait and see. Detailní popis je součástí práce [Z20], kde autor tohoto textu figuroval jako školitel specialista.
- NodeCluster [P20]:
  Uvedený software založený na shlukové analýze navrhne vhodnou infrastrukturu pro výpočet síťové tokové úlohy s ohledem na sledovanou lokalitu, viz práce [Z20]. Software na základě vstupních dat umožňuje měnit detail se zvyšující se vzdáleností od sledovaného (referenčního) subjektu a s vazbou na produkci odpadu. Pro zajištění detailu v okolí sledovaného subjektu je nutné původní souřadnice uzlů či vzdálenosti vhodně transformovat tak, aby vznikla tendence tvořit větší shluky dále od sledovaného uzlu. Implementované algoritmy v NodeCluster jsou K-Means a hierarchické shlukování v programovacím jazyce Matlab.
- NerudaStreet:

Jedná se o optimalizační nástroj pro plánování svozových tras odpadu v rámci obce. NerudaStreet byl vyvíjen v rámci práce [Z18], kterou autor tohoto textu vedl z pozice školitele specialisty. Nástroj lze vedle optimalizace současných svozových tras využít k hodnocení dopadu změn v systému sběru (další separovaně sbírané komodity, zahuštění sítě, apod.) na celkové náklady. NerudaStreet je implementován v prostředí C++ a komunikuje s platformou volně dostupných mapových podkladů OpenStreetMap.

5.3.4 POPELKA

Nástroj POPELKA je webová aplikace obsahující sadu dílčích samostatně fungujících, nebo provázaných modulů. V současné době (9/2022) nástroj obsahuje již dva funkční moduly, které jsou ale plynule dále rozšiřovány na základě zpětné vazby z praktického využívání.

- Modul pro tvorbu plánu meziobecního svozu (Modul 1):
  Základem modulu je webové rozhraní, kde si uživatel spravuje svazky obcí a nastavuje parametry svozu (vozový park, frakce odpadu, dny svozu, frekvence svozu a další). Zadání uživatele vytvoří okrajové podmínky optimalizační úlohy, ta je řešena ve výpočetním jádru ve dvou krocích: 1) routing – tvorba svozových tras a 2) scheduling – rozvržení svozových tras do kalendáře s ohledem na frekvenci svozu pro jednotlivé frakce. Výhodou je možnost sestavení vlastního plánu s následnou částečnou optimalizací pro nezafixované části, takže je snadné zahrnout drobné úpravy (jiný typ sběru v obcí, nový členové svazku atd.) do aktuálního svozového plánu bez nutnosti kompletního přeplánování. Tento modul vznikl na základě dílčích výsledků prací [Z23], [Z24], [Z25] a [Z18].
- Modul pro správu sběrné infrastruktury v rámci obcí (Modul 2):
  Modul umožňuje analyzovat docházkovou vzdálenost a přemisťovat sběrné nádoby manuálně nebo prostřednictvím optimalizačního modelu s ohledem na množství sběrných nádob nebo docházkovou vzdálenost. Detailní sběrná infrastruktura umožňuje propojení s Modulem 1, to zajišťuje reálný odhad času sběru a také možnost dodatečného plánovaní pohybu vozidla v rámci obcí (Modul 1 se věnuje pouze meziobecnímu přesunu vozidel). Tento modul vznikl na základě dílčích výsledků prací [Z26], [Z27], [Z28], [Z29].

Další moduly jsou vytvářeny v rámci aktivit výzkumné skupiny, kterou autor tohoto textu koordinuje, a to se zaměřením na reálné aplikace v praxi.

6 ZÁVĚR

Habilitační práce je zaměřena na využití metod operačního výzkumu v oblastech OH a ObH. V těchto oblastech dochází v posledních letech ke znatelnému nárůstu potřeby evidence dat a jejich shromažďování. Účelem jsou ekonomické úspory a monitoring vybraných ekologických ukazatelů, jejich hodnocení a nastavení následných legislativních zásahů. Velkým přínosem je zde tedy efektivní využívání pokročilých statistických a optimalizačních metod.

Výzkumné aktivity autora pokrývají dvě oblasti. První se věnuje zpracování dat, tvorbě prognóz apod. V druhé oblasti se autor zaměřuje na vývoj optimalizačních modelů spojených s různými prvky celého zpracovatelského řetězce odpadu. Na základě publikovaných prací zejména v impaktovaných časopisech byl ukázán přínos těchto výzkumných aktivit.

Z pohledu využití vyvinutých přístupů pro veřejnou a komerční sféru lze charakterizovat přínos výsledků výzkumných aktivit. Jedná se zejména o vypracování koncepčních dokumentů, kde výše popsané přístupy představují podpůrný aparát, tedy především o dosavadní aplikace nástroje NERUDA. Další aktivity jsou spojeny s tvorbou aplikací (především implementovaných do webového prohlížeče). Zde jsou nástroje dostupné k opakovanému využití podle potřeb uživatele. Jedná se především o nástroj TIRAMISO pro tvorbu prognóz a projekcí, tzv. scénářů, které si definuje uživatel přímo ve webové aplikaci. Dále jde o nástroj POPELKA, který je v první fázi směřován pro potřeby svozových firem, aby mohly operativně zasahovat do svých stávajících svozových plánu. Tento nástroj nalezne zásadní přínos i pro nově vzniklé svazky obcí, které se svozem odpadu teprve začínají a musí nové plány vytvářet.

Výsledky výzkumu jsou rovněž založeny na koordinaci prací řady studentů a mladých výzkumných pracovníků, které autor habilitační práce koordinuje od roku 2012. Cílem další výzkumné práce je pokračování v nastavené trajektorii, která těží z vhodné kombinace výzkumné a pedagogické činnosti a stále se zvyšujícího množství dat v OH a ObH včetně zpětné vazby z komunální i průmyslové sféry.

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Research article

Predictive modelling as a tool for effective municipal waste management policy at different territorial levels

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ABSTRACT

Nowadays, the European municipal waste management policy based on the circular economy paradigm demands the closing of material and financial loops at all territorial levels of public administration. The effective planning of treatment capacities (especially sorting plants, recycling, and energy recovery facilities) and municipal waste management policy requires an accurate prognosis of municipal waste generation, and therefore, the knowledge of behavioral, socio-economic, and demographic factors influencing the waste management (and recycling) behavior of households, and other municipal waste producers. To enable public bodies at different territorial levels to undertake an effective action resulting in circular economy we evaluated various factors influencing the generation of municipal waste fractions at regional, micro-regional and municipal level in the Czech Republic. Principal components were used as input for traditional models (multivariable linear regression, generalized linear model) as well as tree-based machine learning models (regression trees, random forest, gradient boosted regression trees). Study results suggest that the linear regression model usually offers a good trade-off between model accuracy and interpretability. When the most important goal of the prediction is supposed to be accuracy, the random forest is generally the best choice. The quality of developed models depends mostly on the chosen territorial level and municipal waste fraction. The performance of these models deteriorates significantly for lower territorial levels because of worse data quality and bigger variability. Only the age structure seems to be important across territorial levels and municipal waste fractions. Nevertheless, also other factors are of high significance in explaining the generation of municipal waste fractions at different territorial levels (e.g. number of economic subjects, expenditures, population density and the level of education). Therefore, there is not one single effective public policy dealing with circular economy strategy that fits all territorial levels. Public representatives should focus on policies effective at specific territorial level. However, performance of the models is poor for lower territorial levels (municipality and micro-regions). Thus, results for municipalities and micro-regions are weak and should be treated as such.

1. Introduction

The transition of the current waste management (WM) systems in Europe to the circular economy based on waste flows regulation has significant cost effects on WM system users (especially municipalities, but also households) (Tomić and Schneider, 2020). Therefore, there is a high demand for strategies that minimize socio-economic impacts on the European recycling society and for efficient solutions at the municipal level. Especially, strategies concentrated of waste prevention and minimization have a high scientific and practical attention nowadays.

There are lots of empirical studies based on sophisticated modelling approaches aimed at evaluating effects of various factors on municipal waste (MW) generation, or on separate collection and that enable to predict changes aroused by these factors (e.g. Lu et al., 2009; Dai et al., 2011; Ayvaz-Cavdaroglu et al., 2019). The knowledge of these factors is a necessary pre-requisite for the establishment of WM strategies at

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Table 1
Overview of reviewed papers.

Country	Level	Model	MMW	PAP	PLA	GLA	BIO	MET	SEP
Italy (Abrate and Ferraris, 2010)	M	GR	√						√
Spain (Prades et al., 2015)	M	LR		√	√	√	√		
USA (Kontokosta et al., 2018)	B	DT	√	√					√
France (Hatik and Gatina, 2017)	M	DR					√		
Malaysia (Jaafar et al., 2018)	M	DA		√	√	√	√		
Spain (Mateu-Sbert et al., 2013)	R	LR							√
Turkey (Keser et al., 2012)	R	LR	√						
Turkey (Ozkan et al., 2015)	CD	GR		√	√	√		√	
Ireland (Purcell and Magette, 2009)	CD	GIS					√		
Vietnam (Trang et al., 2017)	HH	LR		√	√	√	√		
Nepal (Dangi et al., 2011)	HH	DA		√	√	√	√	√	
Vietnam (Thanh et al., 2010)	HH	LR		√	√	√	√		

M – municipality, B – Building, R – region, CD – city district, HH – household; GR – general regression, LR – linear regression, DR – dimensionality reduction, DA – descriptive analysis, DT – decision tree based, GIS - Geographic information system.

different territorial levels by public bodies. As Lu et al. (2009), and Dai et al. (2011) confirmed mathematical models were developed as a tool for the optimization of municipal waste management (MWM) and planning. However, the explanatory value of these models is highly dependent on the accurate prediction of the waste generation (Jalili and Noori, 2008).

Based on the urban case studies (Beijing, or Istanbul) Dai et al. (2011), and Ayvaz-Cavdaroglu et al. (2019) used mathematical modelling to find optimal MW treatment for minimizing costs and reducing the environmental side effects. Benítez et al. (2008), or Lee et al. (2016) developed models evaluating the correlation between socio-economic factors (e.g. income, or level of education) and MW generation. Both studies provide recommendations for decision-makers how to improve MW treatment using the potential of the suitable infrastructure. Oliveira et al. (2018) developed a model to predict separate collection of packaging waste at the municipal level and concluded that especially inhabitants per bring-bank, relative accessibility to bring-banks, degree of urbanization, number of school years attended, and area affect the participation at the separate collection. Based on household data Alhassan et al. (2020), or Ling et al. (2021) evaluated socio-economic factors influencing the participation of residents in incentive programs of source separation.

As the public policies and WM strategies take place on different levels of the public administration that is equipped with various competences new approaches are needed to define priorities of the MWM policy settings. Our study fills the gap in mentioned modelling approaches by evaluating MW generation at three territorial levels - regional, micro-regional and municipal level. Furthermore, our aim is to identify influential factors that enable to predict MW (and its fractions) generation. The knowledge of influential factors enables the public administration to define a suitable strategy at every territorial level and implicitly, the MW treatment capacities.

1.1. *Predictive modelling in MWM*

The quantity of MW is commonly predicted using social, economic, demographic and other variables. However, according to the results of existing reviews (Beigl et al., 2008; Kolekar et al., 2008; Cherian and Jacob, 2012), little attention has been given to predictive modelling of MW fractions. This problem is even more serious for higher territorial levels (municipalities, micro-regions, regions or their equivalents). The main reason is that such research usually obtains data via surveys, which is costly and time-consuming. Even in case the same pattern of behavior preserves from lower levels, collection of the same influencing factors is challenging and virtually impossible. Thus, it is not possible to carry out such research for a long time or large territory (e.g. region). Since Beigl et al. (2008) reviewed articles until 2005 and other reviews are not so comprehensive (they are not aimed at MW fractions and reviewed up to 20 papers), other research was done by authors of this paper. Time horizon of 2009–2019 was selected as a period of interest. The selection comprises only papers related to waste generation prediction, thus studies concerned with forecasting were not included. Main findings (see Table 1) could be summarised as follows. First, 50% of papers use territorial units smaller than municipalities. These concern city districts, buildings and households, special units closely connected to modelled waste (hospital, construction site, university, restaurant, etc.) were not included due to their irrelevance for this paper. It is remarkable that none of the papers deal with multiple levels of territorial breakdown. Second, a total of 34 (almost 3 per paper) waste fractions were modelled (marked by ticks in Table 1). About 40% of studies dealt with bio (BIO), paper (PAP), plastic (PLA) and glass (GLA) altogether. Other fractions important for this paper were not so common, which is surprising at least in case of MMW as it is the main contributor to MW generation. In some cases (Abrate and Ferraris, 2010; Prades et al., 2015), only total amount of separated waste (SEP) is subject to research and in case of Kontokosta et al. (2018), special "fraction" (MET + GLA + PLA) is collected. Third, the most common approach to analyse MW generation is (multiple) regression models (58%). No paper dealing with metal (MET) or bulky waste (BW) at the level of municipality (or higher) was found. Table 1 shows 12 papers dealing with at least one of the MW fractions relevant for this paper (MMW, PLA, PAP, GLA, MET, BIO, BW).

Prediction models are usually based on socio-economic, demographic and other factors so they are not suitable for forecasting. Forecast of all inputs will be needed for this purpose. Thus, prediction models can be used for estimation of missing or erroneous data as well as for scenario planning. According to above mentioned results, there is a lack of studies that compare different prediction modelling approaches of MW fractions generation for various levels of territorial breakdowns especially those defined by administrative definitions like regions, districts and cities or their equivalents. These are also essential for strategic planning of sorting policy and material recovery. The results are valuable for government advancements in MWM as well as for investors of WtE plants and sorting facilities.

1.2. *Influential factors*

The current scientific discussion about factors influencing the waste generation and recycling involves not only socio-demographics (Miafodzyeva and Brandt, 2013; Rybová et al., 2018) and socio-economics (Saphores and Nixon, 2014), but also technical and organizational variables describing the perceived convenience of the MWM system (e.g. distance to collection points, door-to-door collection, or availability of containers in public space), charging system (Miafodzyeva and Brandt, 2013; Slavík et al., 2020), or environmental values and psychological variables (Slavík et al., 2018). Especially the last group of factors gains increasing attention when socio-demographic and socio-economic factors are characterized by ambiguous results with low predictive power (Rybová et al., 2018).

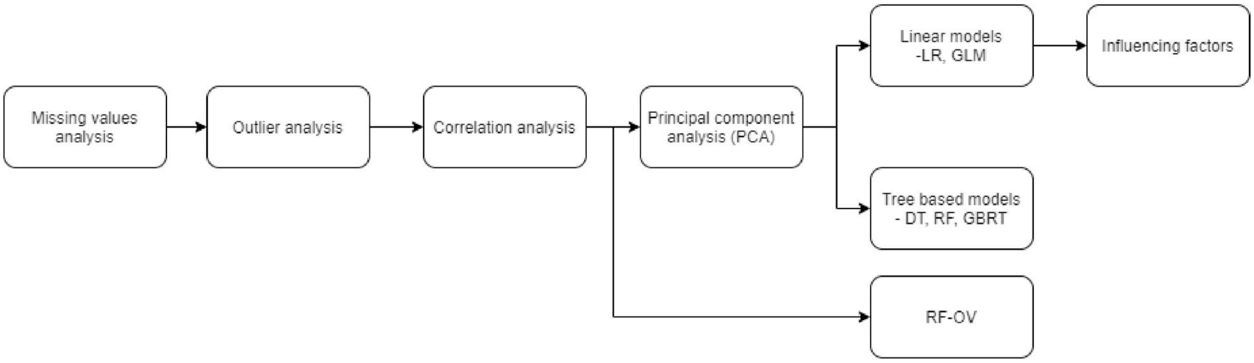

Fig. 1. Paper framework (LR – Linear regression, GLM – Generalized linear model, DT – Decision tree, RF – Random forest, GBRT – Gradient boosted regression tree).

The research of socio-demographic factors includes especially age and gender. Because of the modest lifestyle (Sterner and Bartelings, 1999), higher willingness to participate at separate collection (Saphores et al., 2006; De Feo and Polito, 2015), higher level of environmental knowledge, or education (De Feo and De Gisi, 2010) older people generate less waste and recycle more. However, some authors argue that the relationships between age and the MW generation is very weak, or insignificant (Lebersorger and Beigl, 2011; Miliute-Plepiene et al., 2016).

When analyzing gender Daskalopoulos et al. (1998), or Talalaj and Walery (2015) concluded that because of a higher attention to their appearance, or consumption habits (catalogue shopping, home delivery services) higher share of women in the municipality leads to higher generation of waste. On the other hand, women are also more willing to use the municipal infrastructure for the waste separation and separate waste in the household (Saphores et al., 2006). However, also the relationship between gender and waste generation (or recycling) is ambiguous (Saphores and Nixon, 2014; Miliute-Plepiene et al., 2016).

The research of socio-economic variables influencing the MW generation and recycling involves the average household size (Beigl et al., 2008; Lebersorger and Beigl, 2011), income (Berglund, 2006; Gellynck et al., 2011; Gellynck et al., 2011, 2011), level of education (Sterner and Bartelings, 1999; Hage and Söderholm, 2008; Keser et al., 2012) and other (less obvious) factors (e.g. unemployment rate, share of people employed in agriculture, heating by solid fuels, or population density). Especially heating by solid fuels is important for WtE because it reduces collected waste quantities differently (not all MW fractions are suitable for burning). Solid fuel heating systems have a two-tier impact on waste generation. While Lebersorger and Beigl (2011) concluded that households equipped by solid fuel heating systems generate less waste (because of the by-burning of waste), Dennison et al. (1996) found higher generation of waste in those households induced by the generation of ash.

Keser et al. (2012) concluded that paved roads enable higher collection frequencies and better collection works and therefore, higher amounts of waste can be expected in rural areas. Lebersorger and Beigl (2011) found regions with higher share of people employed in agriculture as regions with lower waste generation. The explanation lies in the higher waste separation and recycling of organic matter. Furthermore, also population density influences waste generation. Johnstone and Labonne (2004) confirmed higher waste generation in regions with higher population density when the crucial infrastructure is missing competing with lack of space.

Beyond socio-demographic and socio-economic variables the MW generation is influenced also by behavioral (or psychological) variables and environmental values (intrinsic variables). Especially waste separation and recycling as alternatives to waste generation stay in the centre of attention. Higher separation rates lead to MMW reduction and change of its structure. Both MMW quantity and structure are crucial for WtE plants.

The last group of factors influencing the waste generation and recycling represent situational variables that reflect the perceived convenience of the MWM system. The better, convenient and user-friendly separation system the higher recycling (and motivation to reduce amount of waste generated). In this context, especially distance to the container (Struk, 2017), its localization (Mattson-Petersen and Berg, 2004; González-Torre and Adenso-Díaz, 2005), or space for waste storage at home (González-Torre and Adenso-Díaz, 2005) are highlighted.

Previous paragraphs suggest that the impacts of socio-economic and demographic variables are often quite weak and thus, reported results are questionable. So possible relationships should be judged not only by 'statistical' significance, but also by 'real world' significance (those are not the same). Moreover, it seems that it is not possible to generalize the results from one country to every other. This is particularly true in case of big differences in population well-being, current state of MWM, urbanization, and other aspects. According to our opinion, it can be misleading to analyse just household or municipality level and generalize these conclusions to upper territorial levels.

Unfortunately, analysis of influencing factors for levels of micro-regions and regions is quite rare in the literature (see Table 1). The only papers found are Keser et al. (2012), Mateu-Sbert et al. (2013) and Mazzanti et al. (2008). However, Keser et al. (2012) and Mazzanti et al. (2008) do not analyse separate collection fractions. Mateu-Sbert et al. (2013) analyses only the impact of tourism.

1.3. Novelty and contribution

This paper aims at exploration and comparison of predictability of main MW fractions for multiple territorial levels. Moreover, influencing factors for each MW fraction and territorial level were examined. The main research questions are:

- Which socio-economic or demographic factors are the most important for micro-regional and regional level?
- Are there any 'super predictors' which are important for multiple MW fractions on the same territorial level or for selected MW fraction across the levels?
- Is it possible to transfer qualitative results from one territorial level to another (e.g. Is it sufficient to analyse factors for municipality level and use them for higher levels or vice versa)?
- How much does the MW fractions predictability vary according to selected territorial level and MW fraction?

The reported analysis provides an example of a framework for predictive modelling and influencing factor identification for MW fractions with problematic MWM records. It was used for case study in the Czech Republic. Moreover it:

- Was done for multiple fractions of MW (MMW, PLA, PAP, GLA, BIO, MET, BW) on different territorial levels, which is not very common.

- Identifies important predictors for each ‘MW fraction’-‘territorial level’ pair.
- Uses multiple modelling approaches.
- Enhances quality of scenario planning for material and energy recovery.

2. Materials and methods

Countries are usually divided by geographical, administrative or historical means into smaller parts like cantons, constituent states, regions, districts, micro-regions etc., which is problematic for intercountry comparison. Data for higher territorial levels are commonly obtained by aggregation from lower levels. Overall problem with data is the existence of various definitions, which are not always clearly defined, and presence of defective input.

At the beginning an analysis of missing values and outlier analysis was performed, followed by correlation analysis, principal component analysis (PCA). By applying PCA, mutually orthogonal principal components (PC) were created. PCs were then used as inputs for various models. Framework of the paper is summarised in Fig. 1. All data manipulation, preparation, modelling and visualisation were done using R programming environment (R Core Team, 2019).

2.1. Data

The Czech Republic is a country in Central Europe with 10.7 million inhabitants and an area of 78,866 km^2. Capital city of the Czech Republic is Prague (1.3 million inhabitants), which is also one of the 14 regions (population of 0.3–1.3 million). The regions consist of 206 micro-regions (8600 to 1.3 million inhabitants) and about 6250 municipalities (up to 1.3 million inhabitants).

Data sets were created for selected territorial units and the time horizon was defined by the availability of data from MWM (2009–2017 for all levels). MWM data from previous years were not included due to methodological changes in the MWM system. The regional-level data set consisted of 126 variables. Datasets containing about 50 (independent) variables were used at micro-regional and municipality level.

Same waste fractions and their definitions were used for all levels, namely MMW, PLA, PAP, GLA, BIO, MET and BW. Finally, MW, defined as the total sum of named fractions, was also included. This definition of MW represents about 93% of total MW in the Czech Republic. All the mentioned waste production variables (dependent variables) were converted to per capita rates. Similar operation was also done for independent variables (e.g. population in the age group of 0–14 was converted to percentage of total population, population to population density etc.). Such operation worsens the correlations between dependent and independent variables. Thus, model performance also gets worse. On the other hand, this helps to reveal and understand relationships in the data. It is well known that for established waste fraction generation rate, population is the most influencing factor. Total population also influences other variables (e.g. population in age groups, gross domestic product, etc.). By using these original data, their impact is masked by the main effect (size of the territorial unit).

2.2. Outlier analysis

Prior to a further data analysis, it is advisable to identify outliers and extreme values. The identification and data modification took place in three steps:

1. Identification and omission of outliers at the lowest level of territorial breakdown (municipal level for data from MWM; for other factors, the smallest territorial unit is given by data availability).
2. Aggregation to higher territorial units, if the data from another source are not available, they are not used for aggregation (i.e. if the data are missing in the municipality, then the value for the given micro-region is calculated without the data from this municipality).
3. Identification and omission of outliers for higher territorial breakdown after the data aggregation.

Boxplots or z-scores are usually used for outlier identification. However, in this case, a more robust measure Q, proposed by Rousseeuw and Hubert (2011), was used, see equation (1) (x is variable of interest). The robust procedure was chosen with regard to the fact that it was necessary to assess about 150 variables (in total), which often lack expertise in the decision on outlying. Moreover, many variables were heavily skewed so traditional tools for outlier detection are not appropriate in this case. The value was marked as outlying (and removed) if its value of Q was greater than 3 (in absolute value). The exact threshold value should not have a major impact (outliers are typically significantly larger).

$$Q = \frac{\left(x_i - \underset{j=1,\ldots,n}{median}\left(x_j\right)\right)}{1.483 \cdot \underset{i=1,\ldots,n}{median}\left|x_i - \underset{j=1,\ldots,n}{median}\left(x_j\right)\right|} \tag{1}$$

The MWM values identified as outliers were removed for further work. Data at higher levels of territorial breakdown were then aggregated based on the data from the lower territorial unit. In case of outliers, neither MWM value nor population of the particular lower territorial level unit was included. Moreover, MW was defined as an aggregate of individual waste fractions. If the value at the municipal level was omitted because of outlying, it was replaced for the purpose of aggregation into MW. If a single point was omitted in the 2009–2017 time series, it was replaced by linear interpolation. If more points in the time series were missing, they are replaced by the average production of the relevant region in the given year.

2.3. Linear models

A linear regression (LR) analysis is a statistical method that is widely used to describe dependencies in data. Based on the literature review, the regression analysis is suitable for the use for MWM data. Generalized linear models (GLM) are not used as frequently in the MWM domain as the other mentioned approaches. However, they are a natural choice when the classical LR is not considered as an adequate tool. Based on the authors’ previous experience, a gamma regression model (with an identical link function) was chosen. Main advantages of GLMs (when compared to LR) are greater flexibility, possibility to incorporate domain specific knowledge and deal with (some) nonlinear dependencies. A disadvantage of generalized models is that the global optimum is not guaranteed when estimating the coefficients and, in some cases, it may be necessary to supply appropriate starting values (Dobson, 1990). Special limitation of Gamma regression is that the dependent variable can only have positive values, so it is not possible to model the cases in which the production is zero.

Model selection was done by backward elimination with Akaike Information Criterion (AIC) for both LR and GLM models. Assumptions of Gauss-Markov theorem were tested by Anderson-Darling test (normality), t-test (zero mean) and Durbin-Watson test (independence).

2.4. Decision tree – based models

Although models of artificial neural network (ANN) and support vector machines (SVM) are used quite often to deal with similar issues (Kolekar et al., 2008), this analysis did not use them. The main reason is the doubts about their inadequacy for the chosen task, especially with regard to quantity and quality of data. Therefore, only models of decision tree (DT), random forest (RF) and gradient boosted regression trees (GBRT) were used. Tree-based models (especially RF and GBRT) are quite popular in general, but they are rarely used in MWM. They are not even mentioned in reviews from the MWM area (Beigl et al., 2008; Kolekar et al., 2008; Cherian and Jacob, 2012). DT may not be of sufficient quality for the actual use, but it may serve as a source of information on the inner working of modelled processes.

DT models are quite popular in machine learning due to their capabilities to deal with complex nonlinear relationships and interpretability (Hastie et al., 2009). They are based on recursive partitioning of the feature space to subspaces. Individual models are then created for these subspaces. In each step of the partitioning process, the point performing the greatest reduction of the residuals is selected as a split point. Tree structure describing important variable relationships is generated by this process.

GBRT model is an extension of DT model which incorporates so-called boosting (Friedman, 2001). GBRT does not try to find the best possible model (as DT model) but creates many weak models (trees). DTs are generated sequentially based on residuals of the previous tree. So, the generating process is basically a gradient algorithm which improves the resulting prediction by adding another tree to minimize loss function in each step. The resulting model is a linear combination of all created trees (more accurate models have higher influence).

RF is another tree-based model (Breiman, 2001). Similarly, to GBRT, RF uses many weak learners and combines their results. Randomness is incorporated during creation of this model in two ways. First, only a randomly selected subset of observations is used for a given tree (so called bagging). Second, for this randomly selected subset, a random subset of features (independent variables) is used to create DT. So different features are used for different trees. Such an approach increases the uniqueness of individual trees across the forest. Bagging meta-algorithm increases stability and precision of the model and decreases probability of overfitting.

2.5. Performance measures

Based on the research, Root mean square error (*RMSE*), Mean absolute error (*MAE*) and Mean absolute percentage error (*MAPE*) were selected as measures for model quality assessment and comparison. General definition of R^2 is not included; it was used just for LR and GBRT models. In other cases (GLM, DT, RF), model specific definitions for given models were used. For GLM, multiple definitions of “pseudo” coefficient of determination are available, deviance residuals version was used, see Dobson (1990) for details. DT algorithm uses relative error and RFs coefficient of determination is defined via mean squared error (MSE). Thus, R^2 values are not fully comparable.

All definitions are taken as in eqs. (2)–(8), where n is number of observations, Y_i actual value and $\widehat{Y}_i$ predicted value.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{n}} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \widehat{Y}_i\right| \tag{3}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \widehat{Y}_i}{Y_i}\right| \tag{4}$$

$$R^2_{GLM} = 1 - \frac{ResidualDeviance}{NullDeviance} \tag{5}$$

$$R^2_{DT} = 1 - \frac{Y_i - \widehat{Y}_i}{Y_i} \tag{6}$$

$$R^2_{RF} = 1 - \frac{MSE}{Var(Y)} \tag{7}$$

Table 2
Overview of outlier identification in MWM data.

Upper bound [t/capita/year]	MMW	PLA	PAP	GLA	MET	BIO	BW
Municipality	0.447	0.032	0.037	0.032	0.031	0.184	0.062
Micro-region	0.318	0.019	0.030	0.018	0.031	0.080	0.057
Region	0.248	0.017	0.022	0.014	0.023	0.059	0.04
Identified [%]							
Municipality	5.3	2.6	4.9	3.3	22.9	3.9	8.1
Micro-region	2.4	0.4	0.8	1.4	3.2	2.4	0
Region	3.2	0	0	0	0	0	2.4

$$MSE = \frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{n} \tag{8}$$

All modelling approaches were compared via cross validation (CV). Dataset was randomly split to training (75% of observations) and testing (25% of observations) datasets five times. For each of these training sets, models were created and performance on testing datasets is reported.

3. Results and discussion

Missing values analysis was carried out for each territorial level. At the regional level, about 8% of data was missing, for micro-regions and municipalities, the number was higher (20% and 26% respectively). Missing data with known cause was replaced by a suitable estimate (where applicable). Proportions of missing values point to the fact that data quality decreases for lower territorial levels. The same phenomena can be expected also for created models.

Waste generation variables (i.e. dependent variables) contained a significant number of missing values. There are cases of municipalities where the generation of MMW is not reported and, at the same time, positive generation of some other MW components is registered. Such a situation was handled as an error. In the case of a missing value in MMW, the MW value was also removed, since the MW is artificially defined as the sum of the respective fractions. MMW forms a large part of MW; therefore, in the absence of information on MMW generation, the value of the MW generation was not used either. For other fractions of waste, it was assumed that the absence of the value was because the collection of the given type of waste is not taking place in the municipality and the missing value was replaced by zero. Legislative changes can also cause missing values as well as other problems.

3.1. Outlier analysis

A process using the above-mentioned robust measure (see equation (1)) was used. In addition, compared to the independent variables, the boundaries were checked based on expertise for waste generation data. Also in this case, the boundary for Q was set to 3.

Table 2 shows the corresponding upper bound values according to which the respective values of different types of waste were assessed. Table 2 also shows the percentages of identified measurements. At municipal level, in case of identification of outliers of some of the fractions, the MW values were also updated. If only one observation was identified in the time series of the respective municipality and fraction, it was (for the purposes of MW updating) replaced by linear inter/extrapolation. At the regional level, only a few observations with MMW and MW were identified as outliers.

At the level of municipalities, approximately 3% of the values for independent variables were identified and removed by this procedure. A total of 2% of the micro-region values were removed. For regions, it was 5% of values. Original dataset contained absurd values of annual MW generation (e.g. over 300 and 20 tonnes per capita for MMW and PLA respectively). However clear boundaries between outliers (i.e.

Table 3
Overview of tests p-values and CV performance measures for LR models – regional level.

	Test p-values			Performance measures			
	Normality	Mean value	Correlation	*RMSE*	*MAE*	*MAPE*	R^2
lr_MW	0.4625	1	0.002	0.01	0.01	3.1	0.74
lr_MMW	0.06101	1	0.072	0.01	0.01	2.59	0.73
lr_PAP	0.2473	1	0.832	0	0	9.83	0.32
lr_PLA	0.01577	1	0.034	0	0	10.64	0.73
lr_GLA	0.4797	1	0.018	0	0	5.33	0.77
lr_MET	0.2868	1	0.168	0	0	34.95	0.68
lr_BIO	0.0006377	1	0.078	0.01	0.01	35.69	0.66
lr_BW	0.3061	1	0.33	0	0	12.05	0.38

errorneous inputs) and extremes (i.e. values distant from majority of data) were not found. Thus, our approach does not make a distinction between extreme values and outliers. This distinction can be quite complicated even if the author possesses expertise in a given field. In case of analysis of data from multiple fields, it is getting even more complicated. One of the possible solutions is to focus just on 'bulk' of data by excluding both extremes and outliers. Such a solution is far from perfect and conclusions should not be generalized to excluded cases. For more proper handling of this problem, distribution properties of analysed variables should be examined in greater detail. Considering waste generation data for each territorial unit separately with respect to specific time development should be also helpful for distinction between outliers and extremes.

3.2. *Principal component analysis*

In the case of many potential predictors which, in addition, are strongly correlated with one another (i.e. a high risk of multicollinearity in regression models), it is advisable to use the principal component analysis (Hastie et al., 2009).

Prior to PCA application, variables containing many missing values (over 20%) and at the same time not strongly correlated with dependent variables (for the regional level about two thirds of all available variables) were removed. The remaining variables were centralized and standardized before PCA was performed (individual variables are often in significantly different orders, which would strongly affect the results).

At the regional level, 40 PCs (10 in use) were created, 19 PCs (6 in use) for micro-regions and 21 (9 in use) for municipalities. The choice about the number of PC in use for further analysis was made based on the so-called Kaiser rule (Kaiser, 1960).

3.3. *Linear regression–based models*

This section describes the results of selected models, including their diagnosis. All models covered by this section were created using PCs as independent variables. Moreover, at the municipal level, so-called dummy variables were added for BIO and MET models to indicate whether they were collected in the given municipality.

3.3.1. *Multiple linear regression (LR)*

For regional data, most models *MAPE* range from 3% to 12%. The results for MET and BIO are significantly worse, but this is not surprising. In some municipalities, the collection of these types of waste is not in place, which may also affect the aggregated data. The R^2 values (at the level of the regions) are in a relatively wide range (from 0.32 for PAP to 0.77 for GLA). It should be noted that a lower value of R^2 does not necessarily mean a bad model; it may be the case that the average value already provides a sufficiently accurate estimate and the deviations from it are not very large. Table 3 shows p-values of performed tests. All models at regional level pass *t*-test, two models (lr_PLA, lr_BIO) violate assumption of normality and three models (lr_MW, lr_PLA, lr_GLA) have not uncorrelated residuals. However, it should be noted that some of the values are close to selected significance level ($\alpha = 0.05$). In such a case, no strict conclusions should be made about the test results.

At the micro-regional level, the accuracy deteriorated dramatically compared to the regional level (most of the *MAPE*s ranged from 10 to 30%); for MET and BW, it was more markedly deteriorating (*MAPE* value over 100%), and for BIO, the absurd value in the order of tens of thousands. This phenomenon is due to the presence of very small productions, where the model makes a small absolute error, but the relative error is very high. Pure zero values were omitted for calculating *MAPE* for BW and BIO; otherwise this calculation would not make sense. Compared to the level of regions, there are already significant problems with fulfilling the assumptions. Strictly speaking, none of the models meet the assumptions; however, virtually, the normality violence or independence of residuals (judged by correlation) in PAP or PLA models were rejected only tightly, and such models could be considered applicable.

At the level of municipalities, another expected deterioration occurs in terms of accuracy for all criteria (with exception of R^2). Out of all modelled fractions, just MW and MMW reached $MAPE < 100\%$. The reason is the same as with BIO at the micro-regional level. Extremely small observations could, of course, be eliminated (as with MMW), but in this case, it would be very difficult to deduce when the value is erroneous and when the low value is because the collection of the given fraction in the area is just beginning. The trend of deteriorating accuracy is not maintained with R^2 for BIO and MET where the improvement at the municipal level is due to the addition of the so-called dummy variable indicating whether waste is collected in a given municipality in a given year. At this level, there is already a severe violence of LR assumptions in all models. Results for micro-regions and municipalities are reported in Appendix A.

3.3.2. *Generalized linear model (GLM)*

GLM models have comparable results to LR models at regional level. At the level of micro-regions and municipalities, it was necessary to specify the starting value of the calculation for some waste fractions; LR estimates served this purpose. With this setting the resulting GLM models were comparable to LR apart from the municipal level (GLMs are better). This is probably due to the omission of zero values in gamma regression models (selected GLM approach). With the lowest units – municipalities, it was not possible to create a model for BIO (therefore performance measures and test results are not reported) and the quality of models was deteriorated due to the presence of zero production. See Appendix B for performance measures and test results.

3.4. *Tree-based models*

Unless otherwise stated, all models in this section are based on the same data as the models of LR and GLM. *RMSE* is minimized to find optimal values of model parameters. The same number remains in terms of considered inputs (PC) and observations.

3.4.1. *Decision trees (DT)*

Commonly optimized parameters of DT are *complexity parameter* (cp – denoted by α in some literature) and *maxdepth* (maximum tree depth).

Table 4
Overview of parameter setup and CV performance measures for RF models – regional level (both PCA and OV versions).

	Mtry		Performance measures - PCA				Performance measures - OV			
	PCA	OV	*RMSE*	*MAE*	*MAPE*	R^2_{RF}	*RMSE*	*MAE*	*MAPE*	R^2_{RF}
rf_MW	7	14	0.01	0.01	2.99	0.75	0.01	0.01	2.79	0.75
rf_MMW	5	15	0.01	0.01	2.51	0.8	0.01	0.01	2.62	0.67
rf_PAP	4	26	0	0	8.74	0.41	0	0	8.27	0.41
rf_PLA	6	8	0	0	9.14	0.86	0	0	8.22	0.82
rf_GLA	6	26	0	0	5.55	0.74	0	0	4.81	0.79
rf_MET	7	8	0	0	46.9	0.54	0	0	36.18	0.67
rf_BIO	7	22	0.01	0.01	37.46	0.75	0.01	0.01	29.7	0.73
rf_BW	7	17	0	0	9.09	0.64	0	0	8.05	0.64

Table 5
Overview of best models (based on MAPE) performance measure values for modelled waste fractions – micro-region and municipality level.

	Model	Micro-region				Model	Municipality			
		RMSE	*MAE*	*MAPE*	R^2		*RMSE*	*MAE*	*MAPE*	R^2
MW	RF-OV	0.03	0.02	7.54	0.50	RF-OV	0.09	0.07	53.92	0.37
MMW	RF-OV	0.02	0.02	8.52	0.56	RF-OV	0.06	0.04	56.84	0.44
PAP	RF-OV	0	0	24.29	0.33	RF-OV	0.01	0.01	307	0.26
PLA	RF-OV	0	0	19.69	0.53	RF-PCA	0.01	0.01	435	0.08
GLA	RF-OV	0	0	13.23	0.44	RF-OV	0.01	0	90.01	0.24
MET	GBRT	0	0.00	126.21	0.09	RF-OV	0.01	0	1369	0.41
BIO	RF-OV	0.01	0.01	25,673	0.44	RF-OV	0.03	0.02	13,400	0.25
BW	GBRT	0.01	0.01	85.66	0.18	RF-OV	0.01	0.01	640	0.28

Their goal is to find a balance between the complexity and the depth of the tree. Both values are first optimized separately due to computational demands. The values found in this way serve as a basis for optimizing both values simultaneously. In both steps of parameters optimization (individual and combined), repeated cross-validation is used with division into 10 subsets and 3 repetitions. The models were subsequently pruned, resulting in the final DT models. In terms of selected performance criteria, DT models appear to be worse (compared to LR and GLM, see Appendix C for regional level results and parameter settings), which was the expected result. However, the results confirm the conclusions of previous models (higher accuracy with increasing levels of territorial breakdowns or the same "problematic" types of waste).

3.4.2. *Random forest (RF)*

The main advantages of RF include high accuracy and little to no need of parameter tuning (Kalmar and Nilsson, 2016). For this reason, only the *mtry* parameter, which specifies the number of randomly selected variables to be selected at each division, is optimized. The default setting for this parameter is one-third of the number of independent variables available, with values ranging from one to two-thirds of the predictors tested during the search. This parameter was optimized at the level of municipalities due to computational demands, so the values corresponding to the basic algorithm settings were used.

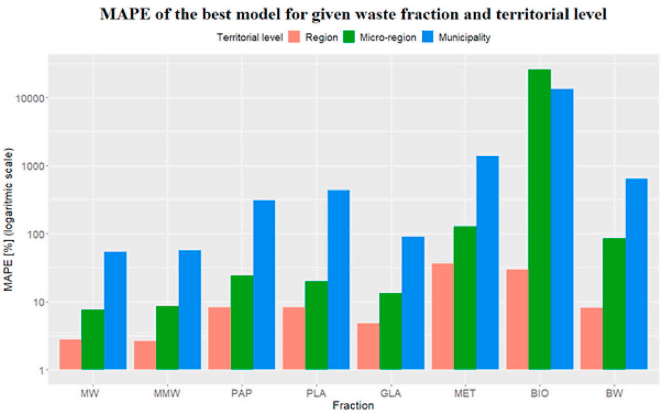

Fig. 2. Comparison of *MAPE* for all modelled fractions and territorial levels (best models).

Since the splitting nodes are only selected from a subset and the model can be easily created in parallel, so the RF for original variables (OV) were also created. The performance results and parameter settings for regional level are given in Table 4.

3.4.3. *Gradient boosted regression trees (GBRT)*

For GBRT, two parameters were optimized, in particular: *learning rate* (eta - lower values reduce the risk of overfitting but leads to a higher computational time) and *maxdepth* (maximum tree depth). To find optimal parameter values, eta values of 0.001, 0.005, 0.01, 0.05, 0.1 were used, *maxdepth* of values from one to the number of variables (PC) were examined. At the same time, the numbers of iterations (*nrounds*) were recorded, after which the values of the purpose function in the last 10 steps no longer improved. Values of selected performance measures and parameter settings for regional level are presented in Appendix C.

The quality of models varies considerably for different territorial levels. Variations and inaccuracies at municipal level are often smoothed for higher territorial units due to aggregation. At the regional level R^2 values vary considerably for different waste fractions, the same is true for *MAPE*. At micro-regional level, RF shows superiority in terms of *MAPE* (see Tables 3 and 5). The use of original variables for RF models brings a slight improvement of *MAPE* in most cases (about 10% in comparison with LR or GLM). However, micro-regional level models bring unsatisfactory results for some of the fractions (MET, BIO, BW). This pattern continues (and strengthens) at municipality level (see Table 5). The results also confirm that RF are strong in 'decorrelation' of predictors (without using PCA).

The results of LR models on municipality level confirm problems with accuracy of modelling of MW (fractions) in the Czech Republic via socio-economic and demographic variables, see Rybová and Slavík (2016), Rybová et al. (2018). In comparison with Prades et al. (2015) or Lebersorger and Beigl (2011), results from the Czech Republic are much worse. One of the reasons could be data quality. Another reason is that Prades et al. (2015) analysed only cities with population over 5000 and Lebersorger and Beigl (2011) results are for transformed variable $MW_t = \log(MW)$. Moreover, Lebersorger and Beigl (2011) analysed only data from one year (with census data available) and only one region of the country. So, none of these results are fully comparable with our results. Our analysis is also more comprehensive. Moreover, findings of this paper may be beneficial even for forecasting models like Ghinea et al. (2016), in two ways. First, better predictors can be found and second, accuracy of the models for other fractions or territorial levels can be estimated.

Up to our knowledge, there is no paper dealing with micro-regional and regional level for the Czech Republic data. For MMW production modelling comparison on regional level, Keser et al. (2012) can be used as Turkish 'provinces' are roughly comparable to Czech 'regions' in terms of population. R^2 of Keser et al. (2012) for MMW modelling ranges from 0.4 to 0.62 depending on the model. Our models for MMW on regional level perform better (see Table 3, Table 4 and Appendix) with DT as the only exception. Moreover, our results are based on CV and thus should be more reliable. Fig. 2 shows comparison of *MAPE* for all modelled waste fractions.

3.5. *Influential factors*

Influencing factors are analysed based on *t-statistics* from regression models. At the municipal level, our results indicate three groups of socio-economic variables with the significant impact on MW generation - age, number of applicants for a job, and amount of expenditures. According to our results elderly people of age 65+ are more prone to separate PLA, GLA, MET, BIO, and BW. Our results are consistent with previous findings (based on individual, household, or municipal level data) that found elderly people more willing to participate at recycling activities (Sidique et al., 2010). Sidique et al. (2010) concluded that older people use drop-off recycling sites more often, especially when the travel distance from home to a site is shorter. Therefore, the localization of drop-off recycling sites matters when encouraging people to separate waste, mainly when elderly people stay in the centre of attention.

Nevertheless, the role of age in explaining the waste (or recycling) behavior seems to be tricky. Our results also found elderly people of age 65+ to generate more MW. Struk and Soukopova (2016) came to the same result for the people aged 50–79. They explained this result by the specific habits of elderly people when they prepare households for being retired - reconstructions, replacement of household goods, or sorting and disposal of goods accumulated during the active life. On the other hand, these results contradict with Sterner and Bartelings (1999) who concluded that based on their frugal lifestyle older people generate less waste. Obviously more detailed work with age groups is needed when explaining behavioral settings of elderly people.

Some authors replace missing data about income at the municipal level by the unemployment rate. Rybová and Slavík (2016) concluded that increasing unemployment leads to a higher MW generation. Our results indicate lower separation of PAP, PLA, and BIO when the number of applicants for a job increases (incl. of those applicants who are in an evidence for more than 12 months). However, the number of applicants for a job seems to be of lower significance when explaining the MW, or MMW generation.

Based on the data on the municipal level our research indicates a significant relationship between MW generation and expenditures of a given municipality. Expenditures are commonly highly correlated with income and thus can be used as a proxy for the economic level of a municipality. Moreover, high expenditures can indicate general development of the municipality. Lebersorger and Beigl (2011) found that per capita tax income of municipality (another possible proxy for economic level) increases MW. According to our results, the same is true also for individual fractions of MW.

Our results for micro-regions and regions are compared mainly to the results of papers at the lower territorial levels, due to lack of relevant papers for higher levels. Socio-economics factors influencing the MW generation and separate collection change at the micro-regional level. The most significant factors are the population density, number of economic subjects with no more than 10, and 50 employees, share of flats in family houses, and age. Our results indicate a positive relationship between the population density and the MW generation, and the separate collection of PAP, PLA, MET, BIO, or BW. These results for MW are in accordance with Mazzanti et al. (2008). However, the negative coefficients for MMW and GLA imply some specific management settings based on density economies - e.g. shared collection containers, or lack of space increases a pressure on waste prevention, minimization, and separate collection.

Our results for the relationship between the number of economic subjects and MW generation are ambiguous. While results for economic subjects with no more than 10, and 50 employees indicate some relationship, results for more than 50 employees are insignificant. Probably, the reason lies in the difference in management of MWM between those economic subjects. While economic subjects with more than 50 employees generate types of industrial waste with lower amounts of waste that is similar to MW and have their own contract to waste company to collect and dispose their waste, economic subjects with 0, or no more than 10, or 50 employees generate waste similar to MW and they are connected on the MWM system (incl. the contract with the municipality). Therefore, the results for economic subjects with no employees indicate higher generation of MMW with an increasing number of these subjects (especially small traders, services etc.) participating in the municipal system and generating waste similar to MW. Results for separate collection fractions are ambiguous. While fractions with their functioning market for secondary raw materials (PAP, MET, or some types of BW) evidence lower generation with increasing number of economic subjects with no employees, the amount of other fractions (PLA, and GLA) increases in the municipal system. The involvement of economics subjects in the MWM system is crucial when planning the financing, operation, and investments in the system. Therefore, the active cooperation between economic subjects and municipalities is considerable.

The share of flats in family houses largely expresses the possibilities of households in the MWM. Barr et al. (2003) confirmed that households living in the family house separate more waste than households in a block of flats. The reason lies in better conditions for the storage of waste and its fractions (e.g. garage). Furthermore, according to Alexander et al. (2008) these households perceive less barriers in the waste separation. Nevertheless, our results seem to be in the contradiction with these conclusions - increasing share of flats in family houses leads to lower amount of PAP (maybe because of the combustion of the PAP in the heating chamber - see Lebersorger and Beigl, 2011), MET (sell for market price), or BW (e.g. combustion of wood components). Higher MMW generation could result from the higher production of ash (Dennison et al., 1996). Another possible reason is that results from lower levels (all references in this paragraph) are simply not preserved for micro-regional level.

Dependence of the MW generation on the age structure at the micro-regional level has analogous results as at the municipal level.

At the regional level especially, following variables are significant: age structure, number of applicants for a job, education, or number of economic subjects. The impact of age structure seems to be the same as for micro-regions and municipalities. Higher share of people aged 15–64 increases MMW generation and decreases separate collection. Age group 65+ and mean age behave in the opposite way. However, the effect on PAP seems to be weak for age structure related variables. In the case of applicants for a job results from the municipal level were confirmed. The increasing number of applicants for a job leads to lower separate collection of PAP, MET, or BIO. Probably, the reason lies in the sale of PAP and MET at the secondary raw materials market. The results for other fractions seem to be insignificant, however, the number of applicants for a job negatively influences the generation of MW (because of lower amounts of PAP, MET, and BIO).

At the regional level the level of education seems to be significant when explaining MW generation. According to our results the increasing

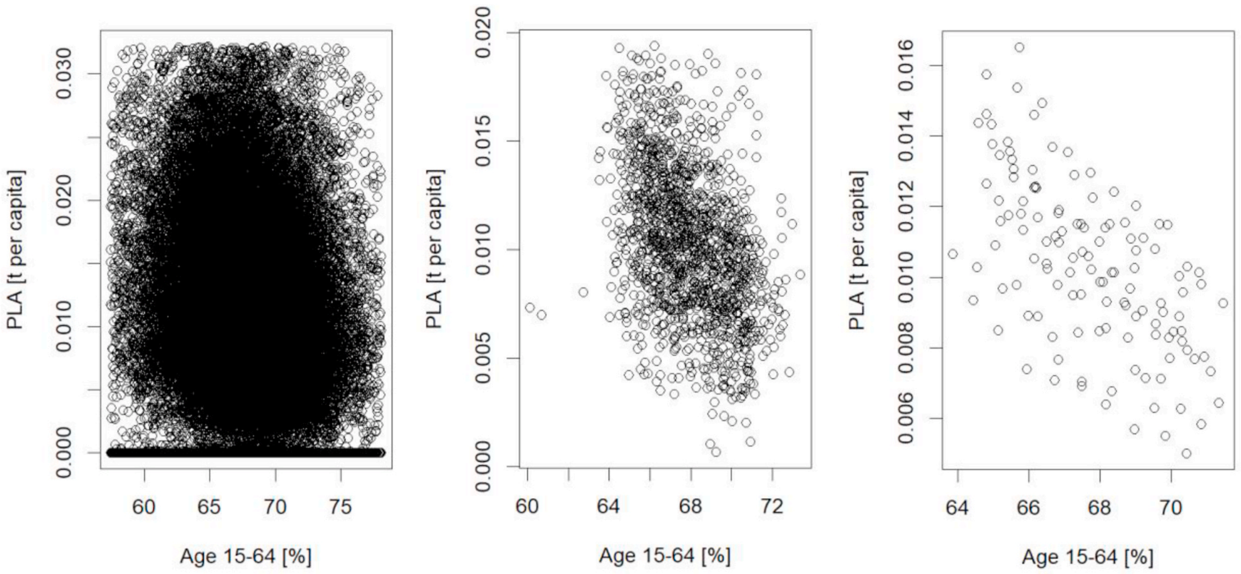

Fig. 3. Example of deterioration of relationship when moving from higher to lower territorial levels. Points graphs for Age 15–64 and PLA for level of municipality (left), micro-region (middle) and region (right).

number of people with secondary education (without graduation) leads to decreasing separate collection and increasing generation of MMW. Because the impact on separate collection is stronger than on MMW generation, MW generation decreases. These results are in accordance with Rybová and Slavík (2016) who found the level of education as a crucial variable. The higher share of higher educated people in the population the higher the separate collection. Our results partially contradict with Keser et al. (2012) who found higher generation of MMW in regions with higher share of higher educated people. However, this effect is significant only for 60% of Turkish regions (Keser et al., 2012). On the other hand, our results in the case of education with graduation show a higher separate collection of PLA, GLA, and BIO.

Considering the number of economic subjects at the regional level our results confirm the results from micro-regional level. The higher number of economic subjects with no employees, the higher generation of MMW and lower separate collection of PAP. Results for other fractions are not significant. Based on the current research of socio-economic variables influencing MW generation especially the average household size seems to be of key importance. Increasing average household size leads to the decrease of average generation of the waste (Lebersorger and Beigl, 2011). Our results indicate the decreasing separate collection of PAP when the average number of household members increases. As Johnstone and Labonne (2004) stated the reason lies in the opportunity to share some types of products (e.g. newspapers, but also books). Therefore, facing the trend of increasing number of single households nowadays, the average amount of (M)MW per person is going to increase. Not only P&E campaigns enhancing environmentally sound behavior (waste prevention and minimization), but also sharing of the waste infrastructure (e.g. containers for MMW) could limit the negative environmental consequences of the changing lifestyle.

Transferability across the levels can be summarised as follows:

- Age structure seems to be important for all analysed levels for most of the fractions. Moreover, the direction of relationships preserves. Higher share of population aged 15–64 increases generation and decreases other fractions as well as MW. Average age and share of population aged 65+ have opposite impact.
- The number of economic subjects for micro-regional and regional level do not behave in exactly the same way, but do not contradict each other.
- Education seems to be important at the regional level since the share of the people with secondary education (without graduation) ranks among the top 5 predictors for all but two (MET, BW) analysed wastes. It could be helpful to use this information also for municipalities and micro-regions, if possible.

Regarding the public policy a significance of mentioned factors at different territorial levels is of key importance for practical decision-making processes. As Dahlén and Lagerkvist (2010) stated influential factors can be divided in factors controlled by local/regional WM authorities, national authorities and factors beyond the possibility of control. Share of the people with secondary education (without graduation) can be considered as ‘super predictor’ for regions, age structure related variables (especially mean age) and share of flats in family houses for micro-regions and expenditures for municipalities. This conclusion is in accordance with the subsidiarity principle that calls for making decision at the level of public administration most appropriate for finding solutions (more in Buclet, 2002, or Deszczka-Tarnowska and Wąsowicz, 2016). While municipal representatives focus on public expenditures determining the socio-economic aspects and convenience of MWM system for households, and other subject using this system (Soukopová et al., 2016), micro-regional authorities are able to influence the efficiency of the system through economies of scale (e.g. Dijkgraaf and Gradus, 2007), and economies of density (e.g. Abrate et al., 2012), and regional authorities could shape the education of students aimed at increasing the general and instrumental knowledge (Slavík et al., 2018).

Revelation of relationships between influencing factors and waste generation enhances quality of scenario approaches for forecasting. This allows decision-makers to make the system more flexible both from short-term (waste collection, material recovery, operation of WtE plants) and long-term (capacity and WtE plants) point of view. It should be noted that conclusions about influencing factors for municipality and micro-regional level are questionable since the quality of these models is quite poor in most cases (especially for municipality level). Moreover, the results should not be generalized to the whole population, since extreme cases were excluded (not distinguished from outliers). Although (spearman) correlations are safely significant (i.e. p-values are far below significance level of 0.05) for multiple predictors, they are very weak (especially for municipality level) as can be seen in Fig. 3. No strong statements and actions should be made based on such results.

4. Conclusions

Multiple predictive models for various MW fractions using social, economic and demographic data were created for different territorial levels of the Czech Republic. Moreover, assumptions of LR and GLM were checked. The results for particular waste fraction are usually quite similar across used models. Therefore, most of the information provided by the input data was probably used. In such cases, “white-box” models like LR should be preferred. The models at the regional level can be considered useful (with exception of BIO and MET). In contrast, the models for lower levels (micro-regions and municipalities) have almost a negligible predictive value and are thus basically useless for description of data dependencies.

Our research confirmed the significance of socio-economic and demographic variables that highly influence MW generation. Especially age, education level, share of flats in family houses, number of applicants for a job, amount of expenditures, or population density matter in MWM. However, the significance of these variables differs considering municipal, micro-economic, and regional perspective of the analysis. Furthermore, the significance of the number of economic subjects confirms the close relationship between MWM and the market for secondary raw materials that absorbs fractions from the separate collection.

In accordance with the subsidiarity principle our results indicated that there is not one single effective public policy dealing with circular economy strategy that fits all territorial levels. Public representatives should focus on policies effective at specific territorial level. To enable public bodies at different territorial levels to undertake an effective action resulting in circular economy the crucial attention should be paid to various factors influencing the generation of MW fractions at regional, micro-regional and municipal level in the Czech Republic.

Furthermore, problems with missing values, outliers (and extremes) and distinction between ‘statistical’ and ‘real-world’ significance were addressed. Future research should involve a more sensible approach to missing values and outliers/extremes in MWM. Another possibility to improve model selection for linear models is to test other ways for model selection (e.g. lasso regression) or use other performance measures (e.g. Bayesian information criterion). At the municipality level creation of more specific models (e.g. according to municipality size) or spatial models (e.g. geographically weighted regression) may be also helpful. Furthermore, the future research should evaluate the environmental effectiveness and efficiency of chosen policy measures on different territorial levels.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.112584.

Nomenclature

MW	Municipal waste
MMW	Mixed municipal waste
PAP	Paper waste
PLA	Plastic waste
GLA	Glass waste
MET	Metal waste
BIO	Biodegradable waste
BW	Bulky waste
LR	Linear regression
GLM	Generalized linear model
DT	Decision tree
RF	Random forest
GBRT	Gradient boosted regression trees
GIS	Geographic information system
WM	Waste management
MWM	Municipal waste management
lr_MW	LR model for MW
lr_MMW	LR model for MMW
lr_PAP	LR model for PAP
lr_PLA	LR model for PLA
lr_GLA	LR model for GLA
lr_MET	LR model for MET
lr_BIO	LR model for BIO
lr_BW	LR model for BW
RMSE	Root mean square error
MSE	Mean square error
MAE	Mean absolute error

MAPE	Mean absolute percentage error
R^2	Coefficient of determination
R^2_{GLM}	Coefficient of determination for GLM
R^2_{DT}	Coefficient of determination for DT
R^2_{RF}	Coefficient of determination for RF
Maxdepth	Maximal depth of tree
Minsplit	Lowest number of observations to attempt split
Minbucket	Lowest number of observations in leaf node
complexity parameter	Minimal improvement needed at each node
Mtry	Number of variables available at each node
Learning rate	Step size for parameter tuning
Nrounds	Number of iterations
OV	Original variables
PCA	Principal components analysis
PC	Principal components
CV	Cross-validation
glm_MW	GLM for MW
glm_MMW	GLM for MMW
glm_PAP	GLM for PAP
glm_PLA	GLM for PLA
glm_GLA	GLM for GLA
glm_MET	GLM for MET
glm_BIO	GLM for BIO
glm_BW	GLM for BW
rt_MW	DT model for MW
rt_MMW	DT model for MMW
rt_PLA	DT model for PLA
rt_PAP	DT model for PAP
rt_GLA	DT model for GLA
rt_MET	DT model for MET
rt_BIO	DT model for BIO
rt_BW	DT model for BW
rf_MW	RF model for MW
rf_MMW	RF model for MMW
rf_PLA	RF model for PLA
rf_PAP	RF model for PAP
rf_GLA	RF model for GLA
rf_MET	RF model for MET
rf_BIO	RF model for BIO
rf_BW	RF model for BW
gbrt_MW	GBRT model for MW
gbrt_MMW	GBRT model for MMW
gbrt_PLA	GBRT model for PLA
gbrt_PAP	GBRT model for PAP
gbrt_GLA	GBRT model for GLA
gbrt_MET	GBRT model for MET
gbrt_BIO	GBRT model for BIO
gbrt_BW	GBRT model for BW
GDP	Gross domestic product
WtE	Waste-to-Energy

Credit author statement

Martin Rosecký: Methodology, Formal analysis, Data curation, Writing – original draft, Visualisation. **Radovan Šomplák**: Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Jan Slavík**: Investigation, Writing – original draft, Writing – review & editing, Funding acquisition. **Jiří Kalina**: Methodology. **Gabriela Bulková**: Conceptualization. **Josef Bednář**: Supervision

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Waste-to-energy facility planning under uncertain circumstances

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HIGHLIGHTS

- Approx. 38% of current municipal solid waste production is still landfilled in the EU27.
- Some regions of the EU27 will have to invest into thermal treatment in the coming years.
- The profitability of a specific project is evaluated with the use of two-stage stochastic programming.
- Various scenarios were designed to describe the uncertainty in significant parameters.

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ABSTRACT

The paper deals with the development and presentation of the use of an advanced computational optimization tool for the conceptual planning of facilities in the field of waste-to-energy.

The determination of the suitable capacity and sizing of an appropriate heat recovery system, according to adopted heat utilization strategy (i.e. either only electricity production or combined heat and power if feasible), represent crucial decisions about each individual incineration plant in its early project stage. The economic feasibility of the project should be guaranteed at the same time. The feasibility is measured by internal rate of return. An optimization model supporting such decisions was built and is introduced.

Building a new incinerator, from the initial considerations to its full operation, is a long-term process with duration at a minimum of 5–7 years. The erection is then followed by an operational phase exceeding 20 years. The unclear future development of important parameters affecting the project sustainability is reflected by implementing principal concepts of stochastic programming.

In the article, a brief overview of principal ideas related to decision making under uncertainty (wait-and-see and/or here-and-now approaches, specification, and use of scenarios) is given first, followed by the description of a mathematical model. Then, the selected approach is demonstrated through a case study involving a municipal solid waste incinerator.

1. Waste-to-energy in Europe and its future potential in the selected region

Municipal solid waste (MSW) represents a worldwide challenge in terms of its effective disposal. The following hierarchy is preferred by EU legislation [1]: 1. Prevention, 2. Re-use, 3. Recycling/composting, 4. Recovery, 5. Landfilling. The fulfilment of this strategy differs from state to state and relates to the local waste management legislation and other socio-economic factors (see Fig. 1).

22% of MSW (approx. 70 Mt) was thermally treated in the EU27 in 2009 [3]. Unfortunately, 38% of current production is still landfilled. The overall MSW production rate in most EU countries has increased in the last 15 years at by least 10% [4]. Waste management in many countries, not only in the EU, will have to undergo significant changes in the coming years, which will include the diversion from dominant MSW landfilling to other treatment options (e.g., material and/or energy recovery) [5]. The phenomenon of decoupling between production and landfilling of MSW in EU is widely discussed in Mazzanti [6]. A comprehensive review on up-to-date technologies in this field incl. assessment of their negative impact to the environment can be found in Ref. [7]. There are several analyses related to individual regions, where the future of a waste management and new waste-to-energy (WTE) plants planning were discussed, e.g. Ref. [8] for the situation in Central Greece and [9] for the situation in Chile. In this paper, we pay more attention to providing data on the current situation in the Czech Republic and its future perspective, since this region is involved in the case study later on.

In the Czech Republic, approximately 18% (638 kt/y) of generated MSW was incinerated in three operating WTE plants (in the cities of Brno, Liberec, Prague) in 2012.

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Notation

C_C	capital cost (EUR)
C_{GF}	gate fee (EUR)
C_{EL}	price of electricity (EUR)
C_{TH}	price of heat (EUR)
DH	district heating
D_{TH}	heat demand (GJ)
EU	European Union
f	first-stage objective function
g_1, g_2	inequality constraints
h_1, h_2	equality constraints
IRR	internal rate of return
MBT	mechanical–biological treatment
MSW	municipal solid waste
p	probability (%)
q	second-stage objective function
$Q(x,\xi_s)$	cash balance
RDF	refuse-derived fuel
s	scenario
S	set of scenarios
ScHD	scenarios for trend of heat demand
WTE	waste-to-energy
x	first-stage decision (waste treatment capacity, steam turbine choice)
x_{CAP}	suggested waste treatment capacity (t/y)
x_{COND}	suggested condenser capacity (MW)
$x_{EL,ExT}$	suggested turbine output for heat-oriented operation (MW)
$x_{EL,MAx}$	suggested turbine output for electricity-oriented operation (MW)
$y(\xi)$	second-stage decision (the operation of a plant – heat or power)
y_{EL}	realized electricity production (MW h/y)
y_{TH}	realized heat production (MW h/y)
ξ_s	realization of uncertain parameter

Since approximately 3350 kt/y of MSW will have to be treated using a method different from landfilling in 2020 [10], the existing waste management system has to be modified. There are two main strategies that are frequently analyzed (their comparison is discussed in Ref. [11]):

- mechanical–biological treatment (MBT) with the utilization of refuse-derived fuel (RDF) in energy production systems [12] and
- waste treatment in WTE plants [13].

A study [14] stresses potential locations of new WTE plants for year 2020. The proposed site-areas are strongly related to existing well-developed district heating (DH) networks, which enhances the positive environmental impact of its operation (discussed in Ref. [14]). The connection between proper placement and its effect on WTE plants' efficiency is described in Grosso [15]. This leads to complex integrated systems requiring proper optimization of their operation [16]. Besides WTE, the concept [10] maps existing plants for RDF utilization, e.g. co-firing in cement kilns, coal-fired power plants, etc. It would enable the attainment of targets in the landfilling of the biodegradable part of MSW for the Czech Republic [5] and, at the same time, it would contribute to effective energy production from waste. The concept assumes the erection of 11 WTE plants with waste treatment capacity of 100–430 kt/y by 2020. The overall WTE capacity, including existing plants, should increase then to 2800 kt/y. The expected heat and electricity production, in the case of incentive conditions for combined heat and power production in Czech legislation, is expected to be 8–14 PJ and 800–1000 GW h/y. The expected overall capital investments have been roughly estimated at 2.3 × 10^9 EUR. The concept is now being elaborated on in more detail by the authorities and regions, as well as selected projects being evaluated and optimized by investors. This procedure should involve the consideration of uncertain parameters, which are important for the intended WTE plant's financial sustainability:

- capital costs (C_C) that address recent technologies with emission levels well below the statutory limits,
- the trend of MSW production and waste composition, which is different from region to region; is related to economic conditions, availability of separate collections systems (for plastics, paper, glass, etc.), and their effectiveness; influences lower heating value and the collection area to satisfy waste treatment capacity,
- payment for waste at the incinerator entrance (gate fee C_{GF}), which is driven by competition in the waste management sector and landfill taxes,
- heat demand (D_{TH}) in DH network and the price of heat (C_{TH}), i.e. the decrease of heat demand may be caused by the implementation of energy savings, the decrease in number of customers, and brake-up of DH network,
- electricity price (C_{EL}) and subsidies, etc.

Uncertainty in these crucial parameters, and their future trends in combination with the multi-disciplinary character of the

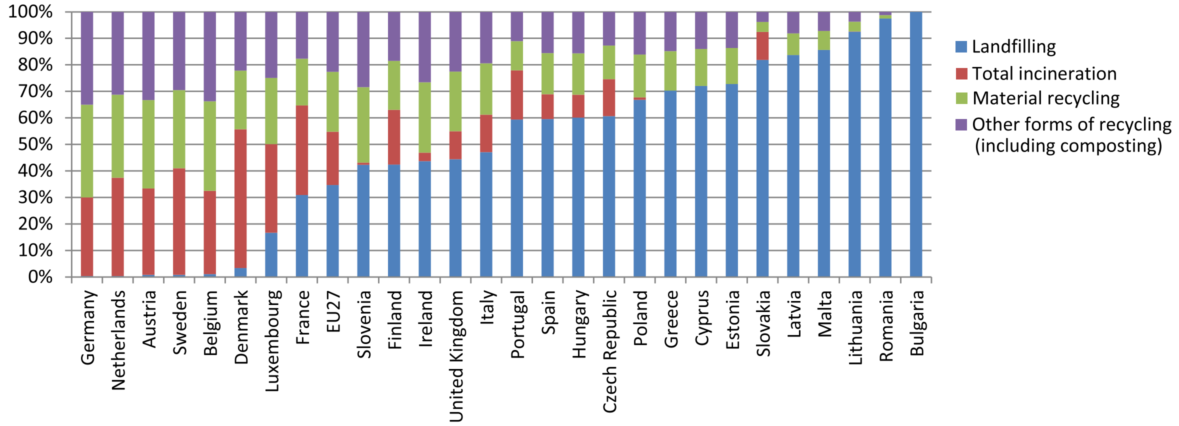

Fig. 1. Municipal waste treatment in EU27 in 2009 [2].

modelling challenges (from waste management to energy generation), make the task of new WTE facility planning quite complex. The challenge is to replace the intuition-based design with an approach involving the use of sophisticated computational tools. The idea was first described in Ref. [17] and an appropriate mathematical model introduced in Ref. [18]. In the paper [19] the model was tested through a case study involving the aforementioned waste management concept coming from Ref. [10]. In this paper a brief summary is provided, and then the original case study from Ref. [19] is updated in terms of its input parameters, recalculated, and elaborated in a more detailed way. The economy of the proposed solution is tested under different scenarios of heat and electricity prices.

2. Advanced computational approaches

Let us focus on introducing advanced computational methods in this section. Firstly, an example of up-to-date technology is described. This technology is further involved in the mathematical model, which represents an original achievement of the authors in this application area. The presented performance characteristics related to the heat and electricity generation within the plant, from previously published papers, create the set of inputs parameters further used in the case study. Then it is used for the development of a suitable mathematical model. Specifically, it is able to work with real-world data and still be solved through the transformation to a nonlinear programme and by the efficient iterative algorithms implemented in the GAMS (General Algebraic Modelling System) set of solvers. The detailed model description and its discussion can be found in Ref. [18].

2.1. WTE plant model

The flow sheet of the technology, with the key components considered for building a mathematical model of the WTE, is presented in Fig. 2. The detailed technology description is provided in Ref. [20]. The same paper discusses the various heat utilization strategies and points out the main parameters affecting the design of MSW plants. From the set of important aspects we focus more on those directly related to the objective of our calculation as depicted in Fig. 2.

The WTE plant model involves steam production with common parameters of 400 °C and 4 MPa to avoid increased high-temperature corrosion risk in boilers [21]. The further general model of an extraction condensing turbine with one extraction is considered. The extraction pressure is 1.5 MPa and subsequent steam export for the district heating system is also taken into account.

The steam turbine represents a key part of the heat recovery system. The method of plant operation, in terms of released heat utilization (electricity and/or heat), has a significant effect on the environmental benefits of the technology (discussed in Ref. [20]). The overall WTE plant efficiency increases with heat delivery to district heating. At the same time, heat and electricity produced in one process (i.e. in a co-generation) reduces the use of fossil fuels in conventional plants (heating stations, power plants), where the production of corresponding energy is omitted (Ref. [14] expressed as *primary energy savings*). The turbine model consists of two stages divided by steam extraction for heating purpose, the backpressure stage and condensing stage. About 10% of steam produced is used in the condensing stage even in the case of a high heat demand (technology constraints). When there is no heat demand, all the steam produced is used in the condensing stage. The complex models for turbine modelling, including its part-load operation, can be found in Ref. [22]. In this paper, a simple model addressing constant isentropic efficiency for a specific turbine capacity (in correlation with waste throughput) was used for simplicity. The linear dependence of isentropic efficiency on turbine (WTE plant) size was obtained by consulting the turbine manufacturer. The isentropic efficiency in ranges 75–80% and 80–85% can be expected for throughputs 100 kt/y and 300 kt/y (discussed also in Medina-Flores [23]). The relation between electricity production and heat production for heat recovery system in Fig. 2 was considered after [20].

A mathematical model reflecting the aforementioned technology layout, mass and energy flows, was implemented in GAMS and further used in the subsequent case study. A detailed description of elements of the model can be found in Ref. [18].

2.2. Two-stage stochastic programming

Stochastic programming techniques seem to be suitable tools to deal with the uncertainty in the similar engineering problems, e.g. see Ref. [24] where scenario-based fuzzy-stochastic quadratic programming was utilized for identifying optimal MSW management or [25] where stochastic linear fractional programming was used for a similar problem. As the result of the research, the proper approach to tackle the problem was further specified as two-stage stochastic programming modelling, and hence, an original scenario-based two-stage stochastic programming model was created.

In general, this approach deals with problems that are time-discrete, and in which, the decisions are made at different points in time. From the decision maker's point of view, the decisions may be classified as follows [26]:

1. Decisions that are made at the beginning when no information on the realization (term frequently used in statistics for future development) of uncertain parameters is available. Such decisions are called first-stage decisions.

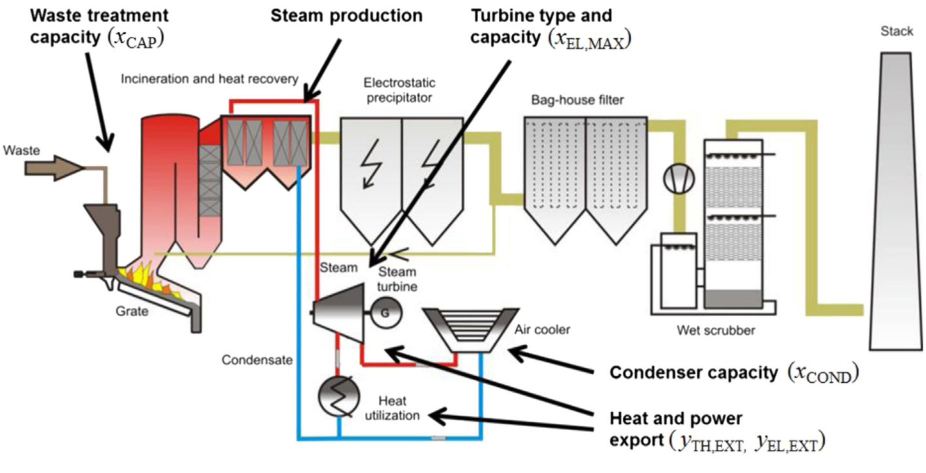

Fig. 2. Simplified flow sheet of typical MSW incineration technology.

2. Decisions that are made after values of uncertain parameters are known. These decisions are called second-stage decisions.

An uncertain parameter is further denoted as ξ, the first-stage decision as x and the second-stage decision as $y(\xi)$. In the case of discrete probability distribution, a lower index is used to make a difference among the individual decisions made for individual realizations of ξ.

In our case study, we can be more specific about the interpretation of random elements and variables. Thus, x is related to decisions on waste treatment capacity, steam turbine choice (backpressure or extraction condensing turbine) and $y(\xi)$ is related to decisions on the operation of a plant (heat-oriented operation or electricity-oriented operation) according to the trend of the key uncertain parameters influencing plant economics (examples were mentioned in Section 1), see Ref. [18] for details.

It is necessary to decide how to model possible realizations of uncertain parameters. Instead of statistical inference and identifying multivariate continuous probability distribution parameters, the use empirical data has been preferred, and related to discrete probability distributions. This directly leads to a so-called scenario-based approach, which is frequently used in industrial applications of stochastic programming, see, e.g. Birge and Louveaux [27].

2.3. Scenario-based approach

Scenarios create a set of realizations of uncertain parameters ξ, which can be enumerated by index s, and denoted as ξ_s. For simplicity, from the whole range of ξ affecting the plant design, only heat demand, heat, and electricity prices and their realizations are included in our scenarios. In the literature, it is often called scenarios; however some authors identify scenarios with indices. The common sense reasoning and utilize both ideas by using the concept of scenarios for indices has been used as well. Therefore, a set of indices is denoted as $S = \{1, 2, \ldots, L\}$, where L is a number of different indices. The scenario s has the probability $p_s \geq 0$, $\forall\, s \in S$ and $\sum_{s \epsilon S} p_s = 1$. If the set S is a set with a large number of elements then the optimization problem can be difficult to solve as its number of variables and constraints exponentially grows with the increase of the cardinality of the scenario set. Therefore, it is recommended to initially include only those scenarios, which are most relevant. It is preferred to select scenarios to be based on expert opinion; hence, the discussion of such choices is in the next section. This approach leads to a case of the set S with a small number of elements, and so all recently developed scenarios are included in the model. It is further assumed that the total expected investments involving the chosen scenarios is minimized. Then, the underlying programme [18] is converted to the stochastic programme, minimizing the expected expenses under all constraints, see Ref. [27]. The following key transformation step is to utilize scenarios, and hence to obtain the scenario-based stochastic programme, which can be treated as a nonlinear programme with a decomposable structure, see Ref. [18]. In short, such a nonlinear programme for the purpose of our paper with the utilization of the ideas of Section 2.2, can be defined as follows:

$$\min f(x) + \sum_{s \epsilon S} p_s Q(x, \xi_s), \tag{1}$$

subject to

$$g_1(x) \leq 0, \quad h_1(x) = 0, \tag{2}$$

where

$$Q(x, \xi_s) = \min_{y(\xi_s)}\{q(y(\xi_s), \xi_s)\}, \tag{3}$$

subject to

$$g_2(x, y(\xi_s), \xi_s) \leq 0, \quad \forall s \in S, \tag{4}$$

$$h_2(x, y(\xi_s), \xi_s) \leq 0, \quad \forall s \in S. \tag{5}$$

So, the first-stage strategic decision x about the WTE plant's capacity is related to the direct investment cost included in the first-stage objective function $f(x)$. The constraints applied to the first-stage decision are in the form of inequality and equality constraints, as it is common in nonlinear programming, and can be defined by multivariate vector functions g_1 and h_1. In our case, they link and bound decisions about capacity and cost, see Ref. [18] for particular form of all mentioned constraints. They also reflect technological dependences, i.e. boiler and turbine balance [20]. The weighted average in the objective function represents the expected cumulative cash balance. The particular $Q(x,\xi_s)$ value for the given first-stage decision x and scenario s is obtained as the optimal result of future plant operation simulation/planning on a monthly basis, i.e. by the optimal second-stage decision that is a wait-and-see decision with respect to scenario s. The second-stage objective function q helps to search for the optimal value of $y(\xi)$. Functions g_2 and h_2 are dependent on first-stage and second-stage decisions and realizations. They specify the feasible region for the second-stage variables under restrictions given by the first-stage decision and realization, i.e. our supply of heat is restricted by capacity related decisions in the first stage. Furthermore, inequality terms in g_2 describe demand needs and technological restrictions, and equalities specify the assessment criteria of project economic efficiency, e.g. internal rate of return (IRR).

So the subject of the first-stage decision is to design the plant (annual capacity, turbine capacity etc.) providing a maximum return on investments. The “here-and-now” approach [27] is used. The second-stage problem deals with an optimal response to the realizations of uncertain parameters (i.e. scenarios), with respect to decisions made in first-stage problem. This approach is called wait-and-see [27]. Both problems can be combined by the substitution of the second-stage objective function with the first-stage objective. The new composed objective function is minimized subject to constraints for both stages.

3. Case study

For the demonstration of the practical usefulness of the model, a particular locality was selected. A new WTE facility, servicing a region of 98 000 inhabitants, is being conceptually designed. Its full operation is planned for 2020. The objective is to find the optimal values of key parameters of considered technology (the layout and topology is fixed and is not subject of the optimization itself and can be studied and optimized to improve the project economy in the future) and evaluate the project's feasibility related to its optimum design. The optimization addresses the determination of (denoted as first-stage variables x in Section 2.3):

- waste treatment capacity of WTE plant, x_{CAP},
- maximum turbine output for electricity-oriented operation, $x_{\mathrm{EL,MAx}}$,
- turbine output for heat-oriented operation with full utilization of turbine extraction, $x_{\mathrm{EL,ExT}}$,
- capacity of condenser for heat rejection after condensing stage, x_{COND}.

Additional information about optimum operation expressed by IRR and heat and electricity production rates y_{TH} and y_{EL}, was obtained at the same time. Price forecasting and local conditions related to the Czech Republic are addressed. It has to be emphasized that forecasting should be made with respect to energy policy, local energy sources, and the expected development of DH in the considered region.

Therefore, the model introduced in Sections 2.2 and 2.3 has been used for computations involving a real industrial case. Input data entering the task and the results obtained are denoted in detail (Appendix 1).

3.1. Capital and operational costs

The WTE plant is a capital-demanding technology. Over decades, it has developed into a complex process securing waste treatment with a minimized impact on the environment, and providing renewable and clean energy at the same time [20]. The cost of technology is influenced by its annual throughput, number of lines, heat recovery system, and off-gas cleaning system layout, etc. There is often a trade-off between maximum energy-efficiency and the lowest negative impact [28]. Several simple cost models related to WTE have been published, e.g. a model involving annual capacity [29] or a model involving electrical output [9]. They commonly reflect the decreasing specific cost with increasing capacity; however they do not address all the aforementioned aspects. A comparison between a simple regression cost model (smooth curve) and the results of preliminary capital analysis related to our layout and different capacities is provided in Fig. 3. The piecewise specified curve in Fig. 3 represents the expected real situation, where more lines for higher throughputs are considered (significantly increased capital for the same throughput). Capital costs 116 × 10^6 EUR for 100 kt/y capacity (i.e. 12.5 t/h at 8000 h/y availability) were considered as a base in both cases. For the applicability in our optimization tool, a simplified approach based on regression was used (smooth curve in Fig. 3).

Operational costs were determined as a result of a complex balance calculation (e.g. slag and dust residues to be disposed, supplementary fuel and chemicals to be purchased), price forecasting (for all items), and comparison with real projects experience (e.g. personal costs, maintenance costs, security, insurance etc.). The approximate structure of costs is introduced in Appendix 2.

3.2. Gate fee

The gate fee represents another key factor influencing plant economy and its competitiveness in terms of securing enough waste to fulfil the plant capacity. The gate fee then depends on the annual capacity, waste density in the area, landfill taxes, etc. The transportation costs should be considered as well. An example of dependence on waste collection and disposal on local policies is described in Ref. [30]. Market modelling and gate-fee prediction thus represent a tricky task. It concerns the synthesis of regional renewable and secondary energy supply networks. An application of an interesting approach based on a P-graph for efficient biomass-based energy production is introduced in Ref. [31]. The influence of transport on overall utilization of waste-based energy potential is discussed in Ref. [32].

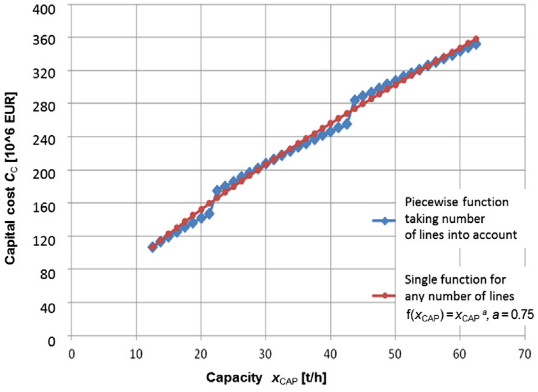

Fig. 3. Function for estimation of capital costs [16].

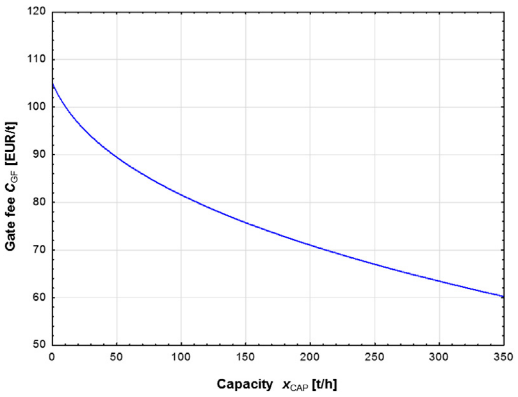

Fig. 4. The gate-fee curve used in the model.

The relationship between plant capacity and the expected gate fee as considered in our case study is depicted in Fig. 4. The curve was generated with the help of a complex tool addressing the logistic optimization problem for competition modelling in waste management. It was developed in-house. The calculation is backed up by several technical-economic models of elements performing the task (WTE, MBT plant, landfills). A detailed description is outside the scope of this paper; however some comments on the usefulness/necessity of this approach follows. Similar curve, which reflects the concept of 11 WTE plants as proposed in Ref. [10] and mentioned in Section 1, is presented in Ref. [19]. In comparison, the curve in Fig. 4 is significantly shifted towards higher gate fees. This is a result of calculations where two potential projects were omitted. This leads to smaller competition in the market and higher prices for waste treatment. A trend of increasing the gate fee for the lifetime period of the WTE plant is taken into account as well.

3.3. Heat and electricity export and prices

Heat generation and its export to the consumers represent a key factor for energy efficient and economically feasible operation [33]. The electricity price development in the next few years was estimated by mapping the current situation in the European Energy Exchange Market [34]. Green electricity and co-generation subsidies were considered as extra income. The electricity export price can be considered equal for all the plants due to the existence of the common market. In contrast, the price of heat purchased from WTE by a third person (e.g. DH network operator) is locally dependent. It is influenced by many factors (such as DH network, share of heat delivered by WTE, fossil fuel availability). The prediction of future development of heat and electricity prices, which has been used in this model, is mentioned next. In terms of heat, the heat price is generally expected to rise significantly within the next few years (Fig. 5). This is due to limited coal reserves in the Czech Republic and additional cost associated with emission abatement required to

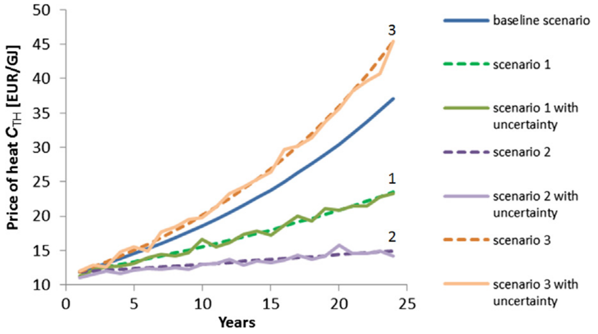

Fig. 5. Scenarios for heat prices.

Table 1
Initial heat demand over a year.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Heat demand D_{TH} [GJ]	322	252	250	123	16	81	79	73	43	153	248	319

fulfil strict emission limits set for coal-fired plants [35]. The increasing price of heat has a positive effect on WTE plant economics only until a maximum acceptable price from DH is reached. Once this is exceeded, the possibility of massive customer-driven disconnection forms a serious threat for the whole of DH and increases the pressure on lowering the heat price from WTE. This situation is also covered by one of our scenarios in the risk-analysis (see Table 2, scenario ScHD 3). More information about the classification of DH systems, their economic feasibility and conditions enabling their future extensions can be found in Ref. [33].

It has been assumed that a large DH with a current total heat demand of 2 TJ/y. The demand varies during the year, as is shown in Table 1. The possibility of heat supply to the DH system has a crucial effect on (1) the decisions about initial investments since it influences the choice of turbine type (backpressure or more often extraction condensing turbine); (2) profits (lower electricity production and higher heat export); and thus affects the optimal design of the plant and its economy. The results are highly sensitive to the uncertainty in heat demand, which then leads to unstable (non-robust) solutions. On this account we decided to use the scenario-based approach (here-and-now, see Section 2.3) with respect to random demand. Generally, it provides us with the solution robustness for any considered realization of an unknown parameter (heat demand). Three scenarios for the heat demand of the lifetime period of the WTE plant were chosen in the presented case study. The initial values of a heat demand in every single month were determined using real operation data (Table 1). Individual scenarios are depicted in Table 2.

It was assumed that all scenarios can occur with the same probabilities. This was tested by repeated calculations in which the proposed design (optimal capacity) is less sensitive to the energy prices than to heat demand. Overall, the project economy, represented here by IRR, depends on the realization of this uncertainty. Therefore, we have decided to deal with a here-and-now scenario approach applied to random demand, and wait-and-see sensitivity analysis with respect to price changes. For this reason, we used the Monte Carlo method (repeated generation of several scenarios and optimization problem solving, see below), which suggests particular optimal values of decision variables for the WTE plant, and then shows the influence of the changes of these unknown random parameters (i.e. energy prices) on the IRR value. Such an analysis extends the methodology and a case study presented in Refs. [17,19]. So, 500 different scenarios for electricity and heat prices were generated — see Fig. 5 for a visualization of selected scenarios. The electricity and heat prices were thought to increase because of inflation. For the constant rate 5%, the base scenario curve was obtained by using a traditional financial formula (Fig. 5). Then, the various rate values constant for each scenario were generated using a normal probability distribution. Iteratively was used for the initial set-up of scenarios, as in the case of base curve. Considering the actual rates, the mean value in the model is set to 5% and the standard deviation is assigned as 1.5%. Utilizing features of normal probability distribution, this obviously leads to the initial annual increase varying between 0.5% and 9.5% with a reliability of over 99%. Due to the focus on IRR calculation, where the real-world profits and costs, and so their rates change with time, additional uncertainty is brought in the predicted scenarios of future progress for each year. For all years, small additive normally distributed errors were added to the initial set-up values of scenarios. The mean value of 0% and standard deviation 3% were chosen. This attempts to simulate the instable economic development in the energy market. Examples of several randomly generated scenarios for the heat price are shown in Fig. 5.

Table 2
Scenarios for trend of heat demand (ScHD).

Scenario	ScHD 1	ScHD 2	ScHD 3
Decrease of heat demand per year	0%	1%	5%

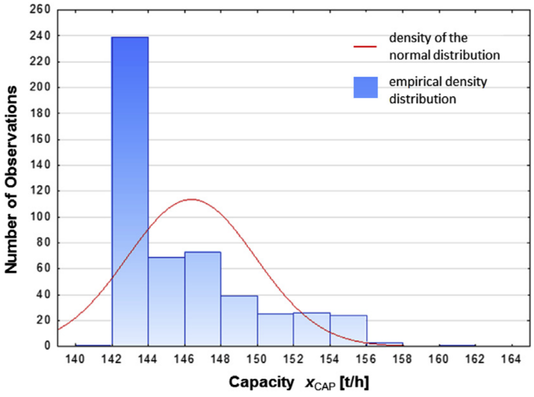

Fig. 6. Optimal capacities for different energy prices scenarios.

3.4. Results

Calculations involving scenario-based programming, where three scenarios with the same probability describe a possible decrease in heat demands, were included in the objective function, and a wait-and-see approach comprising 500 scenarios for future heat and electricity price development were performed. Histograms related to first-stage variable x were also generated and some of the results are discussed below.

The histogram of optimal capacities x_{CAP}, which was the most anticipated result, is depicted in Fig. 6. It shows that the computed capacities are not normally distributed. The mode is 142 kt/y. The median is 144 kt/y and the mean is 147 kt/y. The normal probability distribution is shown in the red curve in Figs. 6 and 7. Considering the shape of the histogram, we decided to select the mode as our optimal value. That gives us about 50% of results near to 144 kt/y. The results are overall fairly stable for any scenario of energy price development. The development mainly affects the economy of the project, represented by the IRR (see below).

The obtained capacity proposals correspond to the sizing of the turbine, where it is also legitimate to expect the maximum turbine output $x_{EL,MAx}$ on the value of mode (9.1 MW). A summary of key parameters related to the proposed optimum design is provided in Appendix 1. Where the results were dependent on different scenarios, the uncertainty was defined by mean/mode and standard deviation. Detailed information about energy production and plant economy

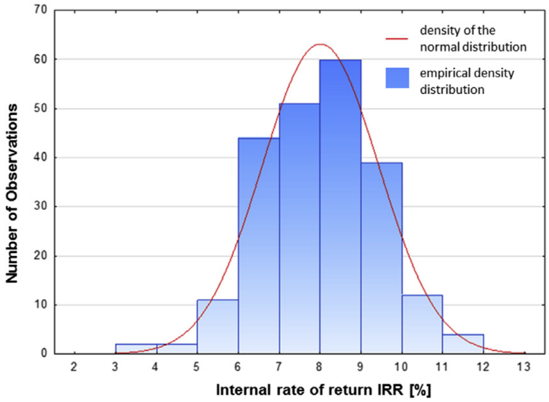

Fig. 7. Internal rate of return.

over its lifetime is available in Appendix 2. The data addresses only the baseline scenarios for heat and electricity prices (see Section 3.3).

A histogram of IRR value is provided for the selected capacity of 142 kt/y in Fig. 7. The IRR is particularly higher than 6% for about 95% of simulations. The results show that, the IRR can most likely be expected in the interval of 8–9%, see Fig. 7. The minimum IRR required by the investors cannot be generalized. It is assessed by complex financial models (capital asset pricing model (CAPM) [36]). Private companies usually demand higher rates than municipalities. In our case study, the value 10% is considered to be the target. A higher IRR can be secured in the future by increasing income related to the treatment of waste (increased gate fee). On the other hand, the availability of the required amount of waste (142 kt/y) at a price higher than 76 EUR/t (see Fig. 4) has to be assessed (e.g. the impact of future regulation in the field). The next possibility for a partial increase of IRR can be seen in the detailed optimization of the subsystems the plant consists of, with the aim of getting a trade-off between capital and operational costs (boiler design and measures preventing corrosion, turbine efficiency optimization, comparison of flue-gas systems, slug treatment system with increased material recovery, etc.).

4. Conclusion

This paper deals with the assessment of investment opportunities to build a new WTE plant in a particular locality. An optimization model (involving scenario-based programming and wait-and-see approach in a new way in this application area) was developed for this purpose. Its practical use was demonstrated through a case study. Since the WTE facility planning is a long-term process, the computations in the assessment were repeated for several scenarios addressing various future prospects of crucial input parameters. The purchase price of energies (heat, electricity) and the amount of heat demanded by customers were identified as key parameters. An optimal capacity of 142 kt/y was proposed following the frequency diagram obtained from the repeated optimization task under different scenarios of the aforementioned parameters. This capacity was then fixed and a proposed design was tested in terms of an expected return on investments (here expressed by IRR). Involving the same scenarios, the results were distributed according to normal probability distribution function with the mean value of 8% and standard deviation of 1.5%. This specific project, under the assumptions made, does not meet the investor's requirements for project profitability, which are 10% in terms of IRR. It is necessary to further analyze the measures able to make the proposal more attractive, which are especially bound with future legislative regulation in the field, and a detailed optimization of plant subsystems.

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Appendix 2. Energy production and plant economy over its lifetime for capacity 142 kt/y and for baseline scenarios of heat and electricity prices development

Year	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Year of operation [–]	0	1	2	3	4	5	6	7	8	9	10	11
Capital cost – 142 kt/y, C_C [10^6 EUR]	154											
Profits												
Gate fee, C_{GF} [EUR/t]		76	78	81	83	86	88	91	93	96	99	102
Amount of waste treated [kt]		142	142	142	142	142	142	142	142	142	142	142
Profit for waste treatment [10^3 EUR]		10 792	11 115	11 449	11 792	12 146	12 510	12 886	13 272	13 670	14 081	14 503
Price of heat – baseline, C_{TH} [EUR/GJ]		12	12	13	14	14	15	16	17	18	18	19
Demand $D_{TH,1}$, scenario ScHD 1 [TJ]		1959	1861	1768	1680	1596	1516	1440	1368	1300	1235	1173
Demand $D_{TH,2}$, scenario ScHD 2 [TJ]		1959	1939	1920	1901	1882	1863	1844	1826	1808	1790	1772
Demand $D_{TH,3}$, scenario ScHD 3 [TJ]		1959	1959	1959	1959	1959	1959	1959	1959	1959	1959	1959
Weighted heat delivery (all 3 scenarios reflected) [TJ]		778	778	777	775	773	772	770	769	767	766	765
Profit from sales of heat for the baseline scenario [10^3 EUR]		9252	9705	10 177	10 664	11 174	11 708	12 270	12 859	13 478	14 127	14 805
Price of electricity – baseline, C_{EL} [EUR/MW h]		71	75	78	82	86	91	95	100	105	110	116
Weighted electricity delivery (all 3 scenarios reflected) [MW h]		15 594	15 634	15 691	15 778	15 867	15 953	16 036	16 115	16 191	16 264	16 345
Profit from the sale of electricity for the baseline scenario [10^3 EUR]		1108	1166	1229	1297	1370	1446	1527	1611	1699	1793	1891
Other variable (green electricity, co-generation, scrap metal, etc.) [10^3 EUR/t]		68	70	72	74	76	79	81	83	86	88	91
Total profit [10^3 EUR]		21 220	22 058	22 928	23 829	24 767	25 745	26 765	27 827	28 935	30 090	31 292
Costs												
Maintenance and reinvestments [10^3 EUR]		246	238	1735	944	1027	10 940	5184	3117	1358	4499	1389
Residues handling [10^3 EUR]		2783	2866	2952	3041	3132	3226	3323	3422	3525	3631	3740
Other variable (chemicals, energy, etc.) [10^3 EUR]		2348	2418	2491	2565	2642	2722	2803	2887	2974	3063	3155
Wages [10^3 EUR]		2309	2447	2594	2750	2915	3089	3275	3471	3680	3900	4134
Other fixed (insurance, security, taxes) [10^3 EUR]		485	500	515	530	546	562	579	596	614	633	652
Total cost [10^3 EUR]		8171	8470	10 288	9832	10 262	20 541	15 166	13 496	12 153	15 728	13 072
Cash flow [10^6 EUR]	–154	13	13	12	13	14	5	11	14	16	14	18
Cumulative cash flow [10^6 EUR]	–154	–140	–127	–114	–100	–86	–81	–69	–55	–38	–23	–5
IRR [%]		–91.5%	–65.7%	–46.4%	–31.9%	–22.0%	–19.1%	–13.7%	–9.0%	–5.3%	–2.9%	–0.6%
Payback period [*y*]	13											

Appendix 1. Technology parameters addressing the proposed optimum design

	Input/calculated value (mean/mode)	Standard deviation	Note
Internal rate of return, IRR [%]	8.1	1.6	Fig. 7
Waste treatment capacity, x_{CAP} [kt/y]	142	3.7	Fig. 6
Waste throughput [t/h]	17.5		Availability 8000 h/y
Lower heating value [GJ/t]	9.5		
Boiler output [MW]	48.2		
Boiler efficiency [%]	81		
Generated steam temperature [°C]	400		
Generated steam pressure [MPa]	4		
Feed water temperature [°C]	129		
Steam flowrate at the boiler exit [t/h]	54		
Maximum turbine output (electricity-oriented operation), $x_{EL,MAx}$ [MW]	9.1	0.2	
Maximum turbine output (heat-oriented operation), $x_{EL,ExT}$ [MW]	3.6		
Turbine thermodynamic efficiency [%]	77		
Electromechanical efficiency [%]	88		
Extraction pressure [MPa]	1.5		
Condensing pressure [MPa]	0.01		
Condenser capacity, x_{COND} [MW]	25.2	0.5	
Heat export, y_{TH} [TJ/y]	786 511	20 228	
Electricity production, y_{EL} [MW h/y]	37 096	1386	
Electricity export [MW h/y]	17 093	633	

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2031	2032	2033	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043
12	13	14	15	16	17	18	19	20	21	22	23	24
105	108	112	115	118	122	126	129	133	137	141	146	150
142	142	142	142	142	142	142	142	142	142	142	142	142
14 938	15 386	15 848	16 323	16 813	17 317	17 837	18 372	18 923	19 491	20 076	20 678	21 298
20	21	22	24	25	26	27	29	30	32	33	35	36
1114	1059	1006	955	908	862	819	778	739	702	667	634	602
1754	1736	1719	1702	1685	1668	1651	1635	1618	1602	1586	1570	1555
1959	1959	1959	1959	1959	1959	1959	1959	1959	1959	1959	1959	1959
763	761	759	757	756	754	752	750	748	746	744	743	741
15 512	16 250	17 020	17 828	18 673	19 553	20 476	21 445	22 462	23 528	24 647	25 821	27 053
122	128	134	141	148	155	163	171	180	189	198	208	218
16 437	16 533	16 637	16 737	16 840	16 953	17 063	17 168	17 270	17 369	17 464	17 556	17 645
1997	2109	2229	2354	2487	2629	2779	2936	3101	3274	3457	3649	3851
94	97	100	103	106	109	112	116	119	123	126	130	134
32 542	33 844	35 198	36 610	38 080	39 610	41 206	42 870	44 606	46 418	48 308	50 280	52 338
16 232	1443	6657	6101	4417	2189	18 040	2567	6858	8767	2741	2782	2782
3852	3968	4087	4209	4336	4466	4600	4738	4880	5026	5177	5332	5492
3250	3347	3448	3551	3658	3768	3881	3997	4117	4240	4368	4499	4634
4382	4645	4924	5220	5533	5865	6217	6590	6985	7404	7848	8319	8818
671	691	712	734	756	778	802	826	850	876	902	929	957
28 389	14 096	19 829	19 816	18 700	17 067	33 540	18 719	23 692	26 315	21 038	21 863	22 685
4	19	15	16	19	22	7	24	20	20	27	28	29
−1	18	33	50	69	92	99	124	145	165	192	220	250
−0.1%	1.5%	2.6%	3.6%	4.4%	5.3%	5.5%	6.2%	6.6%	7.0%	7.4%	7.8%	8.1%

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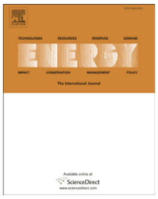

Bulky waste for energy recovery: Analysis of spatial distribution

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ABSTRACT

The data regarding the current potential of unrecyclable waste and its spatial distribution play an essential role in the planning process. As per the circular economy strategies, especially the bulky waste streams suitable for energy recovery are to be identified. The public databases, however, collect data from a variety of sources (production and handling reports), which implies the presence of errors. This paper therefore proposes a multi-objective approach to identification and elimination of such errors to improve the accuracy of the assessment of potential energy recovery. The discussed model tracks the flow of waste from producers to processing nodes and minimises the deviation from the original data. Economic aspects are considered as well by preferring the shortest transport distance. The combination of data reconciliation and network flow enhances performance, as objective functions are solved separately, and only then the normalised individual optima are used in the multi-objective function. The model was tested using a Czech Republic regional-level dataset from 2015. A new perspective on the current state of waste management was provided, and valuable information for future planning was revealed, which can be useful for modelling of flows of other commodities.

1. Introduction

Social development results in a higher use of primary resources. This is associated with the consumption of goods and higher waste production [1]. For environmental and economic reasons, the pressure is currently being put on the reuse of goods and recycling of waste. This causes the gradual transformation of the linear waste management (i.e., the feedstock creates the product, which then creates the waste) to the so-called circular economy [2]. This is a comprehensive system that optimises consumption and management not only of natural resources, but also of wastes whose world production is still growing [7]. Its detailed description, approaches, and aims were identified and implemented by the EU in Circular Economy Package (Directive (EU) 2018/849 [3], 2018/850 [4], 2018/851 [5] and 2018/852 [6]). The present paper aims to uncover the hidden potential of bulky waste as a secondary material or energy source.

The role of thermal treatment with energy utilisation is often suppressed in the circular economy scheme due to the belief that the already minimised residual streams are not suitable for material recovery. However, not all wastes can be recycled and in the future, other ways of waste handling (such as energy recovery [8]) have to be considered. Expected reduced amounts of waste suitable for incineration increase the pressure on proper Waste-to-Energy (WtE) planning. Since the availability of waste presents a serious risk to the future WtE operation (see Ref. [9] for details), all suitable input streams to WtE including their spatial distribution should be properly investigated using the latest data as well as the forecasted values. Only then a sustainable system can be designed and successfully operated.

Bulky waste represents one of the streams which could primarily be affected by the circular thinking, where products might be designed to facilitate their end-of-life recycling. A proper assessment of the current methods of bulky waste treatment and the share of such treatment are needed. The respective waste treatment options are therefore reviewed in Section 1.1, and the potential for improvement in bulky waste reuse is specified. The current approaches to facilities planning, based on the data with spatial distribution, are then mentioned in Section 1.2.

1.1. Bulky waste as an energy source

A waste type-related analysis estimating the corresponding environmental impacts is available in Ref. [10]. According to the

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Abbreviations

C	Corrected data
E1, E2	Amount of waste exported
EU	European Union
I1, I2	Amount of waste imported
K	Known data
LHV	Lower heating value
MMW	Mixed municipal waste
MSW	Municipal solid waste
p	Production
t	Treatment
U	Unknown data
WtE	Waste-to-Energy
x_1, x_2	Realistic value of transported waste

waste specific properties, a suitable disposal grid is to be designed. According to Ref. [11], economic and environmental assessments of the involved facilities must be performed to identify the opportunities in terms of process integration. For example, municipal solid waste (MSW) incineration was assessed from environmental point of view and its global impact was also investigated [12]. Nevertheless, the supply chain review [13] or future possible pinch analysis applications [14] suggest that the ongoing dynamic changes in waste management make the sophisticated models indispensable. The current research direction comes in line with optimisation applied in the public sector, consumer goods, waste management, chemical processes, and biomass to energy. Most of the recent papers on waste treatment options deal with the MSW as a whole [15] or with mixed municipal waste (MMW) and its material or energy recovery [16], while these two terms are often confused. Nonetheless, other waste streams must be identified and studied in terms of their potential utilisation to fulfil the targets in waste management.

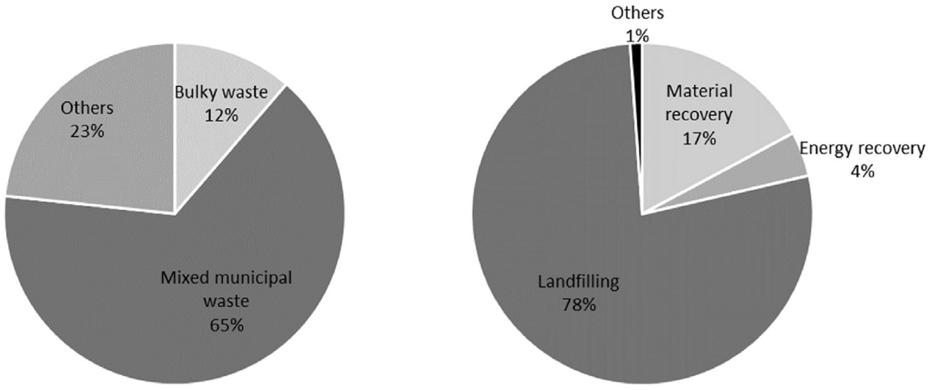
The shift from landfilling to WtE, together with its sustainability, are studied mainly in terms of MSW [17] or industrial wastes. As shown in Fig. 1, however, bulky waste has a huge potential when it comes to the its treatment. This applies not only to the Czech Republic, but also to many other countries [18]. What is more, the potential of bulky waste, which contains a significant percentage of high calorific value components, will increase with newly eco-designed products [19].

The term "bulky waste" refers to large and usually heavy items such as furniture or electrical appliances. According to the Controlled Waste Regulation 1992 (Schedule 2), the definition of bulky waste is as follows: "(1) any article of waste which exceeds 25 kg in weight or (2) any article of waste which does not fit or cannot be fitted into a cylindrical container of 750 mm in diameter and 1 m in length" [20]. Because of the dimensions, collection of bulky waste as part of the automated waste collection system is problematic. Still, according to Czech Statistical Office [21], bulky waste represents roughly 9% of MSW, that is, a non-negligible portion. Information on the two bulky waste disposal options available in the United Kingdom and on the issues related to the disposal of bulky items can be found in Ref. [22], while in case of Austria this is available in Ref. [23]. Estimation of the amount of bulky waste collected in Hong Kong, the way it was treated, and the corresponding environmental impact were analysed in Ref. [18]. This paper suggested that there was a considerable difference between the official and the real bulky waste flow (nearly 320% more) because of incomplete records.

According to Ref. [24], wood and rattan wastes have a large recovery potential, but due to a small amount of waste in official statistics, they are not used. Even though a lot of bulky waste is suitable for reuse, only a small portion of it can actually be reused. A considerable potential for reuse of bulky waste is mentioned by Reeve [25]. Similarly, only 27.5% of furniture and white goods is unsuitable for repair or reuse [26] with the respective percentages being as follows:

- furniture, reusable in its current condition 20%
- furniture, potentially repairable 25%
- white goods, potentially repairable 7.5%
- white goods & other metals, recyclable 20%
- unrecoverable items not suitable for repair or reuse 27.5%

Increased reuse of bulky waste would have a positive impact on the environment and it would also bring social benefits. In view of the waste hierarchy, the second most appropriate waste treatment



a) The share of fractions on MSW landfilling

b) Bulky waste treatment

Fig. 1. Landfilling and bulky waste treatment in the Czech Republic in 2015.

method after material recovery is energy recovery. A recent study [27] therefore focused on the preparation of solid recovered fuels and mentioned also the average values obtained during elemental analysis of bulky waste. This study also listed the higher heating values and lower heating values (LHV) of fractions of this type of waste, which were expressed on the dry and wet bases. Apparently, plastic fractions have the highest heating values (LHV of roughly 40 MJ wet kg^{-1}), followed by foams (ca 25 MJ wet kg^{-1}), textiles (ca 20 MJ wet kg^{-1}), and wood (ca 16 MJ wet kg^{-1}). This shows the potential of bulky waste for energy generation.

1.2. *Planning in waste management*

For adequate planning of waste management systems, parameters of the waste streams should be identified as accurately as possible. The forecast of spatial distributions of waste production and composition is a crucial step, because various factors may influence their development. For the estimation of the number of MSW fractions, population size and age, expected lifespan in the cities, and the total amount of MSW were considered by Ghinea et al. [28]. Several tools for the analysis and forecasting of time series were proposed for the study of MSW generation [29]. Hazardous waste forecasting and the corresponding mathematical model were developed to address the prediction problem with spatially distributed and uncertain data [30]. This model was based on regression analysis and data reconciliation.

Recent research focused on future planning and process integration or optimisation; however, the existing material flows, waste treatment options, and waste production with regard to the accuracy and credibility of input parameters were not justified or examined. The evaluation of a specific region requires up-to-date information on the transportation and treatment. Nevertheless, due to data aggregation, it is difficult to obtain high-quality inputs even though the legislations of countries with well-developed waste management systems force waste producers to submit their waste production and processing data.

In general, the records are kept in a large database, which is available in whole or in part to the public. The challenge here is to process the data in such a way that additional information is obtained for the design and optimisation of the waste management system. For efficient waste management planning, the information on the composition and waste treatment are not sufficient. It is necessary to add the data on waste flows, i.e., from where to where the wastes are transported. For example [31], identified the flows of construction and demolition wastes in China.

For many reasons, public databases on waste management contain inaccuracies and inconsistencies. These can be significant, while in many cases large amounts of data are completely missing. The following errors can typically be encountered:

- inconsistent registration methodology at the regional level;
- systematic errors in data recording and formatting;
- loss of information within the waste flow between waste management entities;
- duplicate data;
- missing data (errors caused by data aggregation).

These errors necessitate the identification of the actual material flows, while the lack of information on waste flows between individual entities involved in waste management represents a crucial problem. A material flow analysis was conducted e.g. for mined landfills and the respective energy consumption was calculated with the emphasis on logistics [32]. Another study analysed the flow of municipal waste for the Maltese Islands [33]. Carbon footprint was then assessed for both the current and the future situation through the estimation of waste flow. Material flow analysis was also used in multi-criteria decision-making [34] for the case when it was not possible to determine how waste from a specific producer was treated. The problem of unknown flows may be caused by e.g. different reporting methodologies. This greatly complicates future planning of waste management, as well as reporting and possible support from legislation applying to smaller regions. The processing chain of waste from wind turbines was identified through material flow analysis in Ref. [35] and the treatable percentage was given.

The mentioned studies deal mostly with aggregated flows due and material flows are evetually resolved within a certain process. Flow problems are addressed, but these are not concerned with information on specific streams between the producers and treatment facilities. However, none of the studies discusses in a complex manner the material flows in terms of their geographical distribution, available transport routes, and the links between the waste producers and the processing facilities.

1.3. *Novel approach*

The majority of published papers focus on predicting the future situation, while the current state of waste management – especially in case of bulky waste – is not properly analysed in any of them. There are no error identification techniques available. Systematic error balancing was therefore studied with regard to individual databases in Ref. [36]. The mentioned approach, combined with the economic aspect and presented as a network flow problem, was discussed in Ref. [37]. This problem is illustrated in the following example, which relates to the practice of reporting waste data (such reporting systems can be found in many countries and for various commodities).

Because waste is not always treated locally, mainly due to its production rate and available treatment capacities, it may be necessary to transport it between nodes (see Fig. 2). In Fig. 2a, the input data (production rates, treatment capacities) are shown and their mass balance has to be facilitated via transport. Fig. 2b and c show just two solutions out of the infinitely many feasible ones.

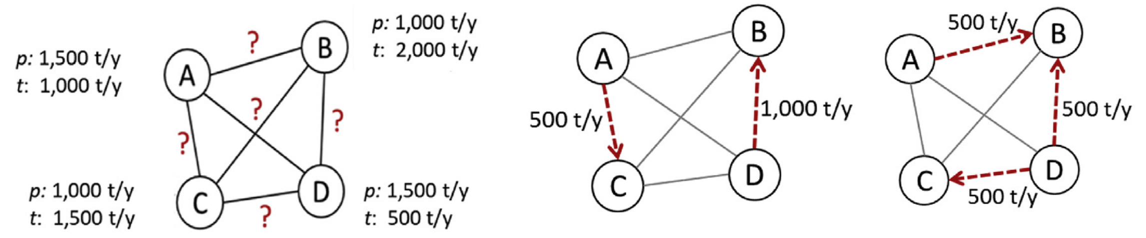
The set of feasible solutions may be further reduced by the application of additional constraints. For example, a minimum transport distance may be considered (see Section 2.2) or additional information on the flows along the edges and treatment options in the nodes may be available (see Section 2.1). This enables the identification of the existing network flows between producers and treatment facilities.

The presented approach concerns the analysis of waste flows and thus obtaining more data for other applications and future planning (establishing of new or extending of existing energy recovery facilities). The case study presented in Section 3 focuses on waste flows and treatment data reconciliation for identification of bulky waste potential for energy recovery. Czech Republic was selected as the region of interest to demonstrate the practical impacts of the presented methods. The flows from the producers to the processing nodes were modelled to discover the following:

- where the waste from a particular producer was processed;
- how the waste was treated in the target node and whether this was done in accordance with the waste treatment hierarchy (material recovery, energy utilisation, disposal).

Knowledge of these facts is key to identifying the potential of waste, analyzing the current state of treatment, and suggesting future plans (see Section 3).

The model introduced in this paper the network flow model principle where the material balance in nodes is guaranteed. It



a) Input data of production and treatment *b) First possible solution* *c) Second possible solution*

Fig. 2. The available sources and sinks with two possible solutions; *p* denotes production rate and *t* treatment capacity.

combines the identification of errors in the reported data (stored in a publicly accessible database) with minimisation of the total transported distance. The paper extends the ideas in Ref. [36], which focuses on the error identification, and [37], where uncertainties were considered in the waste network flows. The combination of both these approaches makes it possible to reveal the previously mentioned key information.

2. Methods

2.1. Mathematical model identifying errors

Credibility of input data plays the key role in network flow models. The data must also be balanced and verified to obtain credible results. Several approaches to data reconciliation are used in the industry [38]. Papers were published on data reconciliation used together with the fuzzy set theory and the underlying physics phenomena to form the constraints [39]. Another proposed application was nonlinear data reconciliation for material flows using the weighted least squares approach [40]. However, in most cases this concerned the identification of measurement errors or isolated systematic errors. For example, in Ref. [36] the effect of a large number of systematic errors in the data, which significantly restricted the applicability of common data reconciliation methods, was investigated. Other solutions are therefore needed to assess the current state and how waste management targets are being met.

The paper presents a mathematical model for elimination of errors in a large database of waste production and waste treatment data. This database is an essential source of information in waste management for subsequent analyses and planning. The data are collected from the entities (both producers and operators of treatment facilities) which, by law, are subject to annual reporting. However, the data are reported at different levels of detail starting with the whole country and continuing with regions and municipalities. They also come from different sources and thus the error rate increases.

Locations where waste is produced or processed represent nodes and the transport routes between them edges. The available data consist of production rates (p) and processing capacities (t) in the nodes, and flows through the edges. The producer and processing facilities for individual portions of the waste, however, are unknown due to the effects described in Ref. [41]. Errors may be present in the database in both the edge and the node data (causing the total production and processed amount being different).

The data in the utilised database are more suitable for the discussed purpose because the edge flows are recorded by two entities (the first entity hands the waste over to the second one, which receives it). This makes it easier to detect errors. The waste is transported from the source through the transfer node to the target facility. The exported amount E1 should be equal to the imported amount I1, and the same applies to E2 and I2. In practice, though, this often is not the case. Fig. 3 shows the case where E1, I1 and E2, I2 do not correspond.

The actual values x_1 and x_2 (further in the model denoted as $x_{j,o}$, where o is the producer and j the edge) in Fig. 3 are unknown due to the presence of errors. Such errors, be them random or systematic (which originate from reporting a value multiple times by different entities), limit the planning of future infrastructure.

The problem of how to handle the errors in the database is considered in this study as a waste flow data reconciliation task. Emphasis is placed on the node mass balances and the requirement on the minimum change from the input data. The total amount of waste that is imported into a node (I in Fig. 3) and produced there (p in Fig. 2) is equal to the amount of waste that is processed there (t in Fig. 2) or exported from this node (E in Fig. 3). Data quality is assessed and considered in a weighted procedure (see the terms in the objective function Eq (1)). If the amount of waste E1 is close to I1, then the weight is higher and there is no reason to assume that the values are incorrect. In any case, the issue described in this paper requires an additional viewpoint to preserve relations from the real operations.

2.2. Mathematical model using distances

The waste management chain consists of waste transfer, possible change in its properties, and final processing. Transport cost can be approximated using the respective distance due to its being proportional to fuel consumption. Environmental protection, especially nowadays when industrial production is increasing, is also a relevant factor. The relationship between transport distance, waste separation, and the corresponding economic perspective was addressed in Ref. [42]. A similar idea was transformed into a larger and more general scheme in Ref. [37].

An approach to determine the reverse logistics flow was proposed in Ref. [37]. The model objective was to optimise the flow of

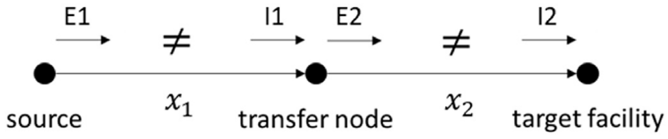


Fig. 3. Schematic chain of flows in the database.

non-utilisable products from producers to facilities. This could include uncertainties due to incomplete or unknown data, and decisions were made on the basis of distance. This criterion had economic background, where closer treatment facilities were preferred due to the lesser cost incurred. Also, scenario-based modelling was employed to allow for more distant facilities to simulate competition and more environmentally friendly options.

2.3. *Complex approach*

The previous sections deal with two mathematical models – the balance model (Section 2.1) and the model using distances to determine the actual waste flows (Section 2.2). The aim of the present paper is combine both models into a single, complex one. This approach provides a more realistic distribution of reconstructed waste flows because financial-based decisions of the producers are taken into consideration. The presented optimisation model maintains the balance in the nodes and detects the errors in the database with the aggregate waste production and treatment data. At the same time, the waste transport distance is minimised. The hierarchy of possible treatment options is considered according to the legislation, that is, the Directive 2008/98/EC on waste [43].

The proposed model (see Appendix A) evaluates and estimates the current state of waste handling and, due to the network structure, it is possible to find the corresponding waste flows. The resulting data must preserve the continuity of flow in the network. Fig. 4 shows a block schematic of the method.

This makes it possible to identify the processing methods for each producer and waste type. Corrective tools can then be proposed and micro-regions which fail to meet the global character of waste management, can be effectively motivated. The proposed approach verifies the historical data and the way they were handled to meet the generally valid balances. This is motivated by the following applications:

- analysis of the current state;
- necessary data for prognoses;
- identification of targets of the European Union;
- identification of wastes suitable for energy recovery (see Section 3 further).

To illustrate how balances are carried out for the nodes, and for simplicity's sake, only two treatment types (energy recovery and disposal) will be considered here. The vertical axis, i.e., the amount of waste produced and treated, is arbitrarily scaled and does not correspond to a real node. The graph (Fig. 5) is also separated into two parts: production and treatment. The overall production (p) can be processed via energy recovery or disposal (marked by different colours), and in the node where it was produced or in a different node to which it was exported (marked by different hatching styles). The combination of colour and hatching style then symbolises the selected treatment in the respective node and export from the node, respectively. Because the treatment capacity of the node is lower than waste production therein, a portion of the waste had to be exported. This is indicated by the differences in column heights. Also, columns are marked using K, U, or C according to the available data. Known data (K) were fixed, unknown data (U) were unavailable in the input database and therefore they were calculated by the model. Corrected data (C; namely the production in the node p_i and the transported amount $x_j^{\pm}$) were taken from the database, but they contained errors and had to be corrected. These were rectified while the relationships between all the node-related values had to be maintained.

To summarise, the goals were:

- Evaluate the methods by which the waste produced in the node was treated (column 3).
- Determine where the waste was treated, i.e., whether this was done directly in the production node or a certain portion was exported (column 5).
- In the case of import, find how the imported waste was treated (column 9).

3. Case study

3.1. *Introductory information and input data*

The approach discussed in Section 2 (i.e., the model described in Appendix A) has been applied to the regional-level(14 regions, see Fig. 6) bulky waste data from 2015 available for the Czech Republic.

The goal was to identify the regional distribution of production, treatment, and transport of bulky waste. Since several treatment methods were analysed, the obtained results were also used to define, on the regional basis, the potential of bulky waste for energy recovery. The amounts of waste which are currently landfilled were taken into account together with the amounts currently treated in WtE plants.

The input data came from the national database on waste management (waste management information system) [44], which has been operated by the Ministry of the Environment of the Czech Republic. The network describing the regional administrative division consisted of 14 nodes and, apart from production (p), the

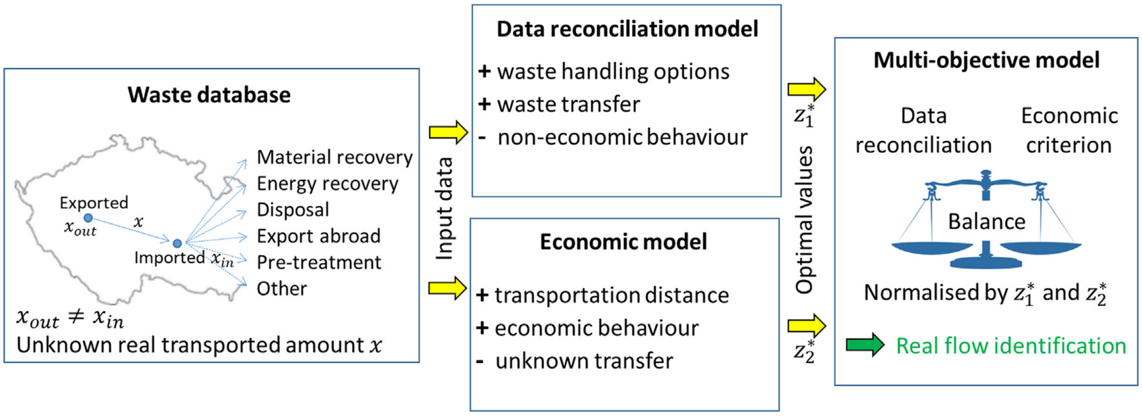


Fig. 4. Database repair – block schematic of flow identification.

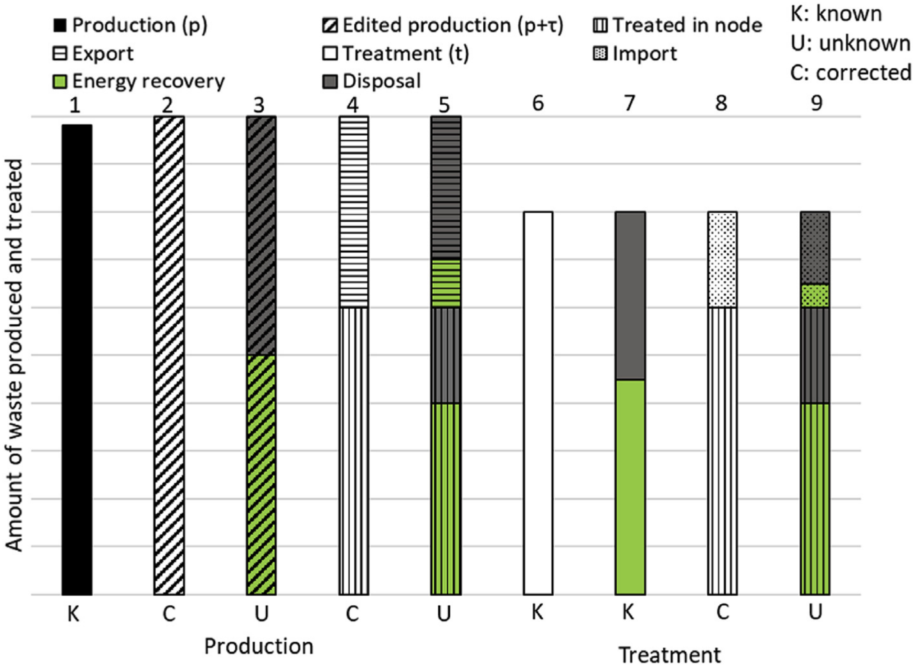


Fig. 5. Node balance.

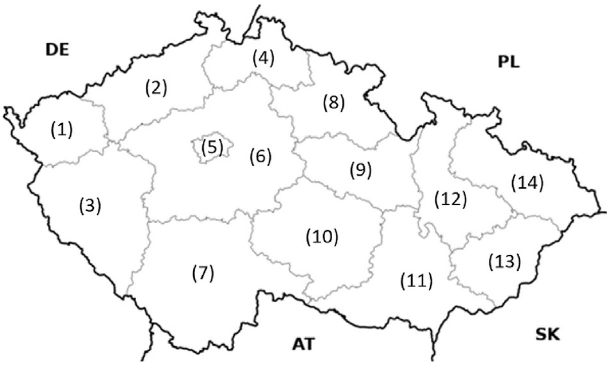


Fig. 6. 14 regions of the Czech Republic.

following treatment methods were considered:

- material recovery,
- energy recovery,
- national export abroad,
- pre-treatment,
- disposal,
- other way of processing.

Bulky waste represents a relatively large portion of MSW and its regional production p and treated amounts t are shown in Fig. 7. It can be seen that transports between regions are necessary. Considering geographical locations of the City of Prague (Region 5) and Central Bohemia (Region 6) and their productions and processing capacities, a significant transfer of waste between these two nodes can be expected.

It is beneficial to track the transfer of bulky waste between nodes. Compared to the example from Fig. 5, more treatment options make this task much more complicated. One should distinguish between:

- treated amounts by specific method l in region i ($t_{i,l}$),
- treated amounts in region i from the producer o by method l ($t^{O}_{i,o,l}$).

The flow in the network was reconstructed using the algorithm described in Appendix A. The lowest possible change from the original data was required. In addition, emphasis was placed on mass balances in the nodes (inherent due to the way the model was constructed). The value of parameter β was set to 0.5, which corresponded to no preferences in the weighted objective function.

3.2. Production and treatment balances

The results provide valuable information on the current handling of bulky waste, but they can be applied to other commodities of waste as well. The transport of waste from a producer through intermediate nodes to the respective processor can be tracked. The obtained data can serve as a basic dataset for future waste management planning. Fig. 8 shows the results with the amounts of treated bulky waste being split by treatment method for all considered regions.

The obtained data also include waste transfers among the regions. For example, in the City of Prague only a portion of the produced waste (ca. 19.8 kt) was treated, and around 48.5 kt were exported to the Central Bohemian Region. As a consequence, the rest of the treated waste was imported, even though the production in this region is higher than the treatment capacity (see the supplementary material). Ca. 0.7 kt were imported from the Karlovy Vary Region, ca. 0.2 kt from the Hradec Králové Region, ca. 0.6 kt from the Plzeň Region, and ca. 16.4 kt from the Central Bohemian Region. It is worth mentioning here, however, that a WtE plant is operated in the City of Prague (i.e., some waste from Central Bohemia was imported to the City of Prague due to a preferable treatment option, which is not available in the region of origin). Such transfers seem to conflict with the mathematical model using distances, but are the consequence of the distance between the City of Prague and Central Bohemian Region being artificially set to zero

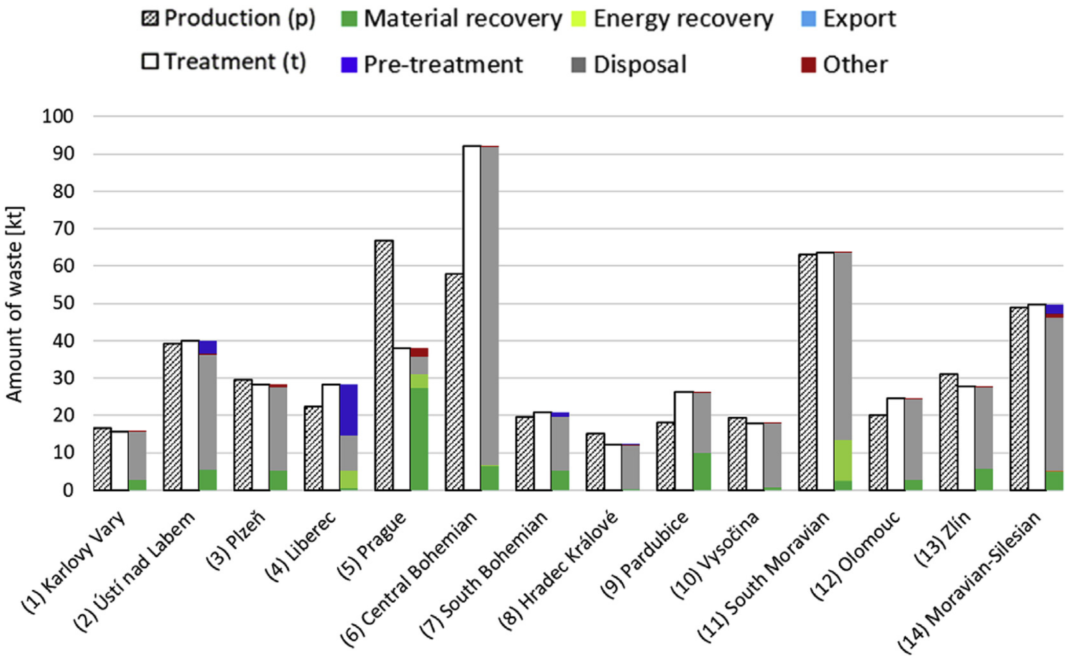


Fig. 7. Bulky waste production (p) and treatment (t) in the regions (input data).

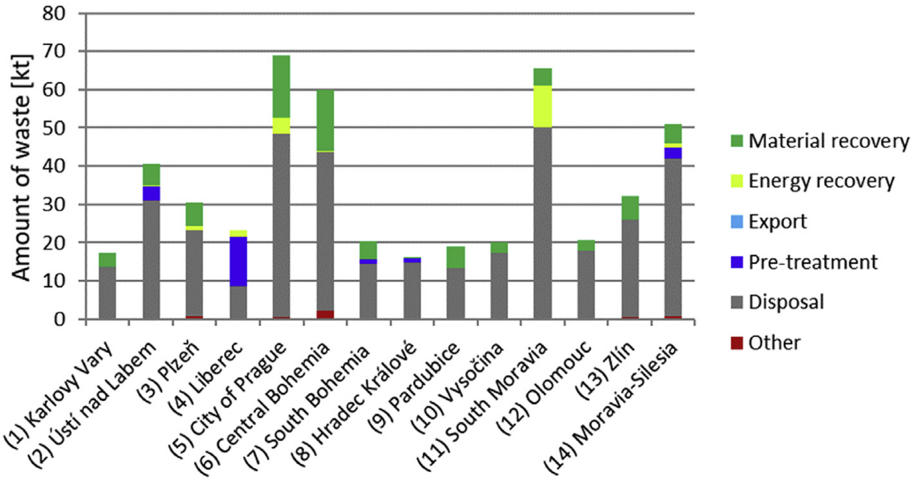


Fig. 8. Results for treatment of bulky waste produced in the specific regions.

because of their geographical arrangement.

Fig. 9 shows the waste treatment methods used in the regions of the Czech Republic. The most common method is disposal (landfilling or incineration without energy recovery; shown in grey). It represents more than 70% in almost all the regions, while ca. 360 kt in total were disposed of using this method in the Czech Republic in 2015.

The second most common treatment method is material recovery (80 kt in total). There were only 3 regions where WtE plants were operated in 2015 (the City of Prague, South Moravia, and Liberec regions). Most of the waste that was used for energy recovery (20 kt) was therefore produced in these regions.

3.3. Transport

The locations where the waste was transported to, were also obtained using the model. To provide comprehensive results, the Pardubice Region was selected for detailed investigation. Fig. 7 shows that the production of bulky waste in the Pardubice Region was lower than the treated amount with the difference being approx. 8 kt. The map in Fig. 10 shows the three regions (except for the Pardubice Region itself) where waste was produced and subsequently transported to the Pardubice Region for final treatment. Specifically, these were the Hradec Králové Region, the Vysočina Region, and the South Moravia Region, which are all adjacent or close to the Pardubice Region. The transport distances were therefore relatively short.

Although not all these regions are the exporting ones (see Fig. 9), transport between them was revealed, which was not apparent from a simple production–treatment balance, $((p + \tau)-t)$. Even the region where the production is lower than the processed amount, $((p + \tau) < t)$, can export waste. This feature is captured by the presented approach.

Most of the waste (18.8 kt, i.e., 71.9%) which was treated in the

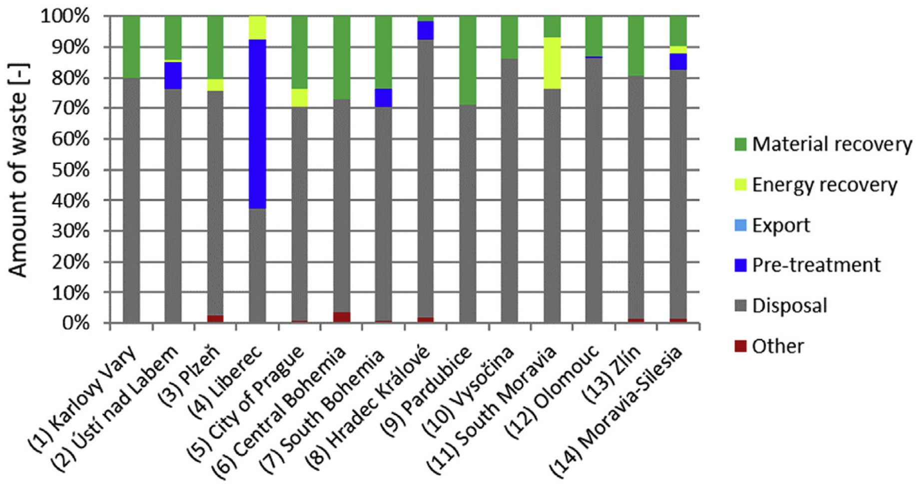
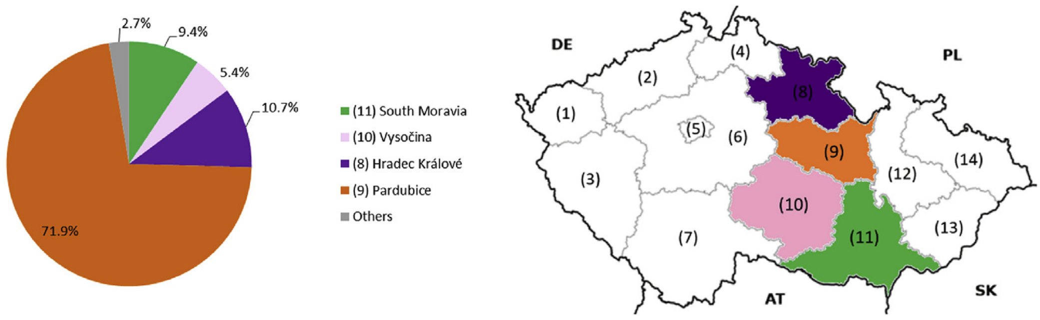


Fig. 9. Utilisation of bulky waste treatment options produced in individual regions.



a) The percentage amount of waste transported to the Pardubice Region

b) Regions handing over waste to Pardubice

Fig. 10. Pardubice Region – sinks for produced waste.

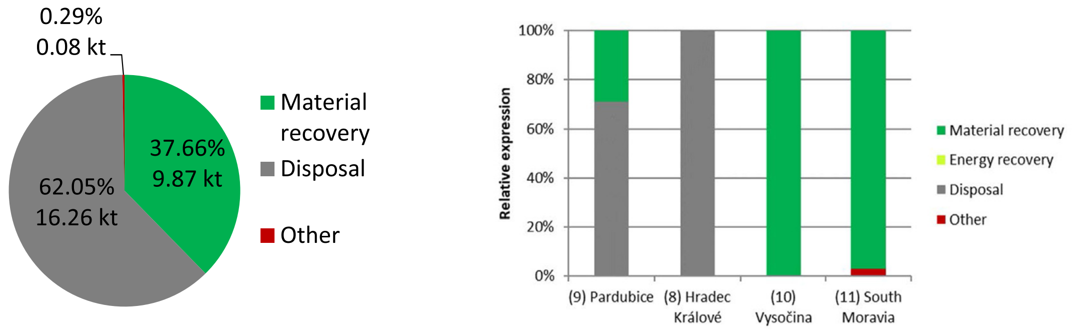
Pardubice Region (coloured orange in the map) originated in the same region. This corresponded to the assumption that waste should be transported the shortest distance possible. The actual transported amounts of waste to the Pardubice Region were 2.8 kt from the Hradec Králové Region, 2.5 kt from the South Moravia Region, and 1.4 kt from the Vysočina Region. Other regions accounted for negligible amounts of waste (0.002–0.4 kt, 0.7 kt in total) imported to the Pardubice Region.

Fig. 11b shows the treatment methods for waste produced in other regions, but treated in the Pardubice Region. The following methods were used there: material recovery (9.9 kt in total), disposal (16.3 kt in total), and other (0.08 kt in total), see Fig. 11a. The waste produced in the Pardubice Region was either disposed of in this region (13.4 kt) or materially recovered (5.4 kt). The waste imported to the Pardubice Region was mostly recovered to produce secondary raw materials (4.5 kt), while almost all the rest was disposed of (2.8 kt). Only a very small amount of waste (0.1 kt) was processed in a different way.

Eastern Bohemia, that is, the Pardubice and Hradec Králové regions, is an area where a future WtE plant is considered. For example, a plant in Pardubice was discussed a few years ago in Ref. [45]. The total heat demand, which is important for efficient operation of such a plant, is about 3500 TJ/year [46]. One of the largest power plants of the Czech Republic is operated in Opatovice nad Labem; only 10 km from Hradec Králové (ca. 93,000. inhabitants) and 15 km from Pardubice (ca. 90,000 inhabitants). The heat produced in the WtE plant could be transported to both cities and the surrounding area via the existing district heating network. This could mean even better utilisation of waste because a portion of the disposed waste could be used to generate energy (waste from the Pardubice Region and the Hradec Králové Region is mainly disposed of as shown in Fig. 11).

The waste transferred to the Pardubice Region is reported to be used in accordance with waste hierarchy (materially recovered). It is not desirable to transport a large amount of waste to treat it by a less preferred method (pre-treatment, disposal, other). However, the mathematical model must respect the input data and thus it sometimes suggests to transport waste to farther treatment facilities. In any case, the results are quite similar for all regions and meet all the objectives (economic and environmental). Transport of waste to different regions is realised mainly for material and energy recovery. In some cases, waste is transported to be treated using other methods. It can be assumed that the model is well designed, but to validate it, data at a higher level of detail (i.e., from individual micro-regions or even individual producers/treatment facilities) would be needed.

The largest amount of waste transported to the Pardubice Region came from the Hradec Králové Region, which leads to the



a) Overall treatment options in the Pardubice Region

b) Treatment options in the Pardubice Region of the waste produced in the specific regions

Fig. 11. The Pardubice Region – transport and processing of waste.

analysis of the waste produced there. Fig. 12 shows that a large amount of the waste produced in the Hradec Králové Region was not transported anywhere, but processed directly in the region. Focusing on the exported waste only, most of it was transferred to the Pardubice Region. The remainder was sent to the Liberec Region, and a small amount to the City of Prague.

Fig. 13 shows how the waste produced in the Hradec Králové Region was processed in the target regions. All the waste transported to the City of Prague was processed by “other” methods. The waste which was sent to the Liberec Region was entirely pretreated. It is likely that, in the end, it was used for energy recovery because there is a WtE plant in Liberec. Otherwise, the waste was disposed of.

With reference to Figs. 12 and 13, it is obvious that bulky waste produced in the Hradec Králové Region was not used in line with the waste management hierarchy. Only 0.2 kt were used for production of secondary raw materials, 1.0 kt was pre-treated (one can assume that it was used for energy recovery), 0.3 kt were processed in other way, and 14.5 kt were disposed of. This means that nearly 91% of the waste was disposed of.

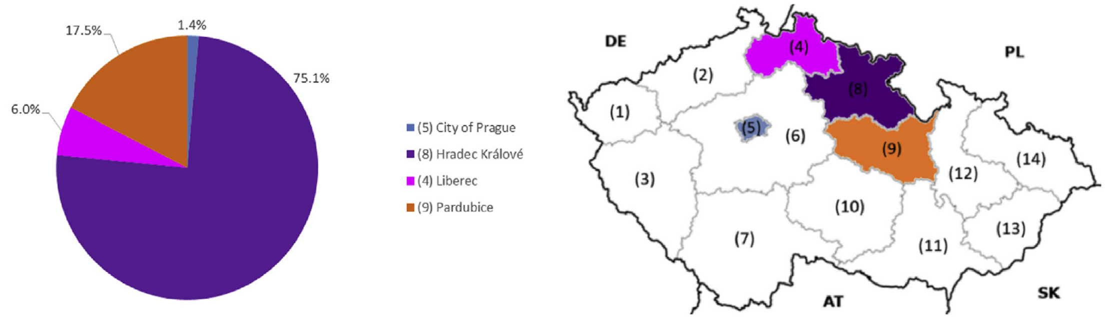
3.4. Bulky waste potential for energy recovery

The results discussed in the previous sections were used to identify the potential of bulky waste for energy recovery. These are summarised in Table 1, which compares the situation from 2015 with the future potential in terms of both the amount of waste and energy content.

Average value of LHV for bulky waste (approx. 20 GJ/t) was taken from Ref. [27]. Considering the total capacity of 650 kt/y of all the WtE plants operating in the Czech Republic, the overall potential for energy recovery from bulky waste was 2,494,710 GJ in 2015. The produced heat would then depend on the actual production efficiency. An analysis of utilisation of such heat in the district heating system and by the industry was done by Putna et al. [47] for the purposes of modelling of heat demand. Compared to the modelling of individual regions, this identified a large energy potential, which meant that there were suitable conditions for building new facilities or increasing the capacities of the existing ones.

4. Conclusions

A complex approach to waste data reconciliation through error elimination and network flow analysis is presented. It takes into account two aspects: detection of errors in input data obtained



a) The percentage amount of waste transported from the Hradec Králové Region

b) Regions taking over waste from Hradec Králové Region

Fig. 12. Transport of waste from the Hradec Králové Region.

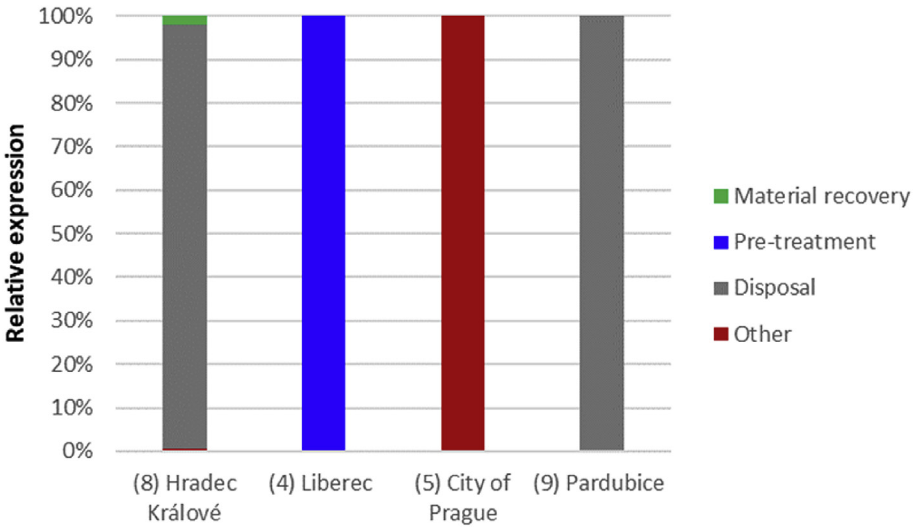


Fig. 13. The percentage amounts of the waste produced in the Hradec Králové Region according to methods of treatment in various regions.

Table 1
Results of potential increase in energy recovery from bulky waste.

Region	Energy recovery in 2015 [t]	Additional Potential in 2015 [t]	Unrealised potential in 2015 [GJ]
City of Prague	4221	52,321	962,000
South Bohemia Region	0	14,285	285,700
South Moravia Region	10,861	60,818	999,140
Karlovy Vary Region	0	13,668	273,360
Vysočina Region	0	17,266	345,320
Hradec Králové Region	0	14,547	290,940
Liberec Region	1722	10,342	172,400
Moravia-Silesia Region	1172	42,380	824,160
Olomouc Region	0	17,929	358,580
Pardubice Region	0	13,425	268,500
Plzeň Region	1135	23,556	448,420
Central Bohemia Region	91	41,821	834,600
Ústí nad Labem Region	365	31,246	617,620
Zlín Region	7	25,472	509,300
Total	**19,574**	**379,076**	**7,190,040**

from the waste reporting database and transport distance, which keeps the results economically feasible. The weights used in the multi-objective function are set according to data credibility, while the segregated nature of the model makes it possible to identify the potential of waste for energy recovery. The presented model therefore takes an incomplete dataset, which also is inconsistent, contains errors, and for which waste treatment methods are not known, and transforms it into a complete dataset with known information on waste flow between producers and treatment facilities, treatment method used, etc.

The model was tested on the Czech Republic waste database data from 2015. Bulky waste management was considered at the regional level and the energy potential was calculated and compared to the current situation. It was found that only 19.6 kt of bulky waste was used for energy recovery in contrast to the remaining 379.1 kt processed otherwise, i.e., the unrealised potential was 7190 TJ. A completely new perspective on the current state of waste management was created, and valuable information for the next waste management planning was provided. Future research should be focused on testing of the model using data corresponding to a lower territorial level (micro-regions). Still, this would bring multiple challenges [48]. Another research direction could be the improvement in the way uncertainties are handled.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2019.05.175.

Appendix B. Mathematical model

The model is built in a form of a multi-objective optimisation problem and, in its present state, is tailored to the specifics of the waste management data reporting system of the Czech Republic. Mandatory reporting applies to all entities handling waste and transported waste is recorded twice – by the sender (scenario (−)) and by the receiver (scenario (+)). Both these record types provide significant information to the model because there are no details about the quality of individual data. The model also minimises transport distances to simulate the economic behaviour of the producers.

Sets			
$i,o \in I$	Nodes	$l \in L$	Waste treatment options
$j \in J$	Edges	$j \in J(i)$	Edges of cycle for node i
Parameters			
$x_j^{\pm}$	Amount of waste transferred on edge$j$ according to the scenario + or − (carry to/take away)	β	The weight of the objective function
$A_{i,j}^{\pm}$	Incidence matrix for the scenario + or −	M	Upper bound-related big constant
p_i	Waste production in the node i	$\delta_{i,o}$	Binary indicator $\begin{cases} 1 & \text{if } i = o \\ 0 & \text{if } i \neq o \end{cases}$
$t_{i,l}$	Waste treatment type l in the node i	z_1^*, z_2^*	Optimal objective function values
w_j	The weight of the edge j, $w_j \in (0;1)$	a	The threshold for the zero penalization
d_j	Length of the edge j	W	Weight of penalization
Variables		**Positive variables**	
z_1, z_2, z_3	Objective functions	$\varepsilon_j^{\pm\pm}$	The positive or negative part of the error ε_j^+ or ε_j^-
τ_i	Error in the production in the node i	$t_{i,o,l}^{O}$, $t_{i,o,l}^{O,dir}$, $t_{i,o,l}^{O,cyc}$	Treatment of the waste in the node i from the producer o type l; divided into direct and cycled treated amount
y_i	Penalization	$x_{j,o}$, $x_{j,o}^{out}$	Amount of shipped waste from the producer o on the edge j; divided into cycled and direct outflows
$\varepsilon_j^{\pm}$	Error on the edge j according to the scenario + or -	$y_i^{\pm}$	The positive or negative part of the penalization y_i

The proposed model consists of three objective functions Eq (1) – Eq (3). The used equations, as well as the nomenclature, are summarised below.

$$z_1 = \sum_{j \in J} \left(\varepsilon_j^{-+} + \varepsilon_j^{--} + \varepsilon_j^{++} + \varepsilon_j^{+-} \right) w_j + W \sum_{i \in I} \left(y_i^+ + y_i^- \right) \tag{1}$$

$$z_2 = \sum_{j \in J} \sum_{i \in I} d_j x_{j,i} + W \sum_{i \in I} \left(y_i^+ + y_i^- \right) \tag{2}$$

$$z_3 = \frac{\beta z_1}{z_1^*} + \frac{(1-\beta) z_2}{z_2^*} \tag{3}$$

s.t.

$$\sum_{j \in J \setminus J(i)} A_{i,j}^+ x_{j,o} + \delta_{i,o} (p_i + \tau_i) \quad \forall i, o \in I \tag{4}$$

$$t_{i,l} = \sum_{o \in I} t_{i,o,l}^{O} \quad \forall i \in I, \forall l \in L \tag{5}$$

$$p_o + \tau_o = \sum_{i \in I} \sum_{l \in L} t_{i,o,l}^{O} \quad \forall o \in I \tag{6}$$

$$\sum_{j \in J} A_{i,j}^+ x_{j,o} + \delta_{i,o} (p_i + \tau_i) = \sum_{j \in J} A_{i,j}^- x_{j,o} + \sum_{l \in L} t_{i,o,l}^{O} \quad \forall i, o \in I \tag{7}$$

$$x_j^+ + \varepsilon_j^+ = \sum_{i \in I} \sum_{o \in I} A_{i,j}^- x_{j,o} \quad \forall j \in J \tag{8}$$

$$x_j^- + \varepsilon_j^- = x_j^+ + \varepsilon_j^+ \quad \forall j \in J \tag{9}$$

$$x_j^- + \varepsilon_j^- \geq 0 \quad \forall j \in J \tag{10}$$

$$p_i + \tau_i \geq 0 \quad \forall i \in I \tag{11}$$

$$\varepsilon_j^- = \varepsilon_j^{-+} - \varepsilon_j^{--} \quad \forall j \in J \tag{12}$$

$$\varepsilon_j^+ = \varepsilon_j^{++} - \varepsilon_j^{+-} \quad \forall j \in J \tag{13}$$

$$y_i = \tau_i - a p_i \quad \forall i \in I \tag{14}$$

$$y_i = y_i^+ - y_i^- \quad \forall i \in I, \tag{15}$$

$$x_{i,o}^{dir} + \sum_{j \in J(i)} x_{j,o} - t_{i,o}^{O,cyc} = \sum_{j \in J \setminus J(i)} A_{i,j}^- x_{j,o} \quad \forall i, o \in I \tag{16}$$

$$\sum_{l \in L} t_{i,o,l}^{O} = t_{i,o}^{O,cyc} + t_{i,o}^{O,dir} \quad \forall i, o \in I \tag{17}$$

The computation is done in two phases. Optimisation problems involving just the objective function Eq (1) or Eq (2) and constraints Eq (4) – Eq (17) are solved first. The obtained optima are normalised using z_1^* and z_2^*. The entire problem including all three objective functions is solved afterwards.

Objective function Eq (1) minimises the weighted total error in the database to ensure the balance in each node. The first summation deals with errors on the edges for scenarios (+) and (−), the weight w_j determines data quality based on both scenarios (see Eq (18)). If the sending and receiving nodes recorded a similar value (scenarios (+) and (−) are similar), then it can be assumed that the data are correct. In such a case the weight w_j is higher.

$$w_j = \begin{cases} M, & x_j^-, x_j^+ = 0 \\ \dfrac{x_j^- + x_j^+}{2\left| x_j^- - x_j^+ \right|}, & otherwise \end{cases} \quad \forall j \in J \tag{18}$$

The second summation in the objective function Eq (1) takes into account penalization in the nodes.

The second objective function Eq (2) minimises the total transport distance, which simulates economic behaviour of the producers. Eq (3) combines the two different factors, which are minimised in the Eq (1) and Eq (2) and normalised by z_1^* and z_2^* from the initial separate computations. The priorities of z_1 (Eq (1)) and z_2 (Eq (2)) in z_3 (Eq (3)) are given by the parameter β.

The first constraint Eq (4) ensures the validity of the balance in each node for edges of cycle for node i. Eq (5) defines the total amount of the treated waste in the node i as a sum of the treated amounts from all producers. Eq (6) says that all waste produced by producer o is treated somewhere by one or more methods l. The data on production p_i and treatment $t_{i,l}$ are known in the node i. The total production ($\sum_{i\in I} p_i$) and treatment ($\sum_{i\in I,\, l\in L} t_{i,l}$) are not equal due to export/import issues or errors. If an error is present, it is expected only on the production side due to the way the data are recorded, and so the production p_i is corrected by error τ_i when applicable. This production adjustment is included in the objective function in the form of the penalty function Eq (14). Also, equality between corrected production ($p_i + \tau_i$) and overall treatment in the specific node i ($\sum_{l\in L} t_{i,l}$) is not ensured because of export and import of waste. This means that the waste transported from a different node can be treated in the node i by a method l. Eq (7) keeps the flow balance for each producer o. The sum of waste shipped to the node i and produced there (if $i = o$) equals to the sum of waste shipped away and processed in the node i. This is achieved through the identification of errors in production data $\tau_i$and transport data $\varepsilon_j^{\pm}$. In the Eq (8), the flow reported in the database is connected with the edge flows (total amounts of the waste match – exported and imported). The equality of both scenarios (+) and (−) is assured by Eq (9), thus the amount of waste that was transported along the edge j is taken over in the appropriate node. Eq (10) and Eq (11) are the constraints for non-negative waste flows on each edge j and waste productions in each node i. Splitting of errors into their positive and negative parts is reflected in Eq (12) and Eq (13). The penalty y_i is calculated according to Eq (14) and splitting of the penalty into its positive and negative parts is in Eq (15). Eq16 and 17 distribute the flows of a producer into the outflows and treated amounts in the respective node while considering cycle edges.

Selection of the threshold for zero penalty a was described in Ref. [36]. Penalization y_i is a part of the objective function Eq (1) because the recorded data can contain errors on case of both the edges $j$and nodes i. The production and processing of waste is recorded in the nodes. Errors are more likely to be expected on the producers' side who are subject to the annual reporting obligation. Data inconsistency can be solved by integrating the penalty into optimisation problems, specifically into all the objective functions. The idea behind the penalty function is shown in Figure A1.

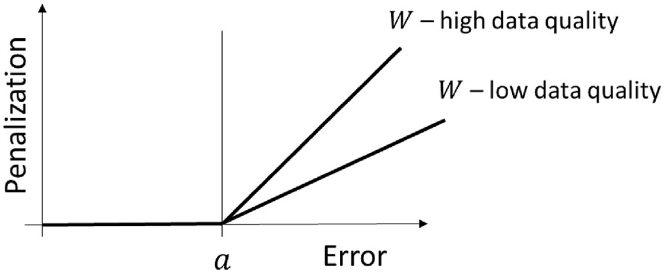

Fig. A1. Penalty function.

The actual threshold for zero penalty a in Eq (14) was set according to Eq (19), which corresponds to the ratio of an average change of production and the average production to maintain the processing–treatment balance. The parameter a actually determines the error ratio for each producer (assuming that each producer contributes to the overall error equally).

$$a = \frac{\sum_{i\in I}\left(\sum_{l\in L} t_{i,l} - p\right)}{\sum_{i\in I} p_i} \tag{19}$$

The calculation of the penalization weight W is done as shown in Eq (20). Essentially, it is the average of edge weights for which the deviation of input parameters is non-negligible.

$$W = \frac{1}{|J|_{j:w_j \neq M}} \sum_{j\in J:w_j\neq M} w_j \tag{20}$$

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Příloha 4: Publikace [A11] – Comprehensive review on waste generation modeling.

sustainability

Review

Comprehensive Review on Waste Generation Modeling

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Abstract: Strategic plans for waste management require information on the current and future waste generation as a primary data source. Over the years, various approaches and methods for waste generation modeling have been presented and applied. This review provides a summary of the tasks that require information on waste generation that are most frequently handled in waste management. It is hypothesized that there is not currently a modeling approach universally suitable for forecasting any fraction of waste. It is also hypothesized that most models do not allow for modeling different scenarios of future development. Almost 360 publications were examined in detail, and all of the tracked attributes are included in the supplementary. A general step-by-step guide to waste generation forecasting, comprising data preparation, pre-processing, processing, and post-processing, was proposed. The problems that occurred in the individual steps were specified, and the authors' recommendations for their solution were provided. A forecasting approach based on a short time series is presented, due to insufficient options of approaches for this problem. An approach is presented for creating projections of waste generation depending on the expected system changes. Researchers and stakeholders can use this document as a supporting material when deciding on a suitable approach to waste generation modeling or waste management plans.

Keywords: waste generation modeling; waste production; waste prediction and forecasting; projection; short time series

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1. Introduction

In developing countries, the prevailing goal is to dispose of waste, while in developed countries (e.g., the ones in the EU), there is an effort to process the waste more sustainably. The preferred methods of waste management (WM) and disposal in the EU have been stipulated in the Waste Management Hierarchy [1] to make use of the waste potential. The EU member states have been implementing the necessary legislative changes, and the next step is to adapt the existing WM systems to meet the respective objectives. Strategic plans for the modernization and construction of waste collection and processing infrastructure require information on the generation and composition of waste, including their expected development, as a primary data source. The aim is to create a WM system that is sustainable from both the economic and environmental points of view. In response to this situation, there is a growing number of publications dealing with waste generation modeling. This review aims to summarize the available modeling approaches and discuss their suitability for different applications in WM.

1.1. Application-Based Targeting

WM is a very complex field in which many tasks and problems can be encountered in decision-making. The direction of WM development is conditioned by the appropriate strategic planning of the various components of the WM system (waste collection, construction of new treatment facilities, change in facility capacity). A whole series of interventions in the system requires several years for the preparation and implementation of the plan. It is therefore necessary to start from well-developed comprehensive strategic plans, which, among other things, take into account the expected development of the generation of the waste fractions in question.

Each task is unique in nature, but all stages of the process require specific input data, differing mainly in their time or territorial detail. The most challenging parameters are the generation rates of different types of waste and waste composition (mostly MMW or separately collected waste, e.g., paper, plastic). Therefore, the tasks are divided into three logical blocks, where their characteristics are described to create models associated with the current or future waste quantities.

1.1.1. Waste Management Legislation and Policy

The proper specification of the recycling or waste prevention targets included in legislation requires reliable long-term knowledge of waste generation and treatment. Historical data can identify the links of various socio-economic and demographic factors to WM development [2]. The connections identified may reveal potential societal changes and, consequently, positively affect waste generation trends and processing methods.

In the context of long-term forecasting (5–20 years), the Circular economy package of the EU is relevant because it sets recycling targets for municipal solid waste (MSW) until 2035 [3] and landfill restrictions [4]. At the country level, the data are usually aggregated annually, and as such, are suitable for forecasting. The disadvantage often is the availability of only short historical data series, due to annual data records. The only reasonable alternative for forecasting is finding the trend that the data follow (Section 4.3.2). Ghinea et al. (2016) [5] considered multiple functions for describing trends, of which the S-curve proved to be the most suitable for MSW. Ayeleru et al. (2018) [6] used a linear dependence to describe the expected city-level rate of the generation of MSW. Other available works dealt with very complex models that are not suitable for forecasting. A complete overview is given in the Supplementary Materials (see Section 2.1).

Modeling waste generation makes it possible to compare mostly very ambitious legislative goals with the forecasted values. The most significant shortcoming of the methods for the longer-term estimation of waste generation is the failure to consider potential interventions in the waste system itself. If the forecast is not in line with the goals, then the projections are modeled. This can reveal the potential for changes in individual territorial units. Within the projections, the forecasts are modified to achieve the set target [7].

1.1.2. Strategic Decision-Making on Waste Management Infrastructure

Strategic decision-making in WM concerns the planning and implementation of long-term projects for facility construction [8]. Compared to the previous part, waste management legislation and policy, waste generation forecasting usually focuses on the regional level. Data at the regional level are often available on an annual basis and estimating trends from historical data is possible. However, the data and trends also usually feature significant volatility, which makes forecasting more complicated and less accurate. It is good to keep in mind the conditions in the surrounding regions that may affect the planned project [9]. A hierarchical territorial division can ensure consistent forecasts between regions and the entire country [10]. The definition of possible scenarios for future waste amounts takes place in the strategic planning. Such scenarios arise from external interventions into the WM system, and they allow for evaluating the impact on the planned projects' sustainability [11].

A significantly shorter time horizon is sufficient for collection strategy planning due to the relatively short service life of collection containers and frequent legislative changes [12]. Models for collection planning usually focus on the daily or weekly data sets. This type of data is common for cities and municipalities, where monitoring is conducted in greater detail and during longer time horizons.

To ensure the financial and technical sustainability of a project, it is necessary to assume, during its evaluation, that several parameters are uncertain, including the generation rate and the waste composition [13]. The current state and outlook for the area of interest are needed to appropriately site a new facility or collection infrastructure with a well-chosen capacity.

1.1.3. Operational Decision-Making in Waste Management

The last point is related to the planning of daily operations. Container level data are needed in waste collection applications that use routing models (a summary of routing problems and their application was presented by [14], which may feature various targets. A typical representative of this is dynamic collection planning, where the waste quantities at the individual collection points are estimated each day. On the other hand, when creating a new collection plan, weekly or monthly data are required to properly set the collection frequency. The frequency itself depends on both the waste properties and the capacities of the collection points. Collection planning is closely related to the siting of the collection points, which was discussed in detail in the previous sections.

1.2. Tasks Encountered in Waste Generation Modeling

When building waste generation models, it is necessary to distinguish whether an estimate of the current or the future generation rate is made. The differences in the terminology regarding prediction, forecasting, and projection are provided in the following sections.

1.2.1. Prediction

The prediction of waste generation is used to describe the current or future situation. Estimating the current waste generation rate is essential to define the links in the system and to develop the models for other territorial units. These links can be used to model the expected future waste generation. A common application is in the modeling of the waste generation rate, depending on various socio-economic, demographic, and other factors. The pitfalls of such models were described by [15] in more detail. The main weakness is that the links in the system can change over time. Problems may occur when the links are modeled using all of the historical data, without regard to their temporal variance. Consequently, this may impact the quality of the future predictions of the respective models.

A common mistake is also to build models using the absolute data, without standardization. Then, multicollinearity is often observed, which negatively impacts the obtained results. In addition, the data yielded by a WM model should always include information on the uncertainty, e.g., via confidence intervals.

1.2.2. Forecasting

Forecasting, sometimes termed prognosis, exclusively concerns the estimation of future development. Most forecasts in WM involve waste generation. Other forecasting targets (waste composition, waste treatment) are rare. When making a forecast, it is necessary to remember that inferring the future development based on the current or historical data is always a difficult—and often largely unsolvable—task.

Forecasting models assume that the respective parameters will evolve in a similar way to their past development. The primary feature of a forecast is that no change in the current conditions is expected. Data from even short-term forecasts must be evaluated carefully. Longer-term forecasts are more indicative in terms of how the development of waste generation might manifest if nothing changes (e.g., without any changes being made to the legislation). When it comes to waste generation, the problem is further compounded by the fact that often only data sets covering very short time ranges are available. If sociology-, economics-, or demography-related data from a "prediction" model are to be used, it is imperative that such a prediction is of sufficient quality.

Forecasts should also consider the links between the waste streams, which are interrelated (higher generation of separated waste leads to lower amount of mixed municipal waste (MMW) etc.). A model should always allocate a certain number of data points at the end of the time series for verification purposes. Even in forecasting, the results should include information on the uncertainty.

1.2.3. Projection

Projections also deal with the estimation of future development; however, in contrast to forecasting, they assume that a change will happen in the boundary conditions (legislative, technological progress). These conditions, which affect waste generation, cannot be forecasted. Therefore, projections are often future scenarios given the specific boundary conditions chosen by the authors. Scenarios can be created with respect to the objectives of the WM, but deviations from the corresponding forecast should be as slight as possible. Due to territorial hierarchy, it is appropriate to consider the division of national targets (i.e., individual regions according to their potential for change). Monotony in terms of waste generation potential should be maintained. Possible links among waste fractions should also be taken into account.

1.3. Research Questions

The underlying goal of this review is to gather supporting material for the development of a comprehensive waste generation model, particularly with regard to its application (see Section 1.1). Before studying the available literature, the research questions that are addressed in the following text are formulated.

- What are the common shortcomings of the available data, and how many data points in a time series are sufficient? Response: Sections 2.1 and 3.
- Which approaches and methods are suitable for certain applications? Response: Section 3.
- Can general recommendations be formulated for data processing? Response: Section 4.
- Can prediction models be used to estimate future data? Under what conditions? Response: Section 5.
- How to implement changes and interventions in WM (legislative interventions, changes in data reporting methodology, introduction of new waste catalogue numbers) within mathematical models? Response: Section 5.

The actual review methodology is described in Section 2. A detailed overview of the studied publications can be found in Supplementary Materials. An extensive review was carried out in order to create an overview of the methods and approaches to date. Based on this, it is possible to choose a suitable approach for other tasks. In the event that the existing approaches are insufficient for some types of tasks, it is appropriate to consider the issue of developing new approaches. Section 3 presents the process of choosing a modeling method. Section 4 then summarizes the modeling processes (preparation, pre-processing, processing, post-processing) in the form of the problems and the authors' recommendations. A SWOT analysis for the individual models is provided for each method in Appendix A. The main benefit of this contribution is the combined approach of forecasting and projection based on a short time series, see Section 5. The presented method is designed as a universal approach for any waste fraction. The lack of a multipurpose approach was found to be a research gap. A common and problematic feature of the available data is a short time series. Considering this feature, the approach is based on a trend analysis of the historical data, followed by data reconciliation. This choice took place according to the decision-making process in Section 3. A brief summary is provided in Section 6, including the suggestions regarding further research directions.

2. Literature Review

First, attention was paid to previously published review papers on the discussed topic, with the aim being to prevent repetition, the summary is in Table 1.

Table 1. Previously published review papers.

Citation	Time Range	Number of Publications	Criteria
(Beigl et al., 2008 [16]);	Until 2005	45	regional scale, MSW waste streams, independent variables, modeling methods
(Cherian and Jacob, 2012 [17])	Until 2011	9	regional scale, MSW waste streams, independent variables, modeling methods, socio-economic factors
(Kolekar et al., 2016 [18])	2006–2014	20	modeling methods, territorial division, amount and frequency of time-dependent data, independent variables, waste stream
(Goel et al., 2017 [19])	1972–2016	106	classification into typical (multiple linear regression—MLR, time series analysis—TSA, factor analysis) and unconventional (fuzzy methods, artificial neural networks—ANN) approaches
(Alzamora et al., 2022 [20])	2008–2021	120	MSW stream, geographic scale, data type, modeling technique, independent variables
(Abdallah et al., 2020 [21])	2004–2019	85	artificial intelligence in WM, identified six applications; described multiple models incl. hybrid ones
(Guo et al., 2021 [22])	2003–2020	40	machine learning methods in organic solid waste treatment
(Xu et al., 2021 [23])	2010–2020	177	ANN models, categories of review scales: macroscale (mainly focused on waste generation), mesoscale (waste properties and process parameters), meso-microscale (waste process efficiencies), microscale (reaction mechanisms or microstructures)

Older reviews clearly specify the as-of-yet unresolved research gap, while the more recent works—e.g., [21–23]—deal exclusively with artificial intelligence and do not consider other methods. As the works by [17,18] described the target periods with only a modest number of published models, a new review for that period has been conducted in the present paper. The contribution [19] presented a relatively extensive review, but further applications require more elaboration in the context of waste fractions. The contribution [20] aims to investigate the relationship between waste generation and socioeconomic factors. Thus, a review of approaches that do not use influential factors for models (e.g., TSA) is not provided. Therefore, the review will be carried out again in this contribution, with a broader scope of the methods used. The review [16] is taken as the starting point, the publication is ca. 15 years old and, therefore, an update is due. The review [16] summarizes the methods used until 2005, but there are no described new approaches that have not been addressed until then. It is therefore not necessary to study the contributions before 2006, as this period has already been well covered in paper [16].

The review is therefore conducted for articles published in 2006 and later. The main databases queried were ScienceDirect and Scopus with the keywords being: “msw prediction“, “msw forecast“, “waste prediction“, “waste forecast“, “waste generation“, “waste production“, “waste forecasting“, “municipal waste prediction“ or “municipal waste forecast“. The articles were sort on “relevance”.

For the articles that matched the listed keywords, their relevance to this review was assessed against the title or abstract. The criterion is that the chosen article presents a model of either the current or future waste generation. When sorting by relevance, the articles suitable for review are first displayed. Then, more occurred, which were excluded from the review. When there were more than 20 non-relevant articles in a row when sorting by relevance, the search was terminated. A total of 359 articles were identified for the detailed examination within the review.

The following text is particularly beneficial because it contains detailed modeling recommendations for specific WM applications. The criteria utilized in [16] have been kept and several new parameters (the amount of data, waste types, etc.) have been added.

2.1. Summary of the Results

This study evaluated the 359 selected publications from several points of view. A detailed overview of all the monitored criteria is available in Supplementary Materials; the main text contains references only to the fundamental publications that the authors have chosen for the citation in individual parts of the text. Supplementary Materials is structured as follows:

- Publication details (columns B–H): title, authors, journal, year, nationality according to the affiliation of the main author, number of citations, keywords.
- Origin of data (columns I–K): state, continent, the source of WM data.
- Data details (columns L–R): number of dependent variables, time interval, number of time intervals, territorial division, number of territories.
- Forecasting (columns S, T): forecasting (yes/no), forecasting period length.
- Waste streams (columns U–AK): MSW, MMW, bio-waste, paper, plastics, glass, etc.
- Influencing factors (columns AL–AT): influencing factors (yes/no), population size, education, age, income, gross domestic product (GDP), etc.
- Utilized methods (columns AU–BF): LR, general regression (GR), TSA, ANN, etc.
- Processing (columns BG–BH): pre-processing (yes/no), verification of assumptions for LR.
- Model quality (columns BI–BM): coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), etc.

2.1.1. Data Pre-Processing

Pre-processing is included in 26% of the papers, but it is often introduced very briefly without a detailed description of the actual procedures used. Only 60 papers out of 359 involved pre-processing and simultaneously evaluated the quality of the developed model. Approximately 32% of these 60 articles with pre-processing used weekly or daily data [24] and about 47% of the articles with pre-processing used annual data. However, the models with annual data are usually created on many territorial units, where, again, it was possible to use common methods such as z-score [25], Grubb’s test, or Dixon’s test [26]. Outliers occurring in a short time series were often dealt with expertly. The authors’ recommendations regarding the pre-processing of short time series are provided in Section 4.2. It should be mentioned that pre-processing did not address changepoint detection in the studied papers, although it can have a major impact on the model.

2.1.2. The Detail of a Dataset

The selected publications focused on different waste types, as shown in Figure 1. The most frequently modeled component was MSW, at 54%. This was followed by the separately collected waste with high potential for material recovery (paper, plastics, glass, bio-waste), with a frequency of about 15%. Separated waste (SEP) was also modeled as one stream, i.e., the separately collected but not individually distinguished components of MSW. It is worth noting that a relatively small percentage of the publications (6%) focused on MMW generation (terminology is not uniform, in some publications also called residual waste). The reason for this might have been that this stream is quite difficult to model due to the relationship between MMW and the sorted components.

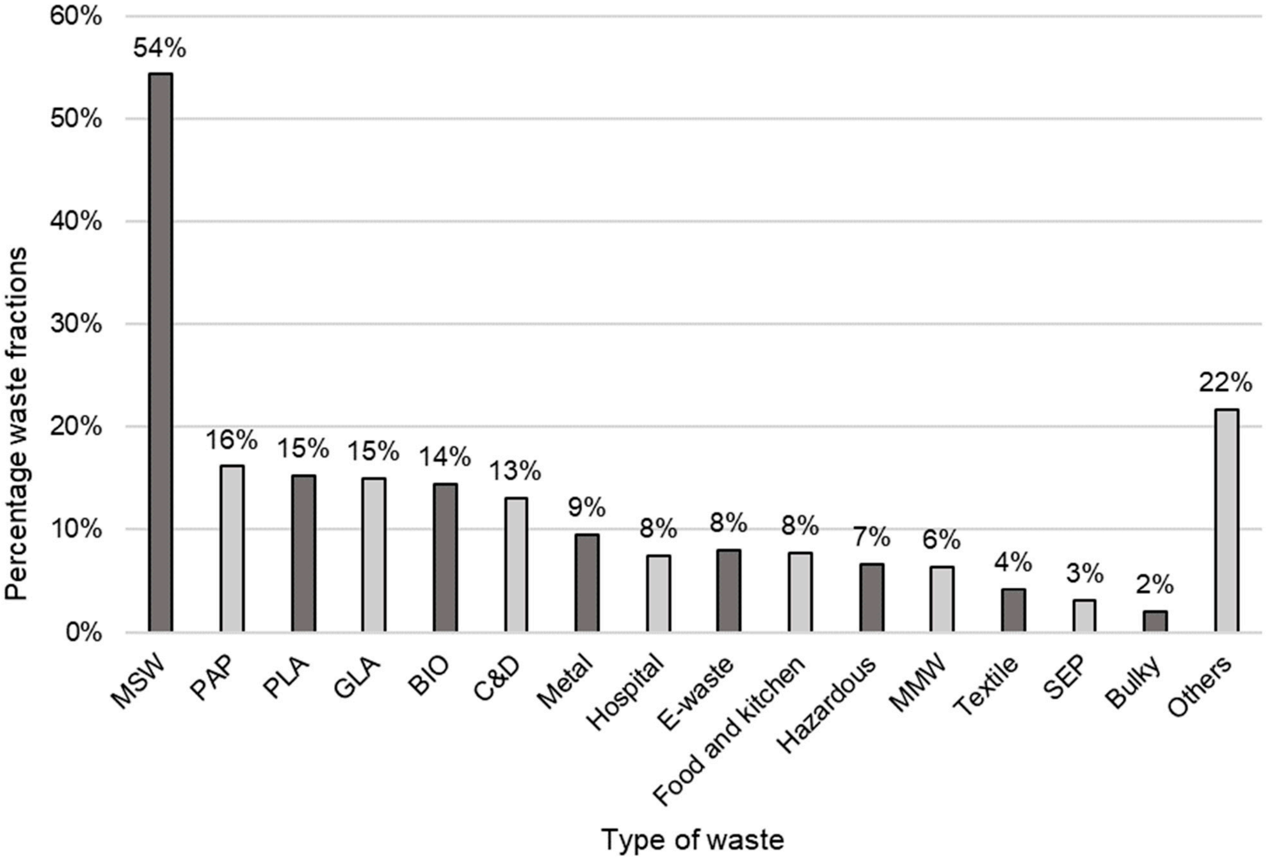

Figure 1. Waste types studied in the evaluated publications. Legend: MSW—municipal solid waste; PAP—paper; PLA—plastics; GLA—glass; BIO—bio waste; C and D—construction and demolition waste; MMW—mixed municipal waste; SEP—separated waste.

The following territorial divisions were monitored: state, region, municipality, household, building, hospital and "others" (which included all the remaining levels due to their infrequent occurrence). Some territorial divisions were directly related to specific waste types, e.g., building (construction and demolition waste), hospital, hotel, or aircraft. Figure 2 shows the relationship of the territorial detail with the time division and the input data acquisition method. The household data were most often available on a daily basis (more than 55%). This was because they came from surveys in which the produced waste was commonly collected from a sample of households and weighed every day. The national-level data, on the other hand, were available yearly in 87% of cases.

Regarding the household-level data (waste generation and socio-economic information), they were usually obtained via surveys or interviews. Existing databases about reports were mostly used as the source for collecting the data for hierarchically higher levels (municipality, region, state).

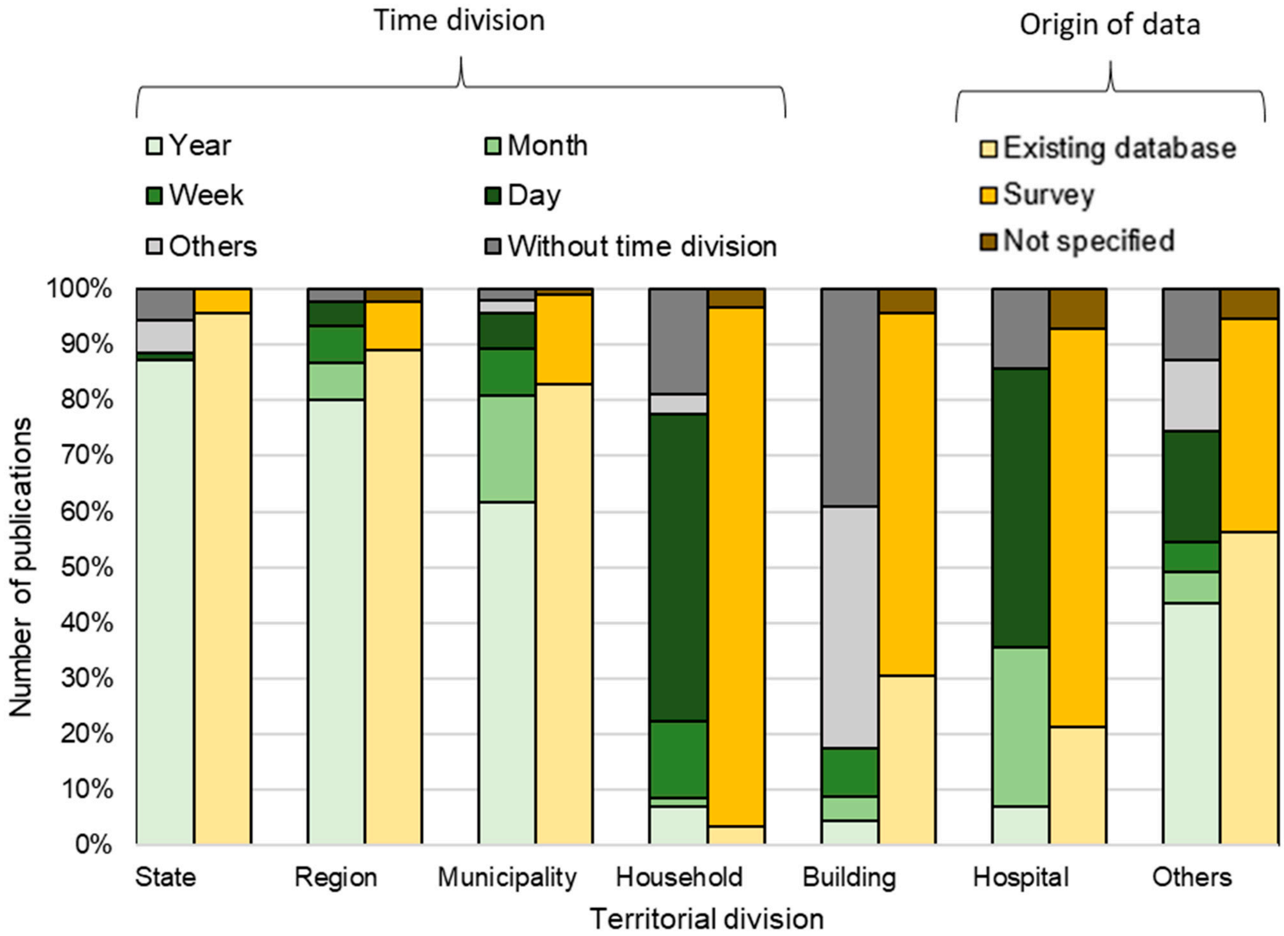

Figure 2. The relationship between data origin and territorial division (left column in each pair), and time and territorial division (right column).

2.1.3. Approaches Applied

The values in Figure 3 indicate the shares of papers utilizing each method (please note that some articles employed multiple methods). The most common method—appearing in 31% of the studies—was MLR. In this case, the waste generation was estimated based on the available sociological, economic, demographic, and other data. ANN, which belongs to artificial intelligence methods and has become increasingly popular in recent years, was the second most used (26% approach), followed by the simple descriptive approach and general regression—GR (e.g., generalized linear model—GLM, analysis of variance—ANOVA, or nonlinear regression). Some publications also featured other methods than those listed explicitly in Figure 3 (grouped under "Others"). These included, for instance, mass balance, the theory of planned behavior, or models based on geographical information systems (GIS). The colors in the respective composite bar chart indicate whether the models described in the evaluated papers were predictive or included forecasting as well.

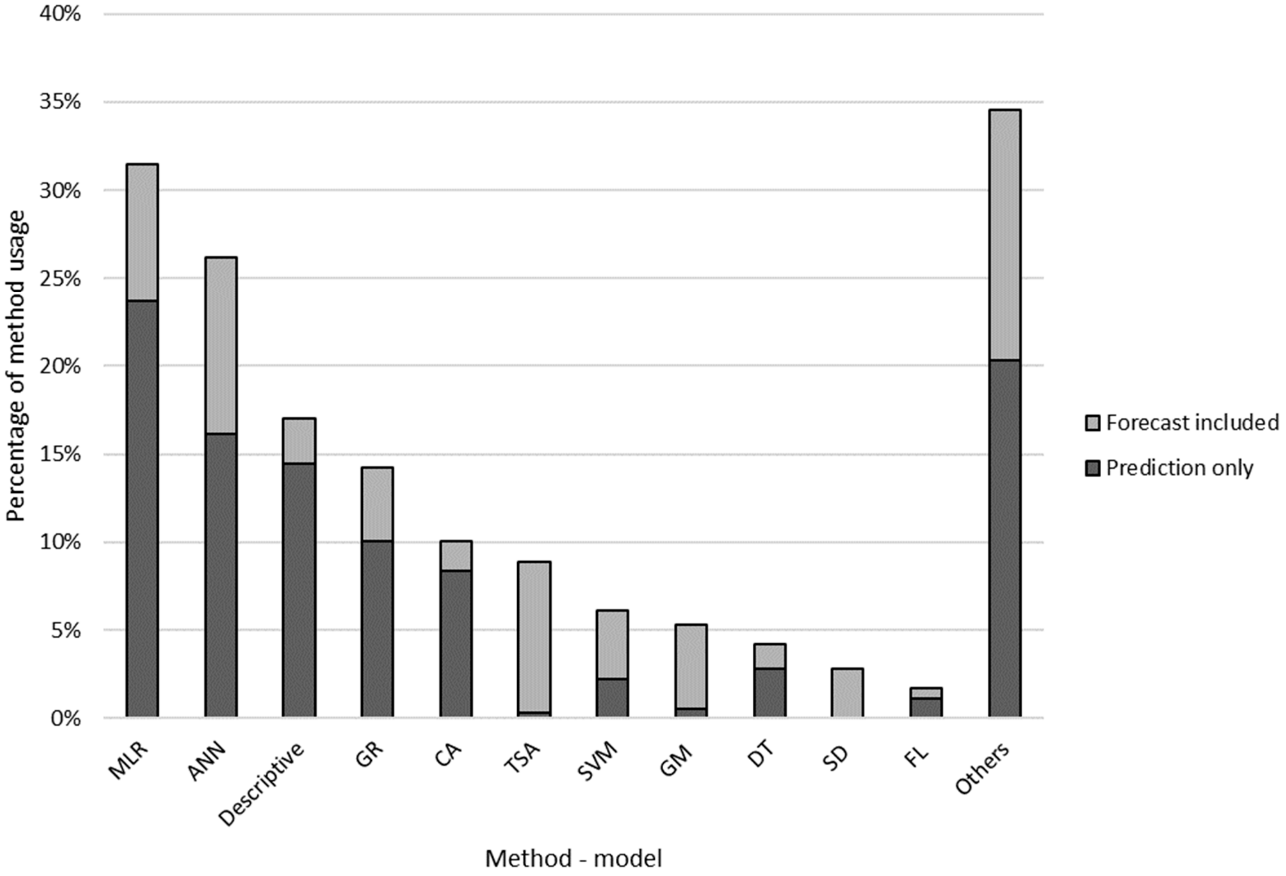

Figure 3. Distribution of methods used in the evaluated studies. Legend: MLR—multiple linear regression; ANN—artificial neural network; GR—general regression; CA—correlation analysis; TSA—time series analysis; SVM—support vector machine; GM—gray models; DT—decision trees and forests; SD—system dynamics; FL—fuzzy logic.

Several models were tested in paper [27], of which the most accurate results were obtained for the utilized data set using gamma regression (GLM). Karpušenkaitė et al. (2016) [28] tested different models for a specific waste fraction (namely, medical waste), and different time series lengths. The result was that no universally applicable model exists, but the GLM models provided the best results for the regional-level data. Kannangara et al. (2018) [29] compared DT and ANN and found that ANN achieved higher accuracy, while the results from DT could be interpreted more clearly. According to [23], 45% of WM papers using ANN worked with at most 100 data points, but ANN have still become popular in WM. Petridis et al. (2016) [30] compared different models for time series, and autoregressive moving average (ARMA) provided the most accurate results, but the Box-Jenkinson methodology (ARMA, autoregressive integrated moving average—ARIMA, and their modifications) achieves good results on long time series. Ghinea et al. (2016) [5] presented S-curve models as the most suitable option for trend analyses depending on the data available.

A different route is followed by hybrid models, which combine the advantages of the individual methods used. Xu et al. (2013) [31] showed that the combination of the seasonal ARIMA (SARIMA) and grey system was robust enough to fit the seasonal and annual dynamic behavior of waste generation. However, the mentioned models are focused on the specific waste fraction, and general applicability cannot be deduced. This is a feature of most of the models in the review. The methodology proposed in [32] combined the S-curve trend and ANN, where for the future construction projects, the S-curve trend was linked to the project characteristics via the ANN forecasting of waste generation. Trend analysis, followed by correcting the estimates to maintain the hierarchical links in the system, was supplemented by data reconciliation in the methodology presented in [33].

The selection of the suitable methods depends mainly on the nature of the input data and the objectives of the model. The evaluation of the model quality presented in various studies is problematic because of the different input data qualities, verification of compliance with method assumptions, or model refitting risk. However, generally, it holds true that higher-quality models can be obtained at higher levels of territorial division due to lower data variability.

2.2. Evaluation of Review

The review showed the possibilities of using different modeling methods, and a summary of the main outputs is shown in Figure 4. The numerical value indicates how many models, out of a total of 359 publications, correspond to the given characteristic. It should be noted that one publication may include several types of models, e.g., for testing reasons or when using a hybrid method. Therefore, the sum of the values in one layer does not have to correspond to the value in a higher layer. Attention is paid to the forecasting models (130 publications out of 359); the prediction models for current waste generation were previously addressed in the publication [15]. Forecasting models can be divided into two basic types. One of them only works with historical data on waste generation and models the development over time. These models use common approaches of TSA. The eventual principles of ANN, GR, MLR, etc. are applied for modeling the trend in the data, where time is the only independent variable. The second type models the links between waste generation and various factors (economic, environmental, sociological, etc.). Based on the expected development of these factors, a waste generation forecast is created. This area includes both conventional and machine learning approaches.

The detail of the time division is crucial because it often determines the length of the time series: the annual data create short time series and higher detail can create long time series. The detail of the time series for both types of method (development in the time and links in the system) was divided into year detail and others in Figure 4. The time division is 28/23 (year/others) models for the methods using development in time series and 64/15 (year/others) models for the methods using links in the system. Thus, a total of 92 models use data in the year detail and only 28 models of 92 use methods based on the development in the time. The fundamental problem of methods that use links in the system is the need to forecast all of the influential factors. Usually, forecasts of these factors are not available in the necessary quality and sufficient forecasting length, see [34]. The authors consider it more appropriate to use methods based on time development due to the smaller requirements for input data.

Furthermore, it is desirable to deal with the issue of territorial hierarchy. In most cases, the model is created for one level of territory (state, municipality, etc.). For WM planning, the waste generation forecasts are necessarily for different territorial divisions, but these forecasts are performed separately without the hierarchical links. The review includes only six models that consider the territorial hierarchy for short time series forecasts, and all of these models were previously presented by the authors of this review. Most authors do not consider territorial links (22 models for short time series), which the authors consider as a one of the research gaps.

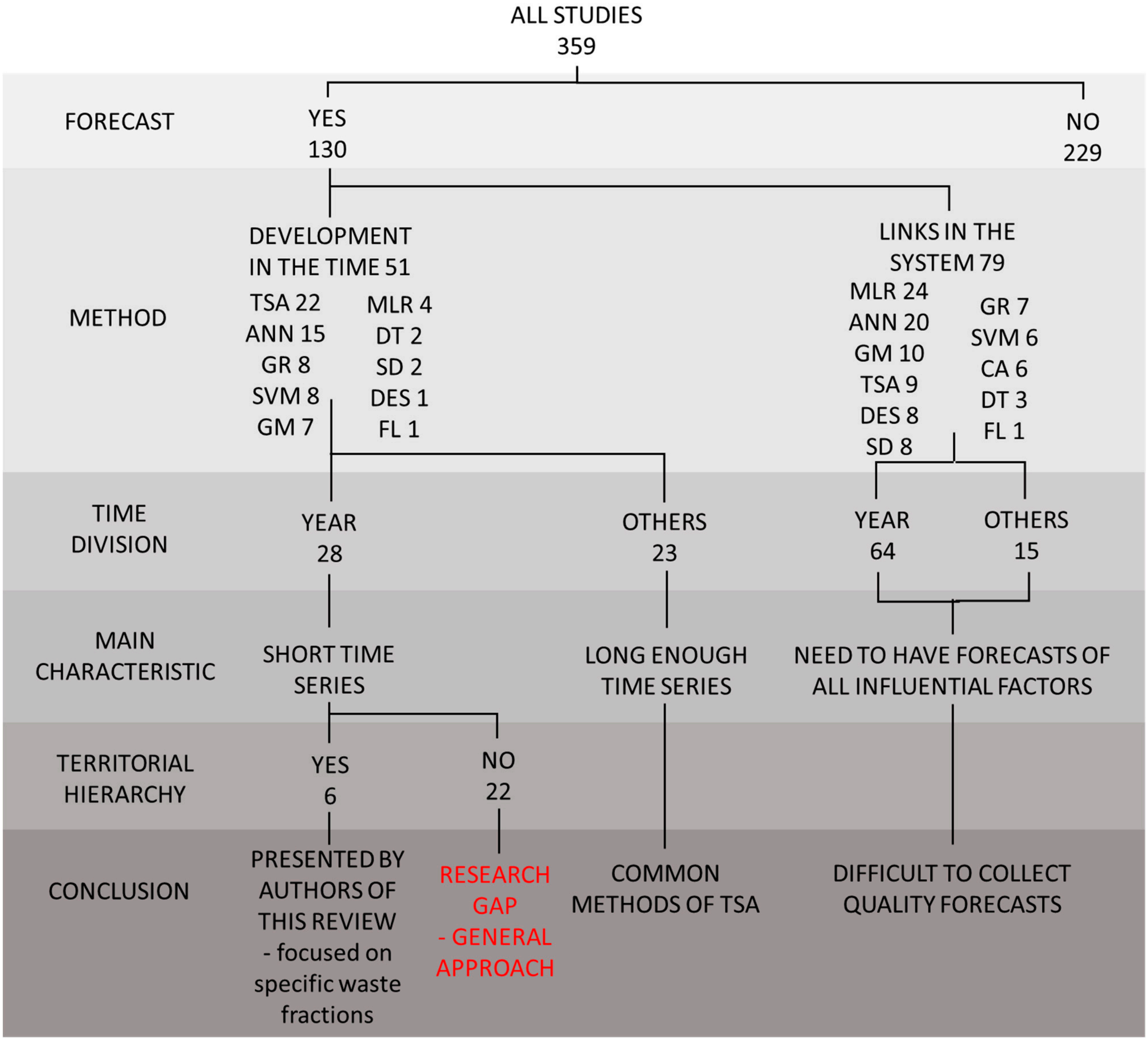

Figure 4. Distribution of methods used in the evaluated studies. Legend: TSA—time series analysis; ANN—artificial neural network; GR—general regression; SVM—support vector machine; GM—gray models; MLR—multiple linear regression; DT—decision trees; SD—system dynamics; DES—description; FL—fuzzy logic; CA—correlation analysis.

- The choice of modeling method (Sections 3 and 4).

The presented studies apply different methods without explaining why a particular method was chosen. Based on the findings, this text provides support for decision-making when choosing a suitable method. Data availability and data properties are primarily taken into account (Section 3). The schematic representation of the suggested decision process is described in Figure 5. In Section 4. the problems found in the modeling and recommendations for their solution are formulated, which should make it easier for the reader to apply the methods further.

- The general approach of waste generation forecasting (Section 5)

The models mentioned in the literature review (Section 2) are focused on specific waste fractions, and general applicability cannot usually be deduced. This is a feature of most models in the review. Within this manuscript, the approach usable for arbitrary waste fraction is presented (Section 5). The main characteristic of the approach is in the interconnectedness of the forecast and projection, which can achieve the results taking into account real conditions.

3. The Decision Process for Method Selection

The selection of a suitable modeling method depends on the target application and available data. For the applications presented in Section 1.1, it is advisable to use the models from Table 2. This table shows only the forecasting and projection models, which are necessary for planning the future directions to be taken in WM. For WM legislation and policy tasks (Section 1.1.1), long-term forecasts with less territorial and temporal detail will be more advantageous. The opposite is true in the case of operational decision-making in waste management (Section 1.1.3); that is, short-term forecasting, which will usually require more detail in terms of territory and time, will be most appropriate for this task. If dynamic planning is required, then it is necessary to also take into account the computational complexity of the methods.

Among almost 360 evaluated studies, no GLM model was found to be applied to forecasting. In the case of methods describing waste generation via the influencing factors (MLR, GLM, DT, ANN), it is necessary to forecast all of the influencing factors in advance. This significantly limits the usability of the mentioned methods because forecasts of influencing factors are unavailable or of poor quality. As for TSA, these are mainly trend models for long-term planning. Short-term time series information, such as seasonal effects and autoregression, are essential for operational decision-making.

Table 2. Representative model types for individual applications.

Application	Most Common Features	Model	Reference
Waste management legislation and policy	- long-term forecasting - smaller data frequency (e.g., years) - larger territorial units (e.g., state)	MLR	[35–37]
		ANN	[38,39]
		TSA	[40,41]
		Scenario models	[7,42,43]
Strategic decision-making on waste management infrastructure	- long-term forecasting - smaller data frequency (e.g., years) - different territorial levels (city, region, state)	MLR	[6,44,45]
		DT	[46]
		ANN	[29,47,48]
		TSA	[5,49]
		Scenario models	[50,51]
Operational decision-making in waste management	- shorter-term forecasting - greater data frequency (e.g., months, days) - smaller territorial units (e.g., municipalities)	MLR	[49,52]
		ANN	[53,54]
		TSA	[55,56]
		Scenario models	[57]

A general guide to selecting an appropriate forecasting method is shown in Figure 5. The choice of a specific method depends primarily on the number and character of the input data. The flow chart also contains the assumptions and requirements put on the input data. The main steps in the process of forecasting are summarized below:

1. I. Conversion of data to unit quantity (with respect to activity rate) and data transformation

Requirement: Activity rate is a significant parameter. Typically, generation per capita is considered to be a unit quantity for MSW. Then, the number of inhabitants represents the activity rate. If desired, the data can be transformed at this stage.

2. II. Data pre-processing (level A in Figure 5)

Detection of outliers and changes in the trend.

3. III. Assessment of significant parameters

   Requirement: Data for all territorial units of the system.

4. IV. Selection of the modeling method (level B in Figure 5)

   Requirement: Validity of assumptions with respect to the selected method. Sufficient time series length for TSA depends on the method used in level C. Generally, the most stringent limitations are set for cyclic and seasonal components and the Box Jenkinson methodology. Expert estimates and average models, on the other hand, can be applied to only a few data points.

5. V. Forecasting via the selected method (level C in Figure 5)

   Requirement: Validity of assumptions for the respective method.

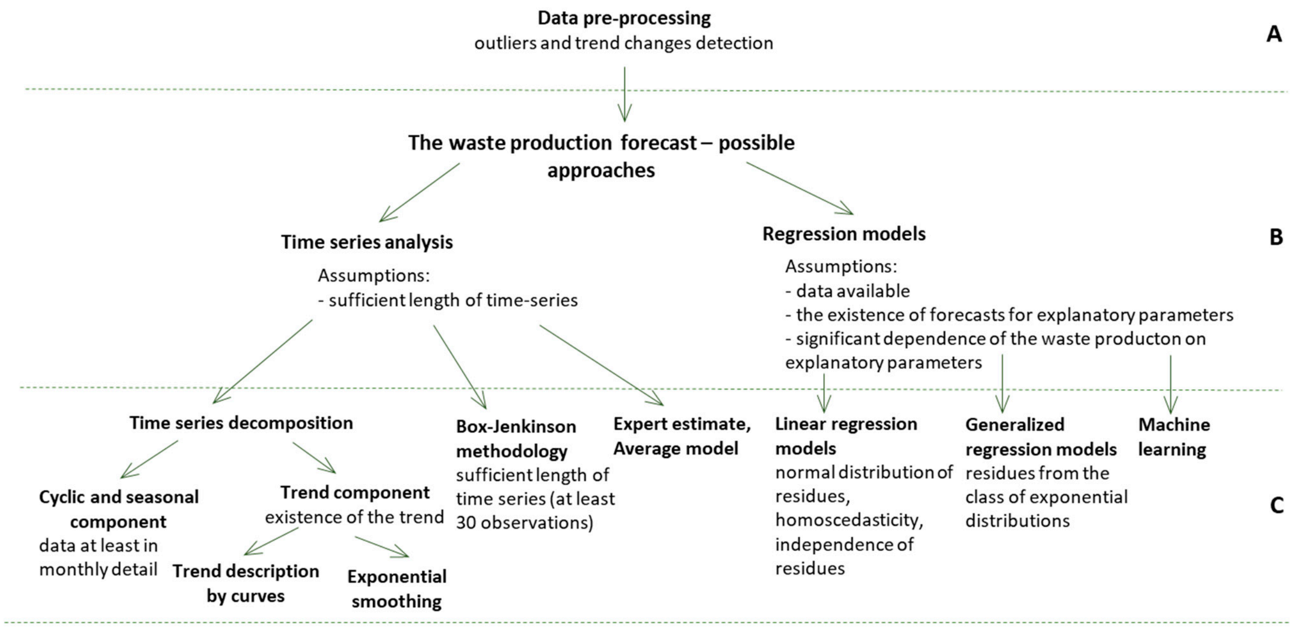

Figure 5. Forecasting method selection procedure.

The final forecast should meet the following criteria:

- Compliance with balances and interactions: balance of estimates on different hierarchy levels. The hierarchical structure of territorial units and waste fractions should be maintained [33], see Section 4.3.3.
- Confidence intervals: the expected uncertainty is integral to the results [58]. In most cases, however, information on model uncertainty is missing.
- Evaluation of the model quality: most models involve at least some quality assessment. Several commonly used criteria are R^2, MAPE, and prediction errors. It is also recommended to verify the quality of the forecast based on the testing data. Before the forecast is made, a certain part of the data at the end of the time series is allocated for this purpose, and then the prediction provided by the model is compared to this pre-allocated data set.

4. Problems and Recommendations for Waste Generation Forecasting

A wide range of theoretical bases for forecasting approaches is provided by [59], but without a link to specific applications in WM. The requirements and processes that are inherent to each waste generation estimate are explained below. Based on the studied publications, the authors of this review proposed a 13-step approach for forecasting, which can be divided into four parts: data preparation, pre-processing, processing, and post-processing. Predictive models are described in detail in the previous papers and will therefore not receive much attention. It is possible to be inspired by predictive models when processing data for forecasting. The following text will formulate the problems (P) and recommendations (R) for the individual forecasting steps based on the experience of the authors and the comprehensive review of the published papers. Almost every article dealing with waste-related data features some steps from Figure 6 and, therefore, potential research gaps will also be specified for issues that have not been sufficiently addressed.

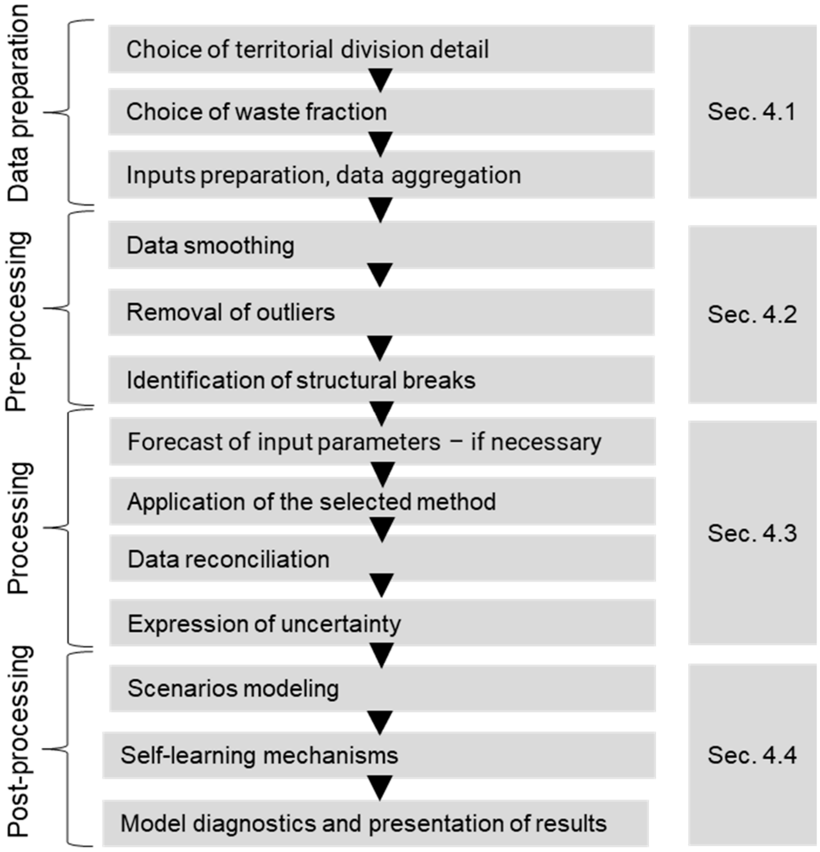

Figure 6. Schematic representation of the waste generation modeling procedure.

4.1. Data Preparation

P1: The use of historical data within time series can be complicated due to a change in the methodology of monitoring and recording this data.

R1: Historical data must be collected using the same methodology. If the methodology changes, it is necessary to delete the data prior to the alteration or to modify the data accordingly. An example is the merging of some waste streams for recording. Then, it is possible to also merge these waste streams in the historical data before the change.

P2: The required data are not available for all variables or territorial units.

R2: The data can be aggregated to obtain the missing values for higher territorial units. Aggregation also reduces data variability, which is more pronounced at lower levels. In addition, the missing data can be added using predictive models (see Section 1.2 [15]).

P3: It is difficult to compare regions in absolute terms due to the different sizes of producers. The analysis is therefore problematic because of extreme values.

R3: The data often needs to be normalized to check the relationships between variables [15]. Normalization or standardization applies to both waste and socio-economic data. The most common is normalization per capita, household or area. The normalization can also be shifted to improve the interpretability (e.g., the number of stores per 1000 inhabitants). If the data are not normalized per capita, it is recommended to discard extreme values in predictive models. Such data usually originate in the capital or other big cities that, due to their size, can have a considerable impact on the model behavior.

P4: Heteroskedasticity frequently occurs in the data.

R4: For some variables, it is recommended to transform the data to obtain a more even distribution of values. Logarithmic transformation is used most often. The logarithm with base 2 is recommended due to the character of the data in WM. However, here, the possible zero values must be treated appropriately. For zero values, the logarithmic transformation is not defined at all, values close to zero will have a disproportionately significant impact in subsequent analyses. At present, the authors do not know a suitable approach for the processing of zero values in logarithmic transformation.

P5: The data on waste generation include waste fractions, which influence the generation of other fractions.

R5: Interdependent waste fractions should be modeled together. For instance, there is a significant interdependence between MMW and SEP [60]. It may be advantageous to forecast the generation of these waste fractions as an aggregate in the absolute value (e.g., MMW + SEP) and, simultaneously, individual fractions as a rate of the total quantity (e.g., MMW/(MMW + SEP)). This will cause smoothing in the data.

4.2. Data Pre-Processing

P1: Historical WM data may be influenced by unknown or complicated regressors (economic cycles).

R1: It is possible to adjust the data for changes in the given parameters over time, such as economic cycles, or one-off situations, such as the COVID-19 pandemic. The adjusted (smoothed) data can then be used for modeling and forecasting.

P2: The presence of outliers negatively impacts the model.

R2: For long time series, it is possible to follow the common methods for the detection of outliers (see, e.g., [24]). These methods, however, are problematic when it comes to short time series (typically annual data) because the methods' assumptions cannot be confirmed. Therefore, it is necessary to use a combination of approaches and supplement them with an expert view. The authors can recommend the Holt method (for trend cleaning) together with the Grubbs' test for the identification of outliers in residues.

P3: The common methods for changepoint detection are not suitable due to their short time series [24].

R3: The following points are recommended for changepoint detection:

- Historical data should be standardized. This makes it possible to specify the same critical limit for each time series.
- Use data visualization if the amount of time series allows.
- Do not identify multiple changepoints in one time series if it is not long enough.
- Focus on the angles between the partial subsequences of the time series and the angles of the historical data lines with the x-axis.
- For further calculations, use the part of the time series behind the changepoint.

P4: It is difficult to detect data anomalies (outliers, changepoints) at the endpoints of the time series.

R4: It is risky to mark an anomaly endpoint as an outlier or a changepoint because no subsequent development in the data is known. It is recommended to test the model with and without the endpoint and compare the output ranges. This will verify the effect of the endpoint on the resulting model. The final decision in the consideration of the. removal of the endpoint due to an anomaly is up to the user.

P5: A time series behaves differently than the other time series (i.e., the whole time series has an extreme generation of waste compared to other producers).

R5: If the entire time series features anomalies, it is advisable to look for influencing factors that may affect it. Another option is to test for a possible correlation between neighboring territorial units because the WM characters may be similar in nearby localities.

Expert judgment is the only way to assess the results and evaluate the pre-processing quality.

4.3. Data Processing

4.3.1. Forecasting of Input Parameters

P1: Finding models that describe the waste generation based on the input parameters with sufficient accuracy is not guaranteed.

R1: Clustering can be applied to territories, and then the model can be built at the cluster level [61]. By compiling a model for each cluster separately, higher accuracy can be achieved due to local conditions. The different links can be described in specific clusters of territories and increase the model accuracy.

P2: Forecasting models require the forecasts of all their input parameters for the desired level of territorial division [62], but for some influencing factors, these are not available. Alternatively, only short-term forecasts of the influencing factors are available, but they do not cover the entire waste generation forecasting horizon [34]. Enormous uncertainty would enter waste modeling right at the beginning (not to mention the fact that it is not desirable to proceed with flawed input data).

R2: The inclusion of the influencing factors in the waste generation forecast is not suitable if the forecast of the influencing factors does not cover the whole forecasting horizon or there is significant uncertainty. Then, it is recommended to use the principles of TSA. Forecasts of demographic influencing factors differ from other socio-economic characteristics, and it is recommended to include demographic development in WM forecasts [34]. Long-term demographic projections are usually of sufficient accuracy, but unfortunately, they may not be available for smaller regions. It must be noted that demographic models are, in fact, projections because they are created in the form of scenarios [63].

4.3.2. Application of the Selected Method

P1: A specific method for TSA must be chosen concerning the data frequency detail and the length of the time series.

R1: If daily, weekly, or at most monthly data are available, then it is possible to monitor the cyclic and seasonal components, and short-term forecasting usually is possible [49]. Otherwise, when only yearly data are available for aggregated territories (region, state, i.e., most data sets commonly provided by states or government strategic planning agencies), solely the trend can be examined by the regression function [5]. In some cases, it can be advantageous to use Poisson regression. In the comparison with the trend in the form of a nonlinear function, the Poisson regression has less accurate results. However, the advantage is lower computational time.

P2: The choice of the regression function for describing the trend in the data is not clear (several different functions can give similar results).

R2: It is advisable to look for a compromise between the quality of the fitting according to the chosen criteria (e.g., R^2, MAPE) and the properties of the selected functions. The authors evaluated the following properties as substantial:

- Monotony—the trend over the forecasting horizon should not change from rising to declining and vice versa, so the trend is assumed to be monotonous. Oscillations around the trend caused by the seasonal or cyclical component are not possible to describe in short time series. Requiring monotony will also reduce the risk of model overfitting. It is recommended to use the power function for trend modeling. The advantage is its wide application for both rising and declining trends [34].
- Limited growth—some time series have a very significant growth in historical data (resp. decline), which may be exponential. Such a trend is usual after the system change, e.g., by collecting a new waste fraction. It cannot be expected to continue this trend over the entire forecast horizon. The more likely development is that the waste generation will slow down the growth. In such cases, it is appropriate to model the trend using an S-shaped curve [34].

It is recommended to model the trend with a simple model and a constant value in the following cases, see [34]:

- By excluding data after pre-processing, the time series remains too short for trend estimation. The minimum number of data can be adjusted to the specific length of the time series.
- The trend model in the data using the functions described above is of poor quality. As a criterion recommends using R2, the critical limit R2 can be customized.
- A simple model with a constant value leads to results that are comparable to a more complex model.
- As a special case, time series containing zero generation of waste in recent years should be extrapolated as a zero value–it is not expected to start generating this waste again.

P3: Attention should be paid to possible special cases of the waste streams. For example, the legislation may change, which may then cause a changepoint, etc. Completely new waste streams may also be introduced after the legislative intervention. Historical data then cannot be used for forecasting in the usual manner.

R3: The mentioned special cases should be detected in pre-processing if the change has already been reflected in the historical data. It is possible to consider the trend forecasting even if not all regions have already responded to the change. In other words, more advanced regions may outline the future directions for the less developed ones (Smejkalová et al., 2020 [64]). An analogous idea can be applied at the state level considering countries with differently advanced WM. Other notable special cases represent waste fractions whose quantities are directly influenced by the developments of specific external factors. A typical example is metal waste, which is linked to the purchase price of raw materials. The purchase price is difficult to forecast due to its cyclic behavior, leading to complicated forecasting of the metal waste fraction.

4.3.3. Data Reconciliation

P1: Historical waste generation data can contain internal consistency links, which form a hierarchical structure: the state comprises the regions, the regions comprise the municipalities. These links are not always maintained after applying the selected method (Section 4.3.2).

R1: The authors recommend correcting waste generation models to restore the system links using, for example, a data reconciliation model [33]. It is assumed that the amount of waste generated at a higher territorial unit is equal to the sum of the amounts in the territories that belong to it (e.g., municipalities located in a particular region). The second type of internal balance assumes links between the waste fractions. An example is the effect of separated waste generation on the amount of MMW [10].

P2: The data reconciliation model is significantly affected by the model weight settings, for example, different importance of the results that are balanced.

R2: It is necessary to pay attention to appropriately chosen weights when balancing; weights should be considered both in terms of total waste generation (preferably in the square root) and in terms of the quality of the estimate. In the case of the balance, percentage changes must also be taken into account [34].

P3: An increase in the generation of one fraction does not mean a decrease in the production of another fraction by exactly this amount; that is, the overflow of waste amounts is not consistent.

R3: The interdependence of waste fractions must be captured in a form that corresponds to reality; the values of the transition between the fractions do not have to be equal; individual waste streams are created and disappear [60].

P4: The possibilities of the chosen solver can significantly affect the success of the calculation when the model is stated as a mathematical programming problem.

R4: The data reconciliation model can be formulated in additive or multiplicative form [34]. The multiplicative form has a significant advantage for wastes with high variability between individual fractions. Producers with significantly different waste generations can occur at different levels of the territory. The additive formulation causes numerical and rounding errors. The setting of the model weights also depends on the formulation. In addition, the multiplicative form works with the percentage change, which is a problem in the case of zero values [34].

P5: The solver is not able to find the optimal solution due to the task size or computational complexity problems.

R5: Usually, at least a relaxed solution is available, i.e., the balances are not met exactly. This may not be a problem for some forecasts. In other cases, it is recommended to reduce the optimization task so that smaller sets of waste streams will be balanced, e.g., only for individual catalogue numbers.

4.3.4. Expression of Uncertainty

P1: Each forecast should provide confidence intervals [65], ideally also prediction intervals. If data reconciliation has been carried out (previous step, Section 4.3.3), it is not possible to use common interval constructs with a normal probability distribution around the model mean value.

R1: The authors suggest simulating the confidence and prediction intervals with the bootstrap method. It is possible to use historical data as one of the possible realizations, and then its variance to generate new data sets. A forecast is made for these generated data, which creates different realizations of the forecast. Based on the properties of forecasts for individual realizations, confidence and prediction intervals are compiled [34]. In the case of a limited number of possible generations within the bootstrap, the variance of forecasts for the construction interval is estimated. In this case, approximately 30 bootstraps are considered sufficient [34].

4.4. Data Post-Processing

4.4.1. Modeling of Scenarios

P1: A forecast does not include possible changes to the system, as described in Section 1.2. Projections deviate from a basic forecast because they must obey the model constraints and predefined boundary conditions. It is essential to ensure the feasibility and consistency of a projection.

R1: Legislative interventions take place at the state level or the levels of other self-governing units. The distribution of the projection changes to the micro-region is essential for determining the potential for future development. For analyses associated with the potential to increase the separation of MSW, it is necessary to have available (or at least estimate) the MMW composition, which allows estimating the potential for change. When using projections, it is recommended to consider the links between waste streams [60]. For the projections, it is necessary to determine the potential for change. The following applies to scenario solutions:

- The scenario does not exceed the potential for change which was set for a specific territorial unit.
- All territorial units show a shift towards meeting the scenario if the potential allows it.
- The individual territories do not overtake in terms of the fulfillment of potential and are monotonous.

4.4.2. Self-Learning Mechanisms

P1: The results must be updated when the input data set changes. The change may occur due to the data editing in the original database or the addition of new data on waste generation from the next period.

R1: During model re-evaluation, one must carry out all the forecasting steps specified in Figure 6. When the data are dynamic in nature, it is necessary to react quickly and develop an adequate methodology [66]. As an example, one might mention forecasting utilizing smart technologies such as weight or fill level sensor-equipped containers.

4.4.3. Model Diagnostics and Presentation of Results

P1: The quality of the models must be verified.

R1: The quality of a forecast should be tested using a pre-allocated test data set. In other words, the forecast should be made using a smaller data set, and the results should then be compared with the remaining values that were not used as the model input data. Model verification can also be conducted via confidence intervals.

R2: Forecasts provided by the models must be presented clearly so that their end-users (the decision-makers) can easily interpret them. Methods for representing results visualization can be found in the paper [45]. Another promising approach for communicating the results and incorporating them into the simulation calculations is the gamification approach [67]. Tools based on gamification for strategic planning in waste management provide interactive feedback with respect to the set criteria [68].

5. Modeling Future Waste Generation and Treatment Based on Short Time Series

Authors of this contribution recommend applying a combination forecast model and a subsequent projection model, see Figure 7. Compared to Figure 6, Figure 7 shows the essential steps of the projection in greater detail. In the first step, a forecast should be created based on historical data, which considers maintaining the current form of WM into the future, see Section 5.1. This part corresponds to data preparation, pre-processing and processing in Figure 6. This is basic information, but waste generation will be affected by systematic changes (legislative, technological etc.) and global trends (sociology, economy etc.) in the real world. Using predictive models, the influence of these factors on waste generation can be estimated, but their development cannot be well forecasted. The expected development of the influencing factors is a matter of expert assessment. Waste generation projection should be a combination of the forecast results with a predictive model, and the impact of the external interventions can be modelled as different scenarios. In the form of scenarios, an estimate of future waste generation can be achieved, which will correspond as best as possible to the real conditions.

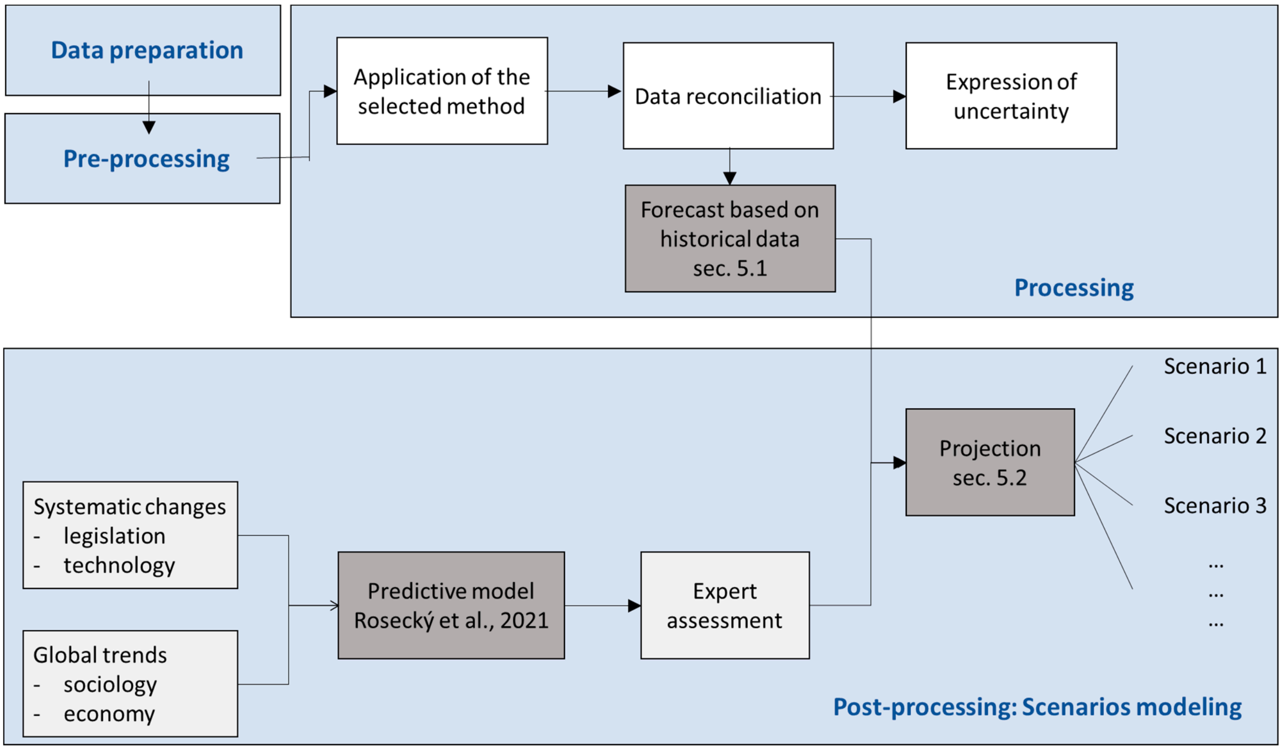

Figure 7. Schematic representation of the integration of forecasting and projection. Predictive model [15].

5.1. Waste Generation and Treatment Forecast

It is recommended to apply a method based on trend analysis with subsequent data reconciliation in order to maintain hierarchical links in the data [34]. The trend in the historical data can be modelled by the suitable curve. The model of the waste generation trend p_t is significantly affected by the type of the curve f_t (1), where t is the index of time including both the historical data and a forecast.

$$p_t = f_t. \tag{1}$$

Designation f_t indicates the curve that is recommended in the form of power function (2) or logistic function (3) based on the data character:

$$p_t = a + bt^c, \tag{2}$$

$$p_t = \frac{1}{1 + e^{-(a+bt)}}. \tag{3}$$

where a, b, c are the regression coefficients. A model that fits the historical data well is extrapolated to cover the entire forecasting horizon.

The trend estimates do not generally maintain the hierarchical links, i.e., the sum of the regional trends does not correspond to the national trend and similarly for other links. Therefore, it is recommended to apply data reconciliation to ensure these links. This is achieved by a set of constraints. For the territorial hierarchy, this is constraint (4), where $A_{j,\bar{j}}$ defines the relations between territories (j is a superior territorial unit and $\bar{j}$ is a lower territory).

$$k_j = \sum_{\bar{j} \in J} A_{j,\bar{j}} k_{\bar{j}}. \qquad \forall j \in J. \tag{4}$$

Constraints in the case of links between waste fractions can also be formulated similarly. Equation (5) connects the waste generation input data p_j in particular time with the model variable k_j and the waste generation data error ε_j in the form of additive notation. In some cases, for reasons of solvability, the multiplicative form of notation is more advantageous.

$$k_j = p_j + \varepsilon_j. \qquad \forall j \in J, \tag{5}$$

Equation (6) represents the objective function for the variant with weights v_j to take into account the size of the producer and weights w_j according to quality of fitting.

$$\sum_{j \in J} (v_j w_j)^2 \left[\left(\varepsilon_j^+ \right)^2 + \left(\varepsilon_j^- \right)^2 \right]. \tag{6}$$

The result of the performed data reconciliation is a forecast based on historical data; this is a basic scenario, further marked *BAU* (business-as-usual scenario).

5.2. Waste Generation and Treatment Projection

Projections of waste generation are usually formed to meet some targets that are set for aggregated territory (national level). The default information is forecast (*BAU*, Section 5.1), which is modified to achieve the conditions formulated in the scenario. It is assumed that interventions can influence waste separation and waste generation prevention. The increase in the waste separation within the scenario is caused by the higher separation of the modelled fraction f (e.g., paper, plastics, glass) from unseparated waste u (e.g., MMW, bulky waste). Thus, the expert assessment includes setting the following parameters:

- percentage waste prevention ($prev^{SC,N1}$: SC—marking the scenario, $N1$—territorial level NUTS1),
- separation rate of individual assessed waste fractions ($SR_{u,f}^{SC,N1}$: u—unseparated waste fraction, f—modelled waste fraction).

The main results of scenario *SC* on aggregated territory *N*1 are:

- Separated waste $k_{u,f}^{SC,N1}$.

The generation of separated waste f, which originates in the unseparated fraction u, is determined according to (7). The expression $k_{u,f}^{BAU,N1} + l_{u,f}^{BAU,N1}$ means the total generation of fraction f according to *BAU*, i.e., separated $k_{u,f}^{BAU,N1}$ originates in u and rest of f in unseparated fraction $l_{u,f}^{BAU,N1}$ amount. From the total generation, the separated amount is determined using the separation rate $SR_{u,f}^{SC,N1}$, and the impact of prevention is also taken into account as $\left(1 - prev^{SC,N1}\right)$.

- Waste f in unseparated waste u: $l_{u,f}^{SC,N1}$.

The result of this point is therefore the composition of the unseparated waste u, and it is determined according to Equation (8). The principle is similar to the previous point for separated waste $k_{u,f}^{SC,N1}$, only the supplement to the separation rate is considered as $\left(1 - SR_{u,f}^{SC,N1}\right)$.

- Total unseparated waste $\left(L_u^{SC,N1}\right)$.

The generation of the unseparated waste u is given by (9). It comes from the generation of u in *BAU* $\left(L_u^{BAU,N1}\right)$, which is reduced by the prevention in the form $\left(1 - prev^{SC,N1}\right)$. The waste that was separated according to the scenario *SC* is deducted from this amount. The separation of waste f in the scenario *SC* is determined as the difference between quantity in *BAU* given by $\sum_{f \in F} l_{u,f}^{BAU,N1}\left(1 - prev^{SC,N1}\right)$ and the new quantity in *SC* scenario given by $\sum_{f \in F} l_{u,f}^{SC,N1}$.

$$k_{u,f}^{SC,N1} = \left(1 - prev^{SC,N1}\right)\left(k_{u,f}^{BAU,N1} + l_{u,f}^{BAU,N1}\right)SR_{u,f}^{SC,N1} \qquad \forall u \in U,\ \forall f \in F \tag{7}$$

$$l_{u,f}^{SC,N1} = \left(k_{u,f}^{BAU,N1} + l_{u,f}^{BAU,N1}\right)\left(1 - SR_{u,f}^{SC,N1}\right)\left(1 - prev^{SC,N1}\right) \qquad \forall u \in U,\ \forall f \in F \tag{8}$$

$$L_u^{SC,N1} = L_u^{BAU,N1}\left(1 - prev^{SC,N1}\right) - \left(\sum_{f \in F} l_{u,f}^{BAU,N1}\left(1 - prev^{SC,N1}\right) - \sum_{f \in F} l_{u,f}^{SC,N1}\right) \qquad \forall u \in U \tag{9}$$

The result of the *SC* scenario at the aggregated (national) level, given by (7)–(9), should be subsequently divided into lower territorial units, down to the municipalities, because the national WM is the result of the activities of the lower units (municipalities). It is recommended to divide the scenario for the national level (*N1*) to the level of municipalities (L2) according to the potential that individual municipalities have for waste separation improvement. A suitable indicator of this potential may be the separation rate.

The goal of the presented approach is a suggestion of a general approach that is applicable to any waste fraction based on short time series. At the same time, it is a unique approach, combining the principles of forecasting with the consideration of influential factors through scenarios. Thanks to modelled scenarios, the expected variability of waste generation is taken into account, which will enable more efficient planning of WM.

6. Conclusions

Over the years, various methods used for waste generation modeling have been proposed. Prediction, forecasting, and projection must be distinguished, while the use of various approaches depends on the specific application in WM. A deficiency was found in that a significant number of past publications have been devoted to designing a suitable modeling method. However, the authors recommend paying attention to the quality of the input data, which has been minimal in the reviewed papers. It is important to remember that input data are essential for every model. In addition, the end-user of a forecast, prediction, or projection must be provided with the model uncertainties in the form of confidence intervals or several scenarios. This is another key part of each model that was missing in the majority of the evaluated papers on WM modeling. Although many methods do not offer a direct way of expressing the model uncertainty, bootstrapping can be used to at least estimate it.

The data set available, its territorial and temporal detail, and the prediction horizon are decisive for the modeling method choice. As prediction models have already been elaborated in greater detail [15], most of the text is devoted to forecasts and projections. The authors formulated the decisive process for the choice of modeling method, which provides unique support for further forecasters. In summary, if the influencing factors and their links to waste generation are used for modeling, the influencing factors must be forecasted as well. The use of TSA is often limited by its requirements of time series length. In addition, the presented methods are intended for specific waste fractions. Based on the mentioned conclusions of the review, the authors presented a general approach for forecasting. To use this method, it is necessary to have a time series of historical data on waste generation. Compared to other TSA-based methods, a significantly shorter time series is sufficient. The calculation of the method is based on the optimization task of nonlinear programming. The user must therefore have software suitable for this calculation with adequate solvers (CONOPT, KNITRO, etc.). The main feature of forecasting is that it models future developments while maintaining historical conditions. The impact of changing the influential factors on waste generation can be implemented in the forecast in the form of scenarios.

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Appendix A. SWOT Analysis

The SWOT analyses, evaluating strengths, weaknesses, opportunities and threats, were performed for several presented methods: multiple linear regression—MLR (Table A1), generalized linear regression—GLM (Table A2), methods using decision trees—DT (Table A3), artificial neural network—ANN (Table A4), time series models—TSA

(Table A5) and scenario approaches (Table A6). SWOT analyses enable better insight into the problems of individual methods and enable very valuable comparison of their advantages and disadvantages.

Table A1. Multiple linear regression.

Strengths
It allows to quantify the influence of individual predictors (including the significance) or their interaction on the dependent variable. It provides a general information on the functioning of the modeled process from both a qualitative (dependency direction) and a quantitative (size) perspective. It is easy to obtain the confidence intervals (CI) and the prediction intervals (PI). It is simple, computational efficient and easy interpretable.
Weaknesses
Necessity of strong assumptions compliance (especially for the normality of residues, homoscedasticity of data and linear dependence with respect to the coefficients), which is often violated in practice. The dependence is restricted to approximately linear/linearizable with respect to the regression coefficients. The risk of multi-collinearity of data, especially in more complex (multidimensional) problems. Accuracy, especially for complex non-linear problems.
Opportunities
The possibility of identification and correction in case of unexpected behavior of the model, leading to better control of the model creation. Data pre-processing methods such as principal component analysis (PCA) can be useful to reduce the dimension and ensure the independence variables [69]. Its main task in WM is to reveal the factors that have fundamental influence [16]. Thus, MLR is useful especially for policy planning and infrastructure decision making (Section 1.1). As grouping municipalities into clusters based on their characteristics can lead to models featuring higher accuracy [70], separate models were then created for each cluster. Implemented in all standard statistical SW tools, often with automatic creation of outputs (especially the graphical ones), which may warn even less experienced users that some prerequisites are not met.
Threats
"Necessity" of manual selection of predictors or of the order of interactions means that smaller number of potential predictors can be used in practice (correlation analysis can be used to reduce their number, but it is also recommended to check the results and it also requires closer inspection of predictors and their dependence). The assumptions are quite strict, and it usually is quite difficult to meet them with WM data, especially at lower territorial levels. WM systems are complex and nonlinear in nature, and the analysis of residuals should be used to evaluate the appropriateness of linear approximation. In case of non-homogeneous data, there are problems with the form of the dependence or with the applicability of created model on the type of data, which was not sufficiently represented in the model creation phase.

Table A2. Generalized linear models.

Strengths
It provides information on the proportion of the explained variability of the dependent variable through the included predictors (independent variables). It provides general information on the functioning of the modeled process from both a qualitative (dependency direction) and a quantitative (size) perspective. Computationally not demanding.
Weaknesses
Assumptions on the distribution of residues, homoscedasticity of data and linear dependence with respect to coefficients. A risk of multi-collinearity of data, especially in more complex (multidimensional) problems. There is no analytical way to estimate the model parameters. Knowledge in WM is essential to determining suitable initial estimates. It also is possible to use the results of MLR as the starting point for another GLM. CI and PI generally do not exist, but there are attempts to construct them for some special cases (e.g., for gamma regression) [71]. Lower accuracy, especially for complex non-linear problems.

Table A2. *Cont.*

Opportunities
The possibility of identification and correction in case of unexpected behavior of the model, leading to better control of the model creation. Better flexibility (compared to MRL). The possibility to include expert knowledge of the process by selection of distribution of dependent variable or by including known effects (offset). The possibility to specify the smoothness or the monotonicity of dependency (suitable also for maintaining the same structure of the model when using new data). Relation of other models such as generalized additive models (GAM), penalized regression (Ridge, Lasso, Elastic Net) or mixed models. Implemented in all standard statistical SW tools, often with automatic creation of outputs (especially the graphical ones), which may warn even less experienced users that some prerequisites are not met.
Threats
"Necessity" of manual selection of predictors or of the order of interactions means that smaller number of potential predictors (of order of tens) can be used in practice (correlation analysis can be used to reduce their number but it is also recommended to check the results and it requires closer inspection of predictors and their dependence). In case of non-homogeneous data, there are problems with the form of the dependence or with the applicability of created model on the type of data, which was not sufficiently represented in the model creation phase. In general, a global optimum, when searching for parameter values, is not guaranteed (does not apply for some special cases). Some GLM types can model negative values. For waste generation modeling it is recommended to use GLM types for which the acquisition of only positive values can be guaranteed (e.g., gamma regression).

Table A3. Methods using decision trees.

Strengths
It allows to describe even complex non-linear dependencies, which often appear in WM. High accuracy, especially in comparison with traditional methods [72]. Models are robust and not as sensitive to the choice of influencing factors as MLR or GLM. Robustness of random forest (RF) and Gradient boosted regression tree (GBRT) [73].
Weaknesses
Computationally demanding, especially for complex models and large number of observations. Interpretation is challenging for RF and GBRT. DT loses high accuracy.
Opportunities
Data assumptions. The selection of a specific DT model also depends on the size of the data set (detail of the territorial division, monitored waste fractions). Automated process with predictors enabling to work with large number of independent variables. Information on the importance of each variable is provided, this helps with their selection. Parameter tuning is less demanding (compared to ANN). The computation of RF can easily be parallelized.
Threats
Generally, the PI construction is more complicated (compared to MLR). Quantile regression or resampling methods may be used. For DT, the intervals construction method was not found, but the intervals of individual models in tree leaves could be theoretically used. GBRT is computationally intensive. In case of RF and GBRT, there is insufficient insight into internal functioning of the model. This means that it is difficult to find the root cause if the model behaves unexpectedly (except for DT). Threat of the model over-fitting.

Table A4. Artificial neural networks.

Strengths
They allow to describe even complex non-linear dependencies. ANN models have few assumptions about the data in the terms of distribution. From this point of view, one could utilize most data sets coming from WM. It is possible to work with many independent variables that influence the form of WM. High accuracy, in comparison with traditional methods [74].
Weaknesses
Computationally demanding, especially for complex models and large number of observations [75]. Requires model specific experience [75]. ANN are not suitable for "on-the-fly" decision making.
Opportunities
Low data assumptions. Input data can be compiled in pre-processing to achieve the highest possible model accuracy. If the parameters are set correctly, the results are most accurate for nonlinear dependencies. However, choosing appropriate parameter values is not trivial, and understanding of WM is required. Automated process with predictors enabling to work with large number of independent variables (even hundreds of variables but considering the computational complexity).
Threats
There is insufficient insight into internal functioning of the model. In general, a global optimum for parameters is not guaranteed. CI and PI are solvable, but it is advisable to keep caution (as with methods using decision trees). Training an ANN is computationally intensive. Models are typically used on large data sets (ideally thousands of data points). Application to smaller data sets, which are common in WM, is problematic. Threat of the model over-fitting. Interpretation challenge (black box models).

Table A5. Time series analysis.

Strengths
It allows to capture the dynamic of development of the observed process. Good theoretical basis. CI and PI creation clear and straightforward (this is similar to MLR).
Weaknesses
Disadvantageous ratio for amount of data needed for modeling and the length of the prediction (high tens or better hundreds of observed values are needed for prediction of order of units). It is difficult to take into consideration external influences (socio-economic, demographic, etc.). Lack of data in the WM area.
Opportunities
Recommended when revealing the links in the system is not important, but only the time development (even in the future). The possibility to better understand the behavior of the dependent variable itself (seasonality, trend, autocorrelation function, etc.), but only provided enough data is available (i.e., seasonal effects on annual data cannot be ascertained).
Threats
Disproportionate confidence in the model built on insufficient data (since it is a "white box" model).

Table A6. Scenario-based models.

Strengths
Combination of benefits of the TSA and the "correlation" approaches. Waste generation can be forecasted including possible interventions which have not yet been reflected in the historical data [34]. Possibility to model different scenarios.
Weaknesses
It is difficult to handle uncertainty (especially in case of input predictions from external sources with insufficient specification).
Opportunities
Possibility to incorporate expert estimates and domain knowledge (e.g., goals and legislative changes). Suitable for modeling of extremes such as the worst/best case scenario (e.g., meeting the legislative objectives) with the current state of WM and after certain interventions.
Threats
There is a risk of models' usage outside the area where they are intended to be used. Each scenario should reflect a potential for change, such as changing separated waste and MMW production [10]. Dependence on the quality of inputs (scenarios).

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Příloha 5: Publikace [A17] – Multi-level stratification of territories for waste composition analysis.

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Multi-level stratification of territories for waste composition analysis

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ABSTRACT

The fundamental knowledge at all levels of decision-making related to waste management is the quantity and composition of waste. Many articles deal with methods for estimating the composition of municipal waste, but most details are given as to how many categories should be chosen and what technical procedure should be followed. In order to obtain a broader view and a reasonable evaluation of the results, it is necessary to select the areas where the analyzes will be performed effectively. Current approaches have insufficiently addressed this issue at the regional and national levels. This paper presents a method that uses multi-level stratification to divide municipalities into similar groups to reduce the number of observations needed to obtain an estimate of the composition of waste in a selected area (region or state level). The method combines expert knowledge with statistical considerations and makes use of cluster analysis. Socio-economic and waste-related parameters are used within the individual steps. Regarding the available financial resources and the required accuracy of the results, the municipalities in which the analyzes should take place are selected. These representative municipalities represent other municipalities in the created groups, and thanks to them, it is possible to estimate the composition of waste in any municipality, region, or larger territory. Waste analysis planning is an essential procedure for waste management, but the respective costs represent a crucial factor at the national level and even more for individual municipalities. Estimating waste composition impacts the transition to sustainable waste management and is thus a key element for further development in this sector. The presented method demonstrates the selection of 10 representative municipalities from the Czech Republic, but an arbitrary number can be set respecting the financial resources. Estimating the composition of the mixed municipal waste for the Czech Republic should cost around 72,000 euros for ten representatives with different distribution of dwelling types. The method is described in general and can be applied to any territory/country in the world, considering local conditions and possibilities.

1. Introduction

The most crucial and usually unknown or estimated is the composition of waste generated at all levels of regional division. The most discussed type of waste is municipal solid waste (MSW – origins from households and similar commercial, industrial and institutional wastes, it includes also separately collected fractions). Citizens are under pressure to effectively sort waste to increase material or energy recovery (Directive 2008/98/EC). A significant part of MSW consists of a residual mixture of waste – so-called mixed municipal waste (MMW – with waste code 20 03 01 according to European List of Waste and Czech legislation). MMW offers the highest potential to increase the separation of individual fractions of waste. Besides, newly separated fractions are being introduced – an example can be textiles, which will be compulsorily collected in EU countries from 2025 (Directive (EU) 2018/851).

The composition of waste, together with its overall production, is the input to several computational tools (Saner et al., 2011). The production of plastic waste and its recycling is important in direction to sustainability (Johansen et al., 2022). E-waste generation and estimation of future trends should be linked to the composition of MMW (Islam and Huda, 2019). Vakalis et al. (2017) identified the household biowaste as important source of energy. Organic fraction of MSW and its utilization was studied also by Montejo et al. (2015), while the contamination of inputs was the most occurring problem. The potential of all materials in the MMW should be examined. The study (Gentil et al., 2009) showed significant differences in global warming factors between EU member states. The reason is, in addition to waste processing technology, also the

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different composition of waste.

This article is based on the assignment of the Ministry of the Environment of the Czech Republic, which aimed to establish procedures (methodology) for a long-term investigation of MMW composition for planning and reporting.

With a larger area, a random selection of bins appears too costly and organizationally complex. Stratification and search for representative locations should be applied. Besides, a suitable representation of each stratum achieves higher accuracy of the results.

Some papers present local results as a generalization to larger territorial units without substantiated statistical and waste-related procedures. The solution can be a quality evaluation of the characteristics of the studied areas that have a significant impact on the quantity and composition of waste – household size, education, employment, age structure (Xu et al., 2016) in China, dwelling type and housing, demographic division (Al-Subu et al., 2019) in Palestine, population density, hydrographic area (Prades et al., 2015) in Spain, or other socio-economic and demographic factors (Davidavičiene et al., 2012) in Lithuania.

The motivation for research in the field of waste composition is based on insufficient knowledge and procedures in the Czech Republic. The methodology towards effective stratification of the country and proposal of locations to start long-term studies on waste composition (representatives) was missing. The results from representative locations, when properly weighted, can be used to get an average MMW composition in the country. The interconnectedness of the environmental and economic areas is evident in waste production, recycling, and the saving of primary raw materials. This article aims to provide an approach to waste composition analysis planning to enable the identification of potential for increased separation and recycling.

The presented paper will address existing approaches to territorial stratification first (*Literature review*). The research challenges and missing features of existing methods will be summarised, which will also justify the novelty and benefits of the newly proposed approach. The approach, which is described in detail in *Stratification method*, represents a new method for area distribution into different groups in terms of production and composition of waste based on crucial influencing factors. Its use is then demonstrated in *Results* in a case study for the Czech Republic. The results serve the ministries to compile a waste management plan with a link to legislative developments in the EU and set targets. The methodology is generally applicable to any country or region.

2. Literature review

In the past, several publications have addressed methods for analyzing the composition of waste. These publications were summarised by the review paper (Dahlén and Lagerkvist, 2008), primarily focused on residual household waste (referred to as MMW following official terminology). The most crucial choices in household waste composition studies were defined as follows:

- to divide the investigation into relevant numbers and types of strata,
- to decide the required sample size and number of samples,
- to choose the sampling location, i.e., sampling at the household level or sampling from loads of waste collection vehicles,
- to choose the type and number of waste component categories to be investigated.

As Staley and Barlaz (2009) pointed out, the correct definition of waste fractions is crucial. There were compared 11 state-wide studies on waste composition analysis (WCA). The conclusion is that inconsistencies in the indications of waste fractions and their definitions are the primary differences. However, sampling methodologies were consistent with the recommended protocol.

Sahimaa et al. (2015) compared 19 studies made in one country – Finland. Three potential methods for sampling in household waste composition studies were specified:

- sampling from waste collection trucks, which have collected waste from normal collection routes,
- sampling from waste collection trucks, which have collected waste according to stratification,
- a sampling at the household level with separate sorting of each household's waste.

2.1. *Waste composition analysis*

The research confirmed that the study methods varied between individual studies, which worsens the interpretation and comparison of the results.

Previous review studies repeatedly mentioned the crucial choice of the sampling method. Most methodologies for WCA studies dealt with the description of the method. However, more factors also have a decisive impact on WCA. Much more decisions influence its credibility. The connection and continuity in individual decisions and activities are shown in Fig. 1.

The articles focusing on the composition of MMW (or other fractions of MSW) are listed in the overview tables. The issue of estimating the composition wastes can be divided into several tasks, see Fig. 1.

The first question (task 1) is to find suitable places where studies should be carried out. Concerning the level of detail, it is necessary to select such municipalities that reliably describe the entire area under investigation. Similarities are sought here in the form of social, economic, demographic, and other factors. Stratification and search for representative locations should be applied to large areas. Otherwise, only the method of a random selection of bins could be used based on some division into similar groups. With a larger area, this approach is already too costly and organizationally complex. Besides, a suitable representation of each stratum achieves greater accuracy of the results. Task 2 deals with the selection of waste streams to be considered in the analysis. Due to the geographical location, the definition of waste fractions may differ slightly. The important point is to establish procedures in accordance with statistical methods (task 3).

The second level includes the selection of individual collection sites (points, bins/containers) where waste analyzes can be performed (task 6). A specific city can be divided based on some factors into groups in which bins will be selected. It is also necessary to choose the frequency of analyzes, both within a week (based on the frequency of collection of the given collection point) and within the whole year, concerning the seasonality of the occurrence of some fractions. It is also possible to repeat the analyzes until the specified accuracy (absolute or relative) is achieved. The variable waste quantity in the analyzes must be considered in this step. The crucial part is the methodology for the analysis of the waste composition (task 5), which can vary highly. There are several standardized methods (SWA-Tool, 2004) or (Zero Waste Scotland, 2015), which are defined by the relevant directives. An important part is the processing of results for collection points. The results of individual analyzes often differ significantly. The application of appropriate statistical methods can determine the accuracy and precision of the results. Task 7 deals with the aggregation of the result for the whole municipality. The last part of the WCA topic (task 8) should propose a method for the generalization of the results using the original division into groups or clusters.

The focus of this paper is highlighted in red. It is necessary to have a complex view because stratification can be adjusted dynamically based on the results obtained, financial resources or additional objectives of the overall analysis.

In the first phase, the studied contributions were classified according to the tasks in Fig. 1. It was monitored which areas of WCA were studied and to what extent. The numbering in this figure corresponds to the

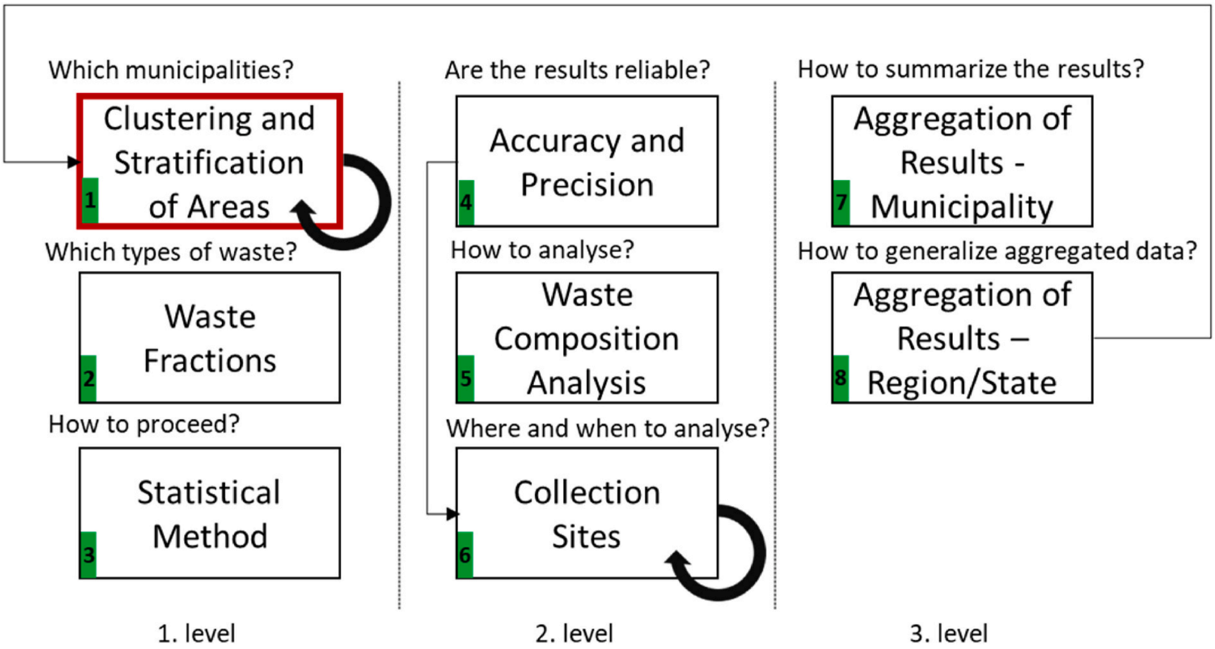

Fig. 1. Block scheme of WCA tasks.

notation in Table 1. The solution scope of these areas is classified into four levels (no, low, middle and high). Each level of solution detail (LSD) is also quantified by a value ranging from 0 to 3.

According to Table 1, publications are in most cases devoted to the description of the analysis methodology, i.e., how the sorting of waste into the required fractions is performed. 19 publications out of 20 addressed the issue of analysis methodology. In some cases, the methodology is described in detail at a high level. Furthermore, the issue of the selection of the waste fractions (16 publications out of 20) and the selection of collection sites (13 publications out of 20) is relatively frequent. This publishing intensity and importance is evaluated by Publishing Importance Score (PIS) based on LSD of analyzed papers. Some areas of WCA, defined in Fig. 1, are addressed rather exceptionally. Table 1 defines areas that provide a gap for further development, and their elaboration in previous publications seems to be insufficient. Specifically, these are Clustering and Stratification of Areas (PIS 13), Statistical Method (PIS 4), Accuracy and Precision (PIS 12), the Aggregation of Results for Municipalities (PIS 9), and Region/State (PIS 6). When selecting municipalities and specific collection sites for analysis, it is desirable to select such samples for analysis so that they have the highest possible informative value from the point of view of the entire territory.

Table 2 further discusses approaches to territorial stratification as one of the under-published topics with very low PIS. The territory distribution is most often carried out at the level of the city or region. The specific selection of areas for analysis then uses random selection or is defined by the analysis staff themselves. The factors considered in the selection differ significantly. In aggregate form, across all studies, they can provide a good basis for examining the effect on the composition of waste. The level of analyzes also differs significantly, with some studies using standardized procedures (stated in mentioned review papers) defined in the methodology. In some areas, waste is divided into multiple categories based on the objective of the study or local conditions.

Standards include the method of waste sorting, the size of sieves for

Table 1

The summary of articles and their level of solution detail.

Articles\Tasks	1	2	3	4	5	6	7	8
Abu Qdais et al. (1997)	low	middle	no	low	low	low	no	no
Abylkhani et al. (2020)	no	low	no	no	high	no	no	no
Bernache-Pérez et al., 2001	low	middle	middle	no	middle	low	no	no
Bolaane and Ali (2004)	no	no	no	middle	low	low	no	no
Cheniti et al. (2013)	low	low	middle	no	low	no	no	no
Chung and Poon (2001)	low	middle	no	no	low	middle	middle	no
Dangi et al. (2011), 2013	no	no	no	no	low	middle	no	no
Edjabou et al. (2015)	no	no	no	no	high	low	low	no
Gente et al. (2007)	no	low	no	no	low	no	no	no
Gidarakos et al. (2006)	low	low	no	no	middle	low	no	low
Guérin et al. (2018)	middle	middle	no	low	middle	middle	no	low
Heikkinen and Spliethoff (2003)	no	middle	no	low	middle	no	no	no
Ibikunle et al. (2020)	low	middle	no	no	low	low	no	no
Lebersorger and Schneider (2011)	low	high	no	middle	middle	middle	low	middle
Liikanen et al. (2016)	no	high	no	low	middle	low	low	no
Miezah et al. (2015)	middle	high	no	low	high	middle	middle	middle
Petersen et al. (2005)	no	no	no	no	middle	no	no	no
Roberts et al. (2010)	low	middle	no	low	low	middle	low	no
Thitame et al. (2010)	no	middle	no	no	no	no	low	no
Zeng et al. (2005)	low	low	no	middle	low	no	no	no
Publishing Importance Score (PIS)	13	30	4	12	32	19	9	6

Table 2
Review of literature – focus on stratification.

	Country	Stratification and Clustering			Waste Fractions
		Variables/Factors	Method	Territory Level	Method
Abu Qdais et al., 1997	United Arab Emirates	socio-economic	expert	city	expert (6)
Abylkhani et al. (2020)	Kazakhstan	no	no	N/A	expert (12)
Bernache-Pérez et al., 2001	Mexico	proportion of population	random	region	Mexican Standard NMX-AA-022-1985 (53)
Bolaane and Ali (2004)	Botswana	income	expert	city	expert (7)
Cheniti et al. (2013)	Algeria	type of habitat, season	expert	city	expert (11)
Chung and Poon (2001)	China	demographic-district, season	expert	city	expert (19)
Dangi et al. (2011), 2013	Nepal	geographic location	no	N/A	expert (10)
Edjabou et al. (2015)	Denmark	no	no	N/A	expert: Level I (10) Level II (36) Level III (56)
Gente et al. (2007)	Italy	no	no	N/A	expert
Gidarakos et al. (2006)	Greece	population, tourism-hotel beds	expert	region	expert (9)
Guérin et al. (2018)	Canada	season, rural/urban area, sectors (close municipalities/ areas)	random	region	expert: Level I (9) Level III (39)
Heikkinen and Spliethoff (2003)	Netherlands	no	random	city	expert (6)
Ibikunle et al. (2020)	Nigeria	dry and wet season	random	city	expert (19)
Lebersorger and Schneider (2011)	Austria	settlement structure, house type, availability of bin	random	region	Österreichisches Normungsinstitut (2005)
Liikanen et al. (2016)	Finland	no	random	city	expert: Level I (11) Level II (27) Level III (38)
Miezah et al. (2015)	Ghana	area – regions, socio-economic areas geographic (coastal, forest, savanna)	random	state	ASTM D5231-92
Petersen et al. (2005)	Sweden	no	no	N/A	expert (12)
Roberts et al. (2010)	Nigeria	population density, Income levels, dwelling type, season	expert	city	expert (14)
Thitame et al. (2010)	India	no	expert	city	expert (15)
Zeng et al. (2005)	Columbia	season, geographic location	expert	region	expert (6)

Note: Description in the column Method – "Expert" indicates the expert determination of fractions, the value in brackets "(x)" indicates the number of fractions.

treatment of the fine fraction, the methodology of weighing, and other procedures of the process. However, the stratification of the population/municipalities is not provided in sufficient detail. It is defined only at the municipal or regional level. SWA-Tool (2004) has been proposed by the European Commission. It standardizes methodology for the analysis of solid waste at a local and regional level. SWA-Tool addresses all aspects of waste characterization – pre-investigation, stratification of population, analysis design and planning, sampling, and necessary conditions. The most recent paper on stratification focused on multi-representative selection (Šramková et al., 2021). Each stratum should have some properties to allow a good statistical evaluation of the results, especially at aggregated levels. This crucial shortcoming is nowhere adequately addressed. The main development opportunity for further research is the definition of important factors influencing the waste composition and the distribution of large area into similar groups. Besides, very limited space is devoted to this issue. The specific contribution and novelty of the paper is described in the following section.

The method for stratification of the territory is used to analyze the current situation. It is influenced by actual socio-economic and environmental circumstances. Therefore, these factors must be considered when grouping territories into disjoint sets. The production of MMW, central heating connection, separation/recycling of municipal waste components (paper, plastic, glass, bio-waste, etc.) can be classified as environmental variables but also others are required for proper stratification process.

2.2. *Contribution and scope of the paper*

Given the complexity of WCA – both time and economic – it is necessary to use sophisticated statistical methods in a comprehensive analysis. Only a limited number of analyzes can be performed, so a key element of the analysis is the appropriate stratification of the area. Existing articles focus mainly on local or regional WCA studies, where only the selection of specific collection sites/households and frequency is decided by socio-economic or demographic parameters. However, some deeper statistical justification is often missing, and decisions are made by expert opinion. Distribution of the larger territory into similar sub-areas is necessary. A local focus in sub-areas is important to describe the more aggregated area. Representative municipalities can be used to represent large strata. The approaches presented so far do not have a consistent procedure for selecting representatives. At the same time, they are defined only for small areas and cannot be applied nationwide.

Waste composition analysis is rarely performed at the regional or national level. The choice of representative is random or does not consider the size of the territory at all, which is statistically wrong. It also has a huge impact on the efficient use of financial resources. The results from reviewed studies do not provide so much information for further environmental management – potential for separation and recycling, saving of raw materials, evaluation and fulfillment of EU goals.

The scheme in Fig. 1 is very extensive and includes several important steps for the overall evaluation. This article will primarily deal with block 1 – Clustering and Stratification of Areas. The main benefit of this article is a new approach to clustering large areas for estimation of waste composition. Its main advantages, which the alternatives mentioned in the review do not offer, meet and ensure:

- multistep stratification enabling assessment of arbitrary size of the area,
- the similarity in terms of waste production quantities,

- the similarity in terms of significant socio-economic and demographic factors,
- a similar size of individual strata, which are convenient for subsequent statistical evaluation,
- the selection of cluster representatives (potentially alternative representatives, which can be used when the first selected cannot cooperate),
- potential expanding the number of clusters due to statistical results and new financial sources,
- target changes for analysis – input for decision-makers in waste management.

Secondary contribution lies also in a case study for the Czech Republic, where the approach is verified, and the results are useable for further research in this area. Field works (data collection through sampling of waste for evaluation of WCA studies) for securing specific results in selected municipalities will follow based on this method. The presented method is general and applicable to any region. The method also recommends how to preprocess data, where outliers and extreme values are identified, noise effects are filtered, and the data are normalized.

3. Stratification method

Let us assume that due to the limited resources (financial and other), it is not possible to investigate the area uniformly (randomly select bins from all the municipalities). The solution is to prefer a limited number of municipalities/sub-areas (e.g., 10, 20, or 40). These municipalities (representatives in the sequel) are chosen to represent the composition of the whole country (region or municipality where the WCA study was not performed), which consists of thousands of municipalities. The number of inspected waste bins is also limited. This section describes a multi-level stratification that can help the researcher to get a reasonable estimate of the waste composition aggregated for the whole territory, see Fig. 2 for the whole stratification method. A stratum usually refers to the subset of the population/area which is being sampled. Since there will be adopted a multi-level approach, where strata on different levels are proposed, the cluster will be used for the second level. Term area/territory states for some geographical area. The study is done for this area, where the average waste composition is the result. The method described can be used in general for any fraction of MSW in which the estimate of composition is desired. The method will be described and subsequently shown for the case of estimating the composition of MMW.

3.1. *Choice of municipalities – representatives*

Information about the size of a given municipality/stratum is required for further steps. This size should ideally reflect the total amount of MMW produced in this municipality/stratum (the amount of MMW can serve as a good measure). Note that although the information about the total amount of MMW in a period of interest will not be typically available, one can use as a proxy the information from the previous periods or the number of inhabitants living in the given municipality. It is suggested that the choice of municipalities is performed through the two-level stratification.

3.1.1. *Primary stratification*

In the first level (primary stratification), several primary strata (of municipalities) are created in such a way that:

- the strata are of a similar size (measured by the total amount of MMW produced in the given stratum),
- the municipalities in the given strata are of a similar size (measured by the total amount of MMW produced in this municipality),
- each municipality belongs to exactly one stratum.

If a municipality covers a large percentage of total MMW production (assuming 10% or more), it is recommended to treat it as a separate stratum/representative. On the other hand, excluding the smallest municipalities (up to 2.5% of MMW production in total) and municipalities with extreme characteristics from the total set of municipalities for stratification is recommended. The reason is that for smaller municipalities, the composition of MMW is more variable. It is assumed that the decrease of the variability of our final estimate gained by excluding

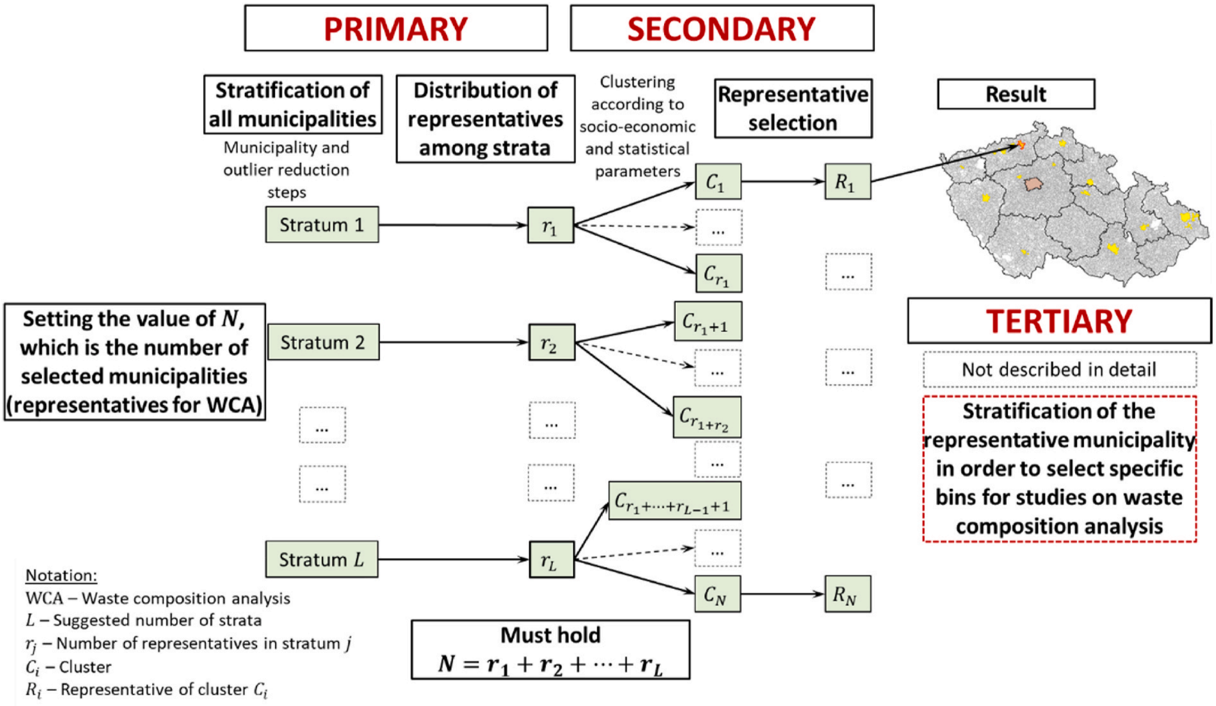

Fig. 2. The scheme of multi-level stratification and selection of representatives.

those small municipalities will outweigh the small potential systematic bias caused by that exclusion. The limit of 2.5% was chosen so that even if these excluded municipalities had a five times larger share of the waste component than in the remaining municipalities (or even did not have this waste component at all), this would only lead to a 10% relative bias. However, the limit of 2.5% can be adjusted according to the requirements. In practice, this value can be set with respect to the distribution of the size of municipalities. The number of strata (L) depends on the number of representative municipalities (say N) for which one has the resources to analyze the composition of MMW. In general, L is lower than N. One extreme would be to use N strata $(N = L)$, but that would rather limit the incorporation of other important socio-economic and demographic parameters. The opposite extreme would be to do no primary stratification. It is recommended to be somewhere in the middle between these two extremes so that the number of municipalities analyzed in each stratum is at least 2.

The idea is to make strata so that the total production of MMW per given stratum is approximately the same and in the given strata were similarly large producers of MMW. The number of strata for the individual scenarios (corresponding to the total number of representatives) is then designed to divide the municipalities into more homogeneous groups according to size. The secondary strata will be created using additional variables.

The primary stratification is then performed according to these steps.

1. Set L as the desired number of strata.
2. Rank the municipalities according to the total MMW production (e.g., descending).
3. Calculate the cumulative total production of MMW and find the appropriate divisions so that the given stratum produces approximately $100/L$% of MMW.

Regarding the number of representatives selected in the individual strata, it is generally recommended to select more representatives in strata with smaller municipalities.

The reason is that it can be expected that in smaller municipalities, the share of a given type of unsorted waste will be more variable. For larger municipalities, this share will stabilize averaging over a larger population. The proposed numbers of representatives are then based on considerations of the variance of estimated ratios in individual strata. After neglecting the variability resulting from the fact that in the selected municipality, only a given number of waste bins is investigated, the approximate variance of the aggregated estimator is given by

$$V(n_1, \ldots, n_L) = \sum_{l=1}^{L} w_l^2 \frac{\sigma_l^2}{n_l} \tag{1}$$

where n_l is the number of representatives in l-th stratum and w_l is the waste share of l-th stratum and $\frac{\sigma_l^2}{n_l}$ is the expected variance of the ratio estimate in the l-th stratum. The crucial quantity in this variance is σ_l^2 which measures the variability of the composition of MMW and is given by

$$\sigma_l^2 = \frac{1}{\overline{T}_l^2 N_l} \sum_{j \in U_l} \left(Y_j - R_l T_j\right)^2 \tag{2}$$

where N_l is the number of municipalities in the l-th stratum, $\overline{T_l}$ is the average size of the municipality in the l-th stratum, U_l is the list of municipalities belonging to the l-th stratum, Y_j is the total waste production of a specific fraction in a given municipality, T_j is the total production of MMW in the given municipality. Finally, R_l is the proportion of the waste fraction in the l-th stratum given by

$$R_l = \frac{\sum_{j \in U_l} Y_j}{\sum_{j \in U_l} T_j} \tag{3}$$

Since Y_j is unknown, a quantity that can be hoped to have a similar distribution between municipalities could be used. The number of representatives proposed then represents a compromise, where the separately collected amount of paper, plastic, glass and biowaste are gradually used in individual municipalities (from the previous year). Since the strata are chosen so that $w_1 \doteq \cdots \doteq w_L$, the function $V(n_1, \ldots, n_L)$ is minimized when the ranges of n_l are proportional to σ_l (i.e., the square root of σ_l^2).

3.1.2. *Secondary stratification*

The idea of the second level (secondary) stratification is to create smaller secondary strata (within primary strata) of municipalities that are similar in terms of significant socio-economic, environmental, and demographic factors. Each primary stratum is thus divided into several disjoint subsets of municipalities, while the cluster analysis approach is recommended. Strata created in this way are further also called Clusters. Similarly, as for the primary analysis, the goal is to create clusters of similar size (in terms of the total amount of MMW produced in the given stratum). The chosen representatives are municipalities that can be considered as the centers (with respect to a given metric) of the clusters. The task is then to select a typical/average representative.

Variables $f \in F$ presented in case study in Table 3 were selected to define the difference (distance) between municipalities in the Czech Republic. There are some general requirements on data to apply the stratification:

- The consistency in reporting – e.g., each waste quantity related variable must be obtained in the same way – the process of data collection.
- The availability of data on the selected territorial level – all variables must have a value – e.g., if one would want the variable to be gross domestic product, it is available only on the state or regional level so it cannot be used to describe similarity of municipalities.

Table 3
Variables for quantifying the similarity of municipalities.

Variable	Unit	Weight (W_f)	Transformation
Population		100	None
MMW production	kg/cap	100	None
The population density in the built-up area	cap/ha	65.2	$\log x$
The population density in the whole area of municipality	cap/ha	35.5	$\log x$
The average population per address point		66.3	$\log x$
Share of occupied dwellings in family houses from total	%	51.1	None
Commuting to work into the municipality	cap/thous. of population	44.4	$\log(x+1)$
Commuting for work outside the municipality	cap/thous. of population	35.4	None
The total number of collective accommodation establishments	cap/thous. of population	44.5	$\log(x+1)$
The number of unoccupied dwellings used for recreation	cap/thous. of population	33.7	$\log(x+1)$
Central heating connection	number of flats/ thous. of population	58.8	None
Production of separately collected plastic waste	kg/cap	65.7	None
Production of separately collected paper waste	kg/cap	68.6	None
Production of separately collected glass waste	kg/cap	63.2	None
Production of separately collected bio-waste	kg/cap	69.5	None

Population and MMW production are also used as a factor in secondary stratification to form clusters with similar sizes of municipalities (municipalities within strata are still highly variable in terms of population and MMW production). In general, any influential parameter can be used in the approach (these can inspire other researchers). The table also shows the weight (W_f) of each variable f (expertly determined) and whether the variable was logarithmically transformed. The logarithmic transformation helps to measure variables whose distributions are skewed or if relative rather than absolute changes of the quantities are significant. If the variable may contain zero values, the transformation $\log(x+1)$ was used. Finally (after a possible transformation), the values of all variables were standardized as follows

$$t(x) = \frac{x - MIN}{MAX - MIN} \tag{4}$$

where x is the value and *MIN* (*MAX*) denotes the minimum (resp. maximum) of a given variable from considered municipalities.

The function that measures the difference between municipality i and municipality j will be denoted $d_{i,j}$ (i.e., the distance in the values of selected variables). The weighted sum of the absolute value of the differences in variables between the two municipalities was used as distance in Eq (5), where $x_{i,f}$ denotes the standardized value of variable f for municipality i.

$$d_{i,j} = \sum_{f \in F} W_f \left| x_{i,f} - x_{j,f} \right| \tag{5}$$

The number of selected representatives from a given stratum is denoted by K. It is recommended to perform a cluster analysis for each stratum. The prescribed number of clusters (secondary strata) would be K. The cluster analysis should be performed so that clusters have a very similar size in terms of the total MMW production of all municipalities in each cluster. Suppose first that the required number of clusters is $K = 2$. Then, in the first step, the division into two clusters is performed to minimize the total weighted distance inside the clusters, where the weights are proportional to $\frac{1}{N_k}$ (N_k is the number of municipalities in the cluster). This corresponds to the solution of the following optimization problem:

$$\min D = \sum_{k=1}^{K} \frac{1}{N_k} \sum_{i=1}^{N} \sum_{j=1}^{N} I_{i,k} I_{j,k} d_{i,j} \tag{6}$$

where $I_{i,k}$ are binary variables that take values 1 only when i-th municipality is in the cluster k.

The average distance $\overline{d}_i$ of municipality i from other municipalities in the cluster will be used to suggest the representative. The municipality with the smallest value will suit as the best candidate for representative. In practice, when WCA cannot be performed in the selected municipality, the next candidate from the ordered list (ascending) will be used.

Clusters are created by k-means algorithm. The resulting distribution of municipalities into clusters typically does not meet the requirement for the same cluster size (measured by the sum of the MMW in the cluster). The individual municipalities are gradually moved from a larger cluster to a smaller one in the next step. Specifically, only one municipality is always selected and moved in such a way that the objective function value in Eq (6) increases the least. The moving procedure is repeated until the condition on the size of clusters is met. Although these shifts may cause a change in the representative, they will guarantee that the representative will be sufficiently informative, i.e., it will represent a sufficiently large cluster. Otherwise, there would be a risk that some representatives would represent only a very narrow and specific circle of municipalities, which in the end would lead to worse estimates of the proportions of individual waste fractions in a given stratum.

A suitable tolerance level is determined since it is practically impossible to achieve the same cluster size. The tolerance level was set to 20%. This means that a larger cluster can have a maximum of 20% more total MMW production than it should ideally have (half the total amount of MMW at a stratum). In other words, the maximum ratio of total MMW production in clusters is 60:40. This is a heuristic procedure that could be modified in various ways, e.g., it would be possible to move municipalities not according to the increase of D, but according to the ratio of this increase and total MMW production of the municipality, and thus does not guarantee ideal clustering under cluster size conditions. However, any differences will typically be only in the municipalities on the border of the clusters, which are not candidates for representatives, because they will have a very high $\overline{d}_i$.

In the case of $K > 2$, the municipalities are first divided into two clusters and then divided into smaller parts until the required number of clusters K is obtained. Compared to the classical use of the k-means algorithm, this modification is advantageous for two reasons:

(i) for a larger number of municipalities, it is much easier to achieve convergence of this algorithm into an optimal solution for two clusters than for more clusters;
(ii) it allows to better monitor and to achieve the desired size of individual clusters.

If, for example, $K = 6$, the municipalities are first divided into two approximately identical clusters according to the above procedure (measured by the total amount of MMW in a given cluster). Then, each of them is divided into two parts in a ratio of approximately 2:1. And finally, the larger part is divided into two almost equal parts. In total, the required 6 clusters are obtained. The only thing that needs to be changed now compared to the procedure for $K = 2$ is the tolerance level.

For K clusters, $\kappa = \log_2 K$ is a division level (maximal number of divisions needed to cluster any municipality), where x denotes the upper integer part of the number x. So, the tolerance level at each division must be $(\sqrt[\kappa]{1.2} - 1) \cdot 100\%$, overall, the size of each cluster differs from the ideal size by at most 20%. E.g., for $K = 6$ the tolerance level for each division will be approximately 6%.

3.2. *Choice of waste bins (in a given municipality) – tertiary stratification*

Once the representatives are chosen, the choice of waste bins is in place. For each of these municipalities, there are restricted resources that enable analyzing only a limited number of waste bins. Some of the standardized methods from the review can be used for this purpose, e.g., SWA-Tool (2004).

To choose those bins, one can also use similar principles as on the national level. First, it might be reasonable to divide the municipality within several strata that contain similar types of households (e.g., the area with a block of flats, the area with family houses). The number of waste bins analyzed in a given stratum should be proportional to the amount of MMW produced in that stratum. If no historical data are available, the number of people living there can be used (or the total capacity of waste bins in that stratum). Next, one should be careful also about the time factor. It is advisable to perform WCA studies uniformly in time to prevent seasonal effects. For example, WCA studies can be distributed into heating and non-heating season.

4. Case introducing method in the Czech Republic

The method was applied in the Czech Republic, which has 6258 municipalities and approximately 10.7 million inhabitants. In terms of waste production, Prague (capital city) is responsible for more than 10% of MMW, which resulted in considering it as a separate stratum/representative. First, all municipalities were ranked according to the total waste production. The smallest producers will be excluded as long as the total MMW production (for all excluded ones) is less than 2.5% of the nationwide MMW production.

The total number of considered municipalities will be reduced to 3950. On the other hand, it is believed that this potential error will be more than offset by improving the accuracy of the estimate for the remaining (non-excluded) municipalities. Besides, those municipalities that have an average annual production of MMW per capita of more than 1000 kg are stated as extreme and will be excluded (the final number of considered municipalities will be 3816).

Municipalities excluded in the above manner will not be considered as representatives. However, when constructing the overall estimate of waste composition for the Czech Republic, they will be considered by increasing the weight of the corresponding strata (strata to which they belong if they were not eliminated). As small municipalities are excluded from the list of representatives, the weight increase will be seen at the stratum with the smallest municipalities.

For the mentioned three scenarios for the total number of representatives, the results are the following (number of representatives are ranked from the stratum with the largest waste producers):

- **10 representatives** – suggested 3 primary strata. The number of representatives in the individual strata would be 2, 3, and 4.
- **20 representatives** – suggested 5 primary strata. The number of representatives in the individual strata would be 2, 2, 4, 5, and 6.
- **40 representatives** – suggested 6 primary strata. The number of representatives in the individual strata would be 3, 4, 6, 7, 9, and 10.

The last representative in each scenario is Prague, the capital with approx. 10% of the population.

From now on, the approach will be presented for the case of 10 representatives. Following the steps from *Primary stratification*, for $L = 3$, the stratum formation is illustrated in Table 4. The municipalities were ordered according to MMW production, and then based on cumulative production of MMW, the primary strata are designed. To create clusters, the k-means function in the MatLab program was used, which also allows the selection of distance or repeated performance of noise analysis from various initial solutions. The selected variables for clustering are defined in Table 3. The list of variables in Table 3 is significantly limited by the availability of data at the municipal level.

The significance of the factors depends on the geographical location (there is a different historical context in each country or territory, which overlaps with the composition of the waste itself). Variables were recommended by an expert team (based on the Czech-related data). The distance was calculated according to Eqs (5) and 1,000 iterations were run with evenly chosen initial solutions. This procedure with regards to steps in *Secondary stratification* forms clusters in each stratum. Finally, the representatives are chosen according to the lowest distance $\overline{d}_i$ from other municipalities in each cluster (see Table 4). The table is illustrative to understand the process (complete results for all municipalities are attached as supplementary material in the worksheet). Since the municipalities are ordered in descending MMW production, the classification into clusters is not sequential.

Table 4
Primary and secondary stratification – illustration of municipality distribution.

Municipality	Cumulative production of MMW [%]	Stratum, Cluster	Distance in the cluster ($\overline{d}_i$)
Brno	3.95	S1, C1	0.123
Ostrava	6.92	S1, C1	0.096
Plzeň	8.51	S1, C1	0.068
Liberec	9.66	S1, C1	0.066
Ústí nad Labem	**10.73**	**S1, C1**	**0.049**
Olomouc	11.68	S1, C1	0.057
….	….	….	….
Most	16.74	S1, C1	0.068
Opava	17.49	S1, C2	0.049
Zlín	18.20	S1, C2	0.055
Teplice	18.81	S1, C1	0.058
….	….	….	….
Sokolov	31.34	S1, C1	0.068
Bohumín	31.58	S1, C2	0.046
Šumperk	31.82	S1, C2	0.046
Krnov	**32.05**	**S1, C2**	**0.041**
Brandýs nad Labem-Stará Boleslav	32.29	S1, C2	0.071
Písek	32.53	S1, C2	0.052
Strakonice	32.76	S1, C2	0.047
Neratovice	33.00	S1, C2	0.062
Žďár nad Sázavou	33.22	S1, C2	0.044
Jindřichův Hradec	33.45	S2, C4	0.055
….	….	….	….

Note: Representatives are highlighted in bold.

The distribution of municipalities of the Czech Republic is visualized in Fig. 3. A red border highlights the representative of each cluster. The last representative is Prague, denoted as C10. It can be observed that the division of municipalities into clusters does not depend on their geographical location, but they are spread over the whole area. Their classification is determined mainly by the size and other characteristics presented in *Secondary stratification*. For example, the first cluster (C1) includes mostly regional cities. Municipalities that have been excluded based on the procedure in *Primary stratification* are marked in white. These are mainly small municipalities and municipalities where an extreme value of MMW production has been identified (errors reported to the central waste management system). Fig. 4 shows one specific cluster (C6) separately. There can be seen a large concentration of municipalities in the southeast of the Czech Republic and then in the Central Bohemian Region, which surrounds the capital city of Prague. Geographical concentration was not assumed as a variable, but it resulted from similar historical context and socio-economic factors.

In each municipality selected as a representative, tertiary stratification will be performed at the level of individual bins according to the types of dwellings or type of area (industrial, tourist, residential, etc.) and other available data defining the diversity within the municipality. The individual bins are then proportionally selected from each area at random.

4.1. *Discussion on the financial resources*

Within the primary stratum, it is recommended to distribute funds among individual representatives according to their size. Regarding the number of inspected waste bins, it is recommended that the total number of inspected waste bins is approximately the same in each primary stratum. It would certainly not be wise to spend as much on a sample survey in Prague as on a survey in a municipality with hundreds or thousands of inhabitants. Therefore, the funds spent on the entire primary stratum should rather be equal.

After the planned waste analyzes are completed, some remaining funds may still be available. In this case, it is possible to add x additional representatives to refine the overall estimate of the waste composition. In this case, however, it depends on the scenario used and the current situation.

The general principles are as follows:

1. If there is already data useable to estimate the variances of ratio estimates for individual strata, then representatives are added to the strata with the greatest estimated variance. If there are already K representatives in a given stratum, then x representatives are added so that $x < K$. In such a case, these x representatives are selected by creating new x clusters analogously as in *Secondary stratification.*
2. Alternatively, the analyzed representatives will be fixed in the calculation of representatives, and the procedure will select additional new ones in the best possible way. The approach presented by Šramková et al. (2021) can be used.

Sometimes it may happen that the chosen municipality will not want

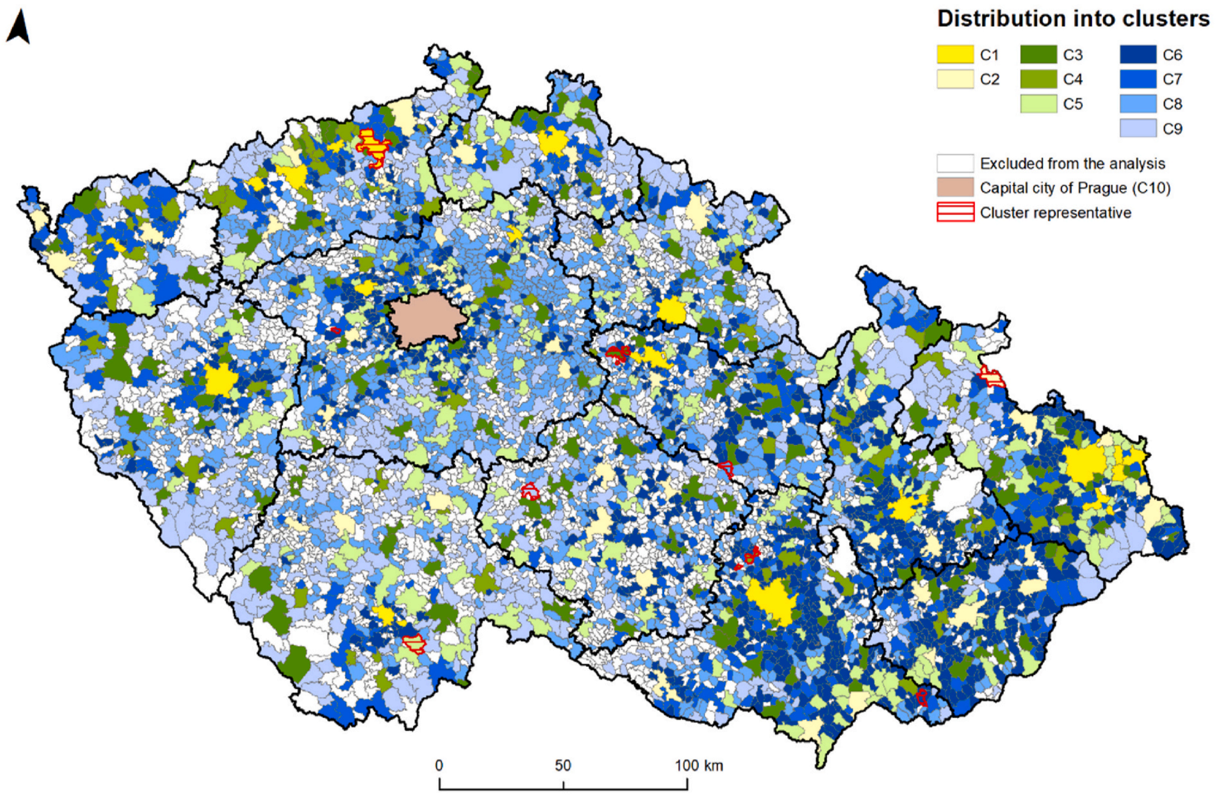

Fig. 3. The map of clusters and representatives (case 10) for the Czech Republic.

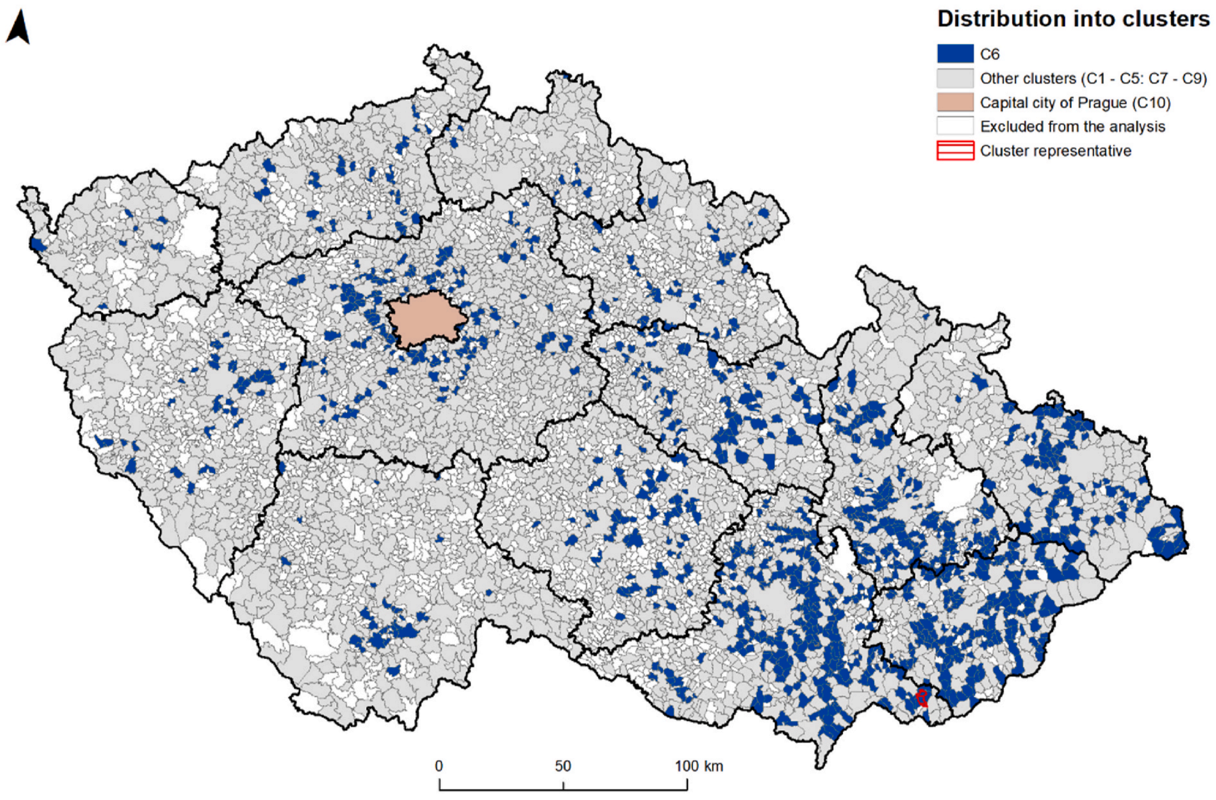

Fig. 4. The map of the specific cluster (C6).

to cooperate with the WCA. In such a case, the second most suitable municipality is chosen as representative. In addition to the willingness of the municipality to cooperate, it is also possible to consider the appropriate spatial distribution of municipalities in the Czech Republic. The following text creates an insight into the WCA's economy. The distribution is performed based on available funds while maintaining the greatest possible accuracy of the results.

The study duration varies according to the type of bin and the properties of the waste. One analysis takes a few of hours for two-to-four-member team, which highly affects costs. Costs are also increased by transport and waste handling.

The cost assessment for obtaining an estimate of the MMW composition with the required accuracy for each fraction is based on parameters from the SWA-Tool (2004). The assumptions for cost calculation are as follows:

- the required accuracy (confidence interval width) is 20%; variability in the data is expected to be around 30% (given by the coefficient of variation) for the more variable components of the MMW; the significance level was set to 95%.
- According to the SWA tool, at least 9 samples must be performed for each representative municipality.
- Seasonality effect will be captured by division into heating and non-heating season. This increases the total number of samples in the municipality to 18 samples.
- Different number of dwelling types (sites with block of flats, residential areas, family houses) are considered for individual representatives, so the representatives are further divided into smaller parts.
- A sample of 1100 L is assumed everywhere (in the case of smaller bins (e.g., 240 L) more bins are combined).

The number of dwelling types is distributed to representatives as follows: in Prague (the tourist area of the city is added) – together four types, in Stratum 1 – three types, in Stratum 2 – two types and only one type in Stratum 3. In total, there will be performed 360 samples.

The cost estimate for the analysis of one sample assumes 4 working samplers and the length of analyzes approx. 4 h. The input costs for materials and measuring technology are not considered. Furthermore, the cooperation of the collection company and the availability of dedicated space for analyzes are assumed. The estimated cost is 200 euros per analysis. For the whole country, the cost for all samples is estimated at 72,000 euros.

The reliable estimate for the whole country helps to set feasible environmental goals and direct waste management to sustainability. Knowledge of waste composition makes possible to plan a suitably complex processing infrastructure (transfer stations, sorting lines, Waste-to-Energy plants, etc.). Furthermore, it is possible to have reasonable goals for individual regions and monitor changes after implementation of promotional recycling strategies. The budget is usually limited and needs to be used as efficiently as possible – to obtain quality waste composition estimates for a minimum number of analyzes, which is the main benefit of this paper.

4.2. Discussion on the environmental policy and waste management

The primary goal of the presented method is to obtain an estimate of the waste composition. This cannot be achieved without good stratification in the case of limited resources, see section 4.1. Once a good estimate of the composition of municipal waste is obtained, steps related to environmental policy and evaluation can be taken. The outputs can then be used for the following points, and without quality stratification, the results in these areas will be greatly reduced.

1. Determination of real separation rate in areas of interest (region or municipality) for different types of waste.
2. Identification of material quantities for recycling – with regard to the selected level of detail of the waste categories (see last column of Table 2), the maximum potential can be estimated. With this knowledge, appropriate interventions in the form of information campaigns or changes to the collection system can be applied. It will also be possible to evaluate both the current and potential situation with regard to the set environmental objectives in the Circular economy package (Directive (EU) 2018/851, Directive (EU) 2018/852).
3. In order to meet some goals, it is necessary to significantly increase the recycling of essential types of waste – food waste, plastic, paper, metal. For example, food waste has been the subject of many studies in recent years. However, in obtaining information, other factions of waste are neglected, and the results are not meaningful in a broader context. Moreover, these studies are often of a local nature and without proper origin-like stratification.
4. Calculation and assessment of the possibility of saving primary resources/materials.
5. Determining the potentials of further unusable components from MSW or MMW for energy recovery in case of unsuitability for material recovery. Lower heating value and components of waste (heavy metals) have a strong connection to flue gas cleaning technology in these facilities.

4.3. Verification of stratification and related research

The easiest way to estimate the waste composition in any municipality is to use the results of the corresponding representative, but it is not the correct approach. The approach for reliable estimates of waste composition for arbitrary municipality should be the subject of further research. If the municipality is too far away or even at the cluster boundary, it is expected that a large error rate will be included in the estimate. The better option is to use results from all clusters – the more data is used the better estimates can be made. A proper way might be to find a regression model that estimates the composition in a given municipality. There must be available a large amount of data (WCA studies in many representatives). Based on the quality of the model, it is then possible to retrospectively identify the suitability of selected factors for the stratification. If the model does not show acceptable quality, the whole process can be repeated. Based on the correlation analysis, it is possible to suggest a new group of influencing factors and a new stratification will be performed. The results of the new stratification and the data from the already performed analyzes define the possibilities of selecting other representatives according to the points summarised in the previous sections.

5. Conclusion

The methodology describes the principles of stratification of municipalities in arbitrary country to select representative municipalities for obtaining an estimate of waste composition. The approach is suitable for estimating the composition of any fraction of MSW. These principles can also be applied if the interest is focused only on a given region and the aim is to select representatives only from this region. The selection of municipalities is carried out using a two-level procedure, which uses practical requirements and socio-economic parameters. After conducting WCA studies in selected representatives, it is possible to estimate the average composition in any region or the entire country. Results allow predicting the composition in any municipality, although no studies have been performed there. The application of regression analysis is recommended in this manner. The number of selected municipalities in total depends significantly on the available funds or other resources. The accuracy of the results is derived from variability in collected data and predefined inputs.

The advantage of the presented method is that it can handle any size of financial budget. Another benefit is the even distribution of municipalities into strata and clusters. The disadvantage of the method may be hidden in the unknown information about the homogeneity of the cluster – whether the selected representative appropriately represents the other municipalities in the cluster. Verification of results is required to identify information about the error and variability in clusters. However, field works of our team were stopped because of pandemic by the Czech Ministry of the Environment, so the data on waste composition just started to be collected in the selected representative municipalities.

Using the proposed method, ten clusters were created within the Czech Republic. Each cluster is described by a single representative municipality where the studies should be carried out. Furthermore, it is appropriate to divide the representative municipality based on dwelling types. Each further division refines the estimate but increases the number of monitored areas. It is recommended that campaigns are distributed into heating/non-heating seasons or vegetation/non-vegetation periods, so that the seasonal effect of some types of waste can be captured (e.g., bio-waste).

The total cost for estimating average MMW composition in the Czech Republic was calculated as 72,000 euros. This amount corresponds to WCA studies in ten municipalities for different numbers of dwelling types in each locality. However, given the variability of the results, additional analyzes may be needed to increase the accuracy of the estimates. The results – information on the composition of the waste – will provide input data for decision-making and application of environmental management as indicated in section 4.2.

Future research can assume selecting more representatives from one cluster and the goal could be changed from the average municipality to the best possible description of the entire cluster. Some novel metrics could be adapted to improve variability coverage. The waste composition should be monitored on a long-term basis and new sites (representatives) should be selected appropriately, considering the results after statistical evaluation. The selected representative does not have to be suitable for characterizing the stratum. In a further study, a multi-stage approach can be developed. The decisions in the first stage would be updated considering the results achieved in the other stages.

Credit author statement

Radovan Šomplák: Conceptualization, Methodology, Formal analysis. **Miloš Kopa:** Methodology, Validation, Writing – original draft. **Marek Omelka:** Methodology, Validation, Writing – original draft. **Vlastimír Nevrlý:** Conceptualization, Methodology, Writing – original draft, Writing- Reviewing and Editing. **Martin Pavlas:** Conceptualization, Supervision, Writing- Reviewing and Editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.115534.

Nomenclature

Abbreviations/Acronyms

EU	European Union
LSD	Level of solution detail
MSW	Municipal solid waste
MMW	Mixed municipal waste
PIS	Publishing Importance Score
WCA	Waste composition analysis
WM	Waste management

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Multi-objective strategic waste transfer station planning

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ABSTRACT

The production of mixed municipal waste changes due to the increase of separation rate, urbanization and other factors. The future changes in the legislation and technology development influences the way the waste is being treated. Thus the method, location and capacity of processing sites are unknown. The realization of future projects can be supported by the developing of transportation infrastructure. Such a feature may be represented by a robust transfer station grid, which can be designed to handle all possible future realizations and technological solutions (establishment of waste treatment facilities). The paper presents an approach utilising a mathematical model for the design of transfer stations. It is formulated as a multi-objective two-stage mixed-integer stochastic programming problem, where the trade-off between the environmental aspect and the economic viability is considered. The model is tested through a case study for the Czech Republic, where the waste treatment of over 6,000 municipalities is analysed. The solutions for different preferences are assessed throughout the principle called out-of-sample stability with 10,000 scenarios. The optimal decision consists of the robust transfer station grid with selected locations and their respective capacity. The particular solution with respect to the potential trade-off suggests to save 1.148 mil of travelled kilometres with only 0.77 mil EUR. The output in the form of decision support can serve possible stakeholders from the field of waste management to plan more sustainable projects.

1. Introduction

Most countries are struggling with changing demographic conditions. The population growth can be identified in developing countries, while in developed nations the age of the population is steadily growing (World Bank Open Data, 2018). The paper by Klemeš et al. (2017) is worth mentioning, because they summarized the progress in the sustainability applications from the recent years. At the same time, there is an ubiquitous technological boom and a change in the lifestyle associated with it. These aspects have an impact on products that are reflected in the waste produced, in terms of the absolute amount (Lou et al., 2017) and the waste composition (Chen, 2018a). Apart from the economic aspect, also the areas focusing on saving primary raw materials (Chen, 2018b) and reducing the emissions (Fan et al., 2018a) are becoming more prominent. An example may be a package for circular economy issued in May 2018 by EU (Directive (EU) 2018/849, 2018/850·2018/851 and 2018/852 – required to transpose the directives into national law of the member states by 5 July 2020) or an earlier document (from the year 2008), that anchors the preference of waste management in “waste hierarchy” (Directive (EU) 2008/98/EC). This hierarchy has been analysed (Gharfalkar et al., 2015) in more detail. The EU legislation is reflected by the local legislation of the EU member states, where binding milestones with fixed deadlines are defined.

Changing the way of waste treatment is only possible with the corresponding development of the waste processing infrastructure. Experts in this field are focused on the development of new sophisticated approaches for complex planning, where the main decision criterion is not only the cost but also the environmental point

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of view (Barbosa-Póvoa et al., 2018). The optimization models regarding the waste management can be divided into main categories:

- location problem, see Wichapa and Khokhajaikiat (2017),
- allocation problem, see Boonmee et al. (2018),
- network flow, see Tian et al. (2018),
- supply chain, see Islam and Huda (2018),
- and other.

The tasks mentioned in the bullet points are significantly affected by transportation cost. The other point of view represents the carbon emission production, which can be also used as a criterion in such tasks. The transition to high levels of renewable energy is included in future plans (Walmsley et al., 2015). Infrastructure building is influenced by local trends that are evolving due to legislative changes. For new projects, the economic sustainability is the essential aspect. The planning of the facility commissioning in waste management is difficult due to a long approval period (Putna et al., 2018). The projects are significantly affected by local environmental organizations, that often stop the project (Hsu, 2006). For these reasons, the forecasting of future waste handling is very difficult. Specific forecast contains many indeterminate factors which are projected in the main indicators (Cervantes et al., 2018). The current state of the waste handling, which is an important input for the simulations of future development (Šomplák et al., 2017) was analysed.

Since, the transportation is the key part of the whole chain of waste flow, deep evaluations of its component are needed. Most mathematical models solve the transport within the optimization of processing capacities, but their locations are set (Peri et al., 2018). However, the resulting flow allocation is not effective when changing the parameters of the terminal facility. On the other hand, transport and infrastructure models are usually solved with fixed processing grid (existing processing infrastructure). There exist several location allocation models in waste management. Bojic et al. (2013) examined the problem of allocating solid biomass power plants in Serbia. Sarker et al. (2018) focused on designing a logistic system for bio-methane gas production. However, these models do not include any sources of uncertainty and focus only on a single objective.

In the case of strategic decision-making in transport (Boonmee et al., 2018), all possible networks in the debris operation process were considered. It consists of waste collection and separation sites, processing and recycling sites, disposal sites and market sites to solve the post-disaster supply chain. Gambella et al. (2018) addressed a tactical problem of waste flow allocation from a waste operator point of view with the aim of minimizing the total management cost with considered profits from special subproducts. Coban et al. (2018) studied the possible disposal techniques for municipal authorities that could be applicable to Turkey with regards to the ever-growing amounts of the municipal solid waste. Another point of view was proposed by Zhao et al. (2016), where the complex network design problem was investigated. It considers the regional hazardous waste management system and searches for the transfer routes. The goal was to minimize the total cost and the inherent risk at the same time. Waste transfer stations and their locations were examined in the city of Nashik (India) by Yadav et al. (2016). The introduced study considers various waste treatment options, but the evaluation of new processing capacities is not included. The multi-objective approach for eco-design was proposed by Ji et al. (2016) and solved by Pareto optimization to obtain optimal transportation strategy. None of these approaches reflect the future possible legislation changes which can be projected in the development of certain technology while due to the local conditions, different locations are suitable for a realization of the different projects. This results in unstable optimal solutions when the corresponding legislation changes. Even when some similar thoughts were provided, big simplifications were considered, which limit the application to real problems.

This paper introduces the planning of transport infrastructure for municipal waste processing, specifically the location of the transfer stations with the capacity selection. The new approach is based on two-stage stochastic programming. The uncertainties are projected through the model parameters. The result is the suggestion of transfer stations placement, which is robust for future realization of unknown parameters. These unknown parameters were analysed separately in the following papers:

- The possibility of different processing facilities (Asefi and Lim, 2017) – sorting line, Waste-to-Energy plant, Mechanical-biological treatment plant, Monoblock, co-incineration with coal.
- The capacity of facilities (Rudi et al., 2017).
- The price variability – a requirement for the return of the investment – municipal or private investor (Ferdan et al., 2015), the development of the price and the demanded heat (Putna et al., 2018).
- The competitive waste market – construction of new facilities (Šomplák et al., 2014).
- Exporting/importing the waste (as a raw material) abroad (Botello-Álvarez et al., 2018).
- The legislation changes (Tomić et al., 2017).

From the above-mentioned points it is clear, that it is advantageous to consider a large number of scenarios for the description of the possible future realizations of the indeterminate parameters. The above-mentioned papers mostly focus on the testing instances or highly aggregated task with NUTS 3 (Nomenclature of Territorial Units for Statistics), which is very limited for practical use, especially for design of low-capacity facilities. This paper considers the analysed area on the more detailed level, which corresponds to LAU 2 (Local Administrative Unit). Such an approach entails significant demands on the compilation and the implementation of the mathematical model. The solvability and acceptable time and resources for computations play a crucial role. The approach will be described in detail in Section 5. The developed optimization model is multi-objective, providing a desired level of trade-off between the ecological and the economic objectives. This is achieved by minimizing the overall building and managing costs, and minimizing the total distance travelled by all the vehicles (and, hence, the emissions produced by those vehicles, see Fan et al. (2018b) for extensive review on air emission assessment) simultaneously.

2. Problem description

The main focus of the developed optimization model is to serve as a decision support on the selection of the location and the capacity of waste transfer stations. The purpose of these transfer stations is to be a transportation hub where the waste from the neighbouring municipalities is gathered, compressed, and loaded on a more cost-efficient vehicle before it is shipped to a waste treatment facility. See Gregor et al. (2017) for the evaluation of related costs. The decision on the placement and the capacity of these stations is a strategic one, as it needs to be made in advance, and has a lasting impact on the behaviour of the system (in this case, on the flows through the transportation network and the resulting costs and emissions). In the language of stochastic programming (Birge and Louveaux, 1997), these decisions are called the "first-stage" decisions, as they need to be made without the knowledge of the particular realization of the uncertain parameters. These decisions must be made robust enough to be suitable for a wide range of possible future values of the uncertain parameters.

The optimization variable representing the decision on building the transfer station in a specific place is inherently binary, making the problem a mixed-integer one and adding extensive computational complexity. The relation between the cost of building a transfer station and its capacity is nonlinear, and (what is even more important) nonconvex, making the problem even more challenging. The non-linearity is caused by the purchasing of press equipment which decreases per unit of processed waste. This difficulty is overcome using the special ordered set of type 1 (or SOS1) variables (Williams, 2013), that linearize the cost function and help to decrease the computational complexity.

The other decisions, namely the transportation of waste, the usage of the transfer stations, and the choice of the waste treatment facility are all operational ones – they can adjust to the uncertain prices at the waste treatment facilities. In stochastic programming terms, these decisions are called “second-stage”. To describe the transportation of waste (which essentially is a network flow) between the municipalities, a fitting mathematical structure is needed. In this case, because of the two different modes of transport (“normal one” and the one from transfer stations), two separate graphs are used. The first one has each municipality represented by a node and arcs describing the available road network between those municipalities (cf. Fig. 1 in the Case Study). The second graph describes the network using the transfer stations – the nodes are only the municipalities where there is either a possible transfer station location, or a waste treatment facility. The arcs describe the shortest paths between all pairs of possible transfer stations and waste treatment facilities.

The multi-objective nature of the model stems from the desire to design systems that are both economical and with as small environmental impact as possible. In this case, the environmental impact of a solution is measured in terms of the total distance travelled by all the vehicles used in the transportation of waste. The modelling technique employed to tackle the multi-objectivity of the problem is the standard scalarization one (Boyd and Vandenbarghe, 2004), where the two objectives are given different weights. These weights are used to construct a new single objective function that is minimized. By appropriately changing the weights, one obtains the desired trade-off curve (or a Pareto frontier) between the two objectives, as well as the corresponding optimal decisions.

As already stated in Section 1, there is a multitude of uncertain factors that need to be accounted for. This uncertainty in data is modelled as different possible scenarios, with the objective computed as an average (trade-off between costs and distance) over these scenarios. Intuitively, as the number (and the quality) of the considered scenarios grows, so does the quality of the decision that is based upon them. However, with rising number of scenarios comes an increase of computational difficulty, as to each scenario corresponds a separate set of second-stage decisions. This difficulty is addressed by the use of an appropriate optimization method described in Section 5.

3. Model formulation

All the necessary notation used to describe the mathematical model is summarized in Table 1. The mathematical model of the problem is developed using a combination of description styles to ease the notation. Most notably, the scalar product of two column vectors x, y is denoted as $x^T y$ (all vectors considered are column vectors). In the equations, some subscripts are hidden, meaning that the full vector of values is used – e.g., in Eq (3), the subscript j is missing to indicate that the inequality should hold for all of the corresponding values (component-wise for the two vectors).

The weighted objective function is given by Eq (1). The first

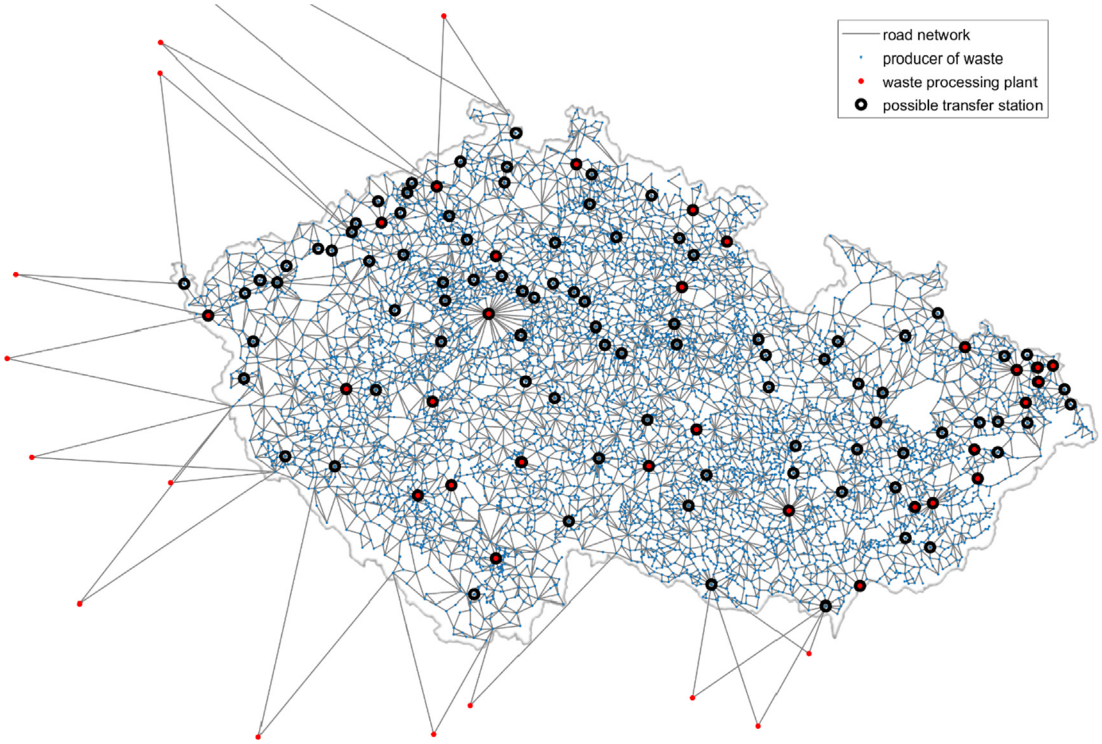

Fig. 1. A map showing the layout of the case study.

Table 1
The notation.

Type	Symbol	Description [unit]
Sets	$s \in S$	Set of scenarios
	$j \in J$	Set of nodes (municipalities)
	$i \in I \subset J$	Set of possible transfer stations
	$t \in T$	Set of possible options for transfer station capacities
Parameters	A_1	The first incidence matrix (connections between municipalities) [-]
	A_2	The second incidence matrix (transfer stations – treatment facilities) [-]
	d_1	Distances on the first incidence matrix (on A_1) [km]
	d_2	Distances on the second incidence matrix (on A_2) [km]
	c_1	Transfer costs, without the transfer stations (on A_1) [EUR/t]
	c_2	Transfer costs, using transfer stations (on A_2) [EUR/t]
	b_1	Capacity of vehicles on A_1 [t]
	b_2	Capacity of vehicles on A_2 [t]
	p_s	Probability of a scenario s [-]
	$e_{i,t}$	Cost of a construction of a transfer station at location i, with capacity option t [EUR]
	$k_{i,t}$	Capacity of a transfer station at location i, with capacity option t [t]
	$f_{j,s}$	Cost of processing waste at node j, scenario s [EUR/t]
	r_j	Production of waste at node j [t]
	q_j	Waste processing capacity of node j [t]
	λ	Scalarization parameter [-]
Variables	$\delta_{i,t}$	Decision on building the transfer station at location i, with capacity option t; binary (SOS1), first-stage [-]
	$x_{1,s}$	Flows on A_1 in scenario s; continuous, second-stage [t]
	$x_{2,s}$	Flows on A_2 in scenario s; continuous, second-stage [t]
	$y_{j,s}$	Amount of processed waste in node j, scenario s; continuous, second-stage [t]

addend denotes the expected costs, that are associated with the construction of the transfer stations, waste processing, and transportation. The second addend denotes the expected distance travelled by the vehicles transporting waste. Its computation is based on the amount of transported waste on the arcs of the networks and the capacity of the vehicles used on the two different networks (with and without the use of the transfer stations). The scalarization parameter $\lambda \in [0,1]$ is used to describe the level of trade-off between the two objectives.

$$\text{minimize } \lambda \cdot \left(\sum_{i \in I, t \in T} e_{i,t}\delta_{i,t} + \sum_{s \in S} p_s \left(c_1^T x_{1,s} + c_2^T x_{2,s} + f_s^T y_s \right) \right) + (1-\lambda) \cdot \left(\sum_{s \in S} p_s \left(d_1^T x_{1,s}/b_1 + d_2^T x_{2,s}/b_2 \right) \right) \tag{1}$$

The constraints describing the model take the following form:

$$A_1 x_{1,s} + A_2 x_{2,s} + y_s - \mathrm{r} = 0, \ \forall s \in S \tag{2}$$

$$y_s \le q, \ \forall s \in S \tag{3}$$

$$\sum_{\mathit{flows\ from}\ i \in I} x_{2,s} \le \sum_{t \in T} k_{i,t}\delta_{i,t}, \ \forall s \in S, \ \forall i \in I \tag{4}$$

$$x_{1,s}, x_{2,s}, y_s \ge 0, \ \forall s \in S \tag{5}$$

$$\sum_{t \in T} \delta_{i,t} \le 1, \ \forall i \in I \tag{6}$$

$$\delta_{i,t} \in \{0,1\}, \ \forall i \in I, \ \forall t \in T \tag{7}$$

The constraint Eq (2) describes the "conservation of waste" – the net balance of the amount of waste that is produced in a municipality, transported (by the two different networks) in and out of a municipality, and processed in a municipality must be equal to zero. The constraint Eq (3) denotes the waste-processing capacities of the different municipalities (with the ones without a waste processing facility having $q_j = 0$). The constraint Eq (4) links the decision of building the transfer stations with the use of the associated network – the sum of the transported waste from a node i by the transfer station network must be less than the installed transfer station capacity in that node. The constraint Eq (5) ensures that the transportation and processing variables will be nonnegative. The two last constraints Eq (6) and Eq (7) together define the SOS1 variable – at most one of the possible capacities of the considered transfer stations must be chosen (with the possibility not to build any).

4. Case study

The case study involves the transfer station planning in the Czech Republic for the mixed municipal waste. In terms of scale, it deals with the most detailed description of the road networks and municipality structure available. In total, 6258 nodes (municipalities producing waste), 44 waste processing plants (15 of which were foreign, allowing a potential export of the waste to Germany or Austria) and 116 possible places for the transfer stations were considered (these sets are not mutually exclusive). For every possible transfer station 6 options for its capacity were considered.

The waste processing sites have the possibility to utilise potentially produced heat from waste, i.e. existing district heating systems, see Putna et al. (2018). In such locations, the construction of new facilities (Waste-to-Energy, Mechanical Biological Treatment, Processing of Refuse Derived Fuels) is considered. These technologies can effectively utilise residual municipal waste (Šomplák et al., 2014). The newly created facilities comply with (Directive (EU) 2018/850), which aims to move away from landfilling through the use of waste (material or energy recovery). The robust design of transfer stations promotes the financial sustainability of new projects and is therefore an important aspect of the transition to a more efficient waste management anchored in (Directive (EU) 2008/98/EC).

The first road network (connecting the municipalities, described by the incidence matrix A_1) had 24,770 arcs and is depicted in Fig. 1. In order to differentiate between the transportation of waste that does or does not use the transfer stations, a separate road network was computed – for each possible transfer station was found the shortest path to each waste-processing plant. In this pre-processing step, 5075 shortest path optimization problems were solved, resulting in the second network (described by the incidence matrix A_2) with 5075 arcs (omitting the ones that started and ended at the same place). The transfer of waste when using the transfer stations is assumed according to (Gregor et al., 2017). Flows on the first network are considered to be serviced by vehicles with capacity $b_1 = 10$ t, and the flows from transfer stations are serviced by vehicles with capacity $b_2 = 24$ t. For the purpose of simplification, the vehicles are assumed fully loaded. This assumption has an undeniable effect on the resulting optimal solution. The model could be refined by considering less aggregated data (on a weekly/monthly basis instead on the yearly basis) and by obtaining the information about the utilization of the vehicles collecting the waste. Additionally, as pointed out by How et al. (2016) adding both weight and volume constraints significantly increases the precision of the transportation model.

The first-stage of the optimization problem consisted only of the planning decisions (on where to build the transfer stations) and is described by 696 binary variables. The second-stage of the optimization problem used 29,889 continuous decision variables.

The uncertain parameter that is considered in the model is the cost for processing the waste at the 44 different plants, which correspond with the legislation development and local conditions (such as the demand for heat, etc.). To appropriately capture the nature of the inherent uncertainty, 1000 possible scenarios for the waste treatment costs were constructed to be used within the optimization. The resulting optimization model had almost 30 million variables. The total number of constraints that depend on scenarios was 36,307, meaning that the optimization model had over 36 million constraints.

5. Optimization method

Because of the enormous number of variables of the considered optimization model, a specialized optimization method had to be employed. The particular block angular structure (see Birge and Louveaux, 1997) of this two-stage stochastic optimization problem is very well suited for the so-called Benders decomposition algorithm. This algorithm was originally developed as a method of solving large mixed integer optimization problems and it is thoroughly described by Kůdela et al. (2017). The variant of the algorithm that was used to solve the optimization problem further utilized the warm-start cuts developed by Kůdela and Popela (2017). The method works by decomposing the optimization problem into two different ones, namely the master problem and the subproblem. In the considered case, the master problem consists of all the first-stage variables, constraints that contain only the first-stage variables (constraints Eq (6) and Eq (7)) and a part of the objective function with only the first-stage variables. An additional continuous variable is attached to the master problem and is used as a link between the master problem and the subproblem.

The subproblem then includes every other variable and constraints Eq (2)-Eq (5). The algorithm progresses by alternating between solving the master problem and solving the subproblem, where the value of the first-stage variables is being fixed (i.e. the first-stage variables appear as constants in the subproblem). Depending on the solution of the subproblem, the master problem is augmented by the so-called feasibility and optimality cuts until an optimality criterion is met and the solution (the first-stage decision) is declared to be the optimal one (or to be within a specified optimality gap).

The real strength of the algorithm comes into light when solving the subproblem. The structure of the optimization model is such that the subproblem is naturally separable by scenarios, once the first-stage decisions are fixed. This means that instead of solving one large optimization problem with 30 million variables, one needs to solve 1000 problems with 29,889 variables instead – this can be done with the help of modern solvers and equipment in a reasonable time frame.

To further take the advantage of modern solvers, the concept of lazy constraints, proposed by IBM (International Business Machines Corporation) that develops the CPLEX solver (CPLEX, 2019), was utilized. Instead of solving the mixed-integer master problem completely for each newly generated optimality or feasibility cut, the cut-generation is moved to be within the solution procedure of the master problem. This is achieved by using the lazy cuts – each time a new incumbent solution for the mixed-integer master problem is found, the subproblems are solved and a depending on the result, new cuts are added (the incumbent is rejected), or the solution is deemed optimal (the incumbent is accepted). A flowchart describing the algorithm is depicted in Fig. 2.

The optimization was carried out for 7 different values of λ to obtain a set of advantageous and diverse trade-off decision. To test the computed optimal first-stage decision on building the transfer station network, a new set of 10,000 scenarios was generated. On these new scenarios, the transfer station network was fixed, and the optimization was carried out only with respect to the operational decision (transportation and waste treatment), which was done separately for each scenario. This evaluation is based upon a principle called out-of-sample stability (King and Wallace, 2012). Using this method, it was found that the objective function values from the optimization were less than 1% off from the results of the evaluation (suggesting that the 1000 scenarios used for optimization were "enough" to obtain out-of-sample stable solutions). The computations took about 1 h for each value of λ.

The optimization model and the decomposition algorithm were programmed in the high-performance dynamic language JULIA (Bezanson et al., 2017) with the JuMP package for mathematical optimization (Dunning et al., 2017), that is very well suited for large-scale scientific computing. The solution of the mixed-integer master problem was obtained using a branch-and-cut method (with the aforementioned lazy cuts), calling the CPLEX 12.6.3 solver

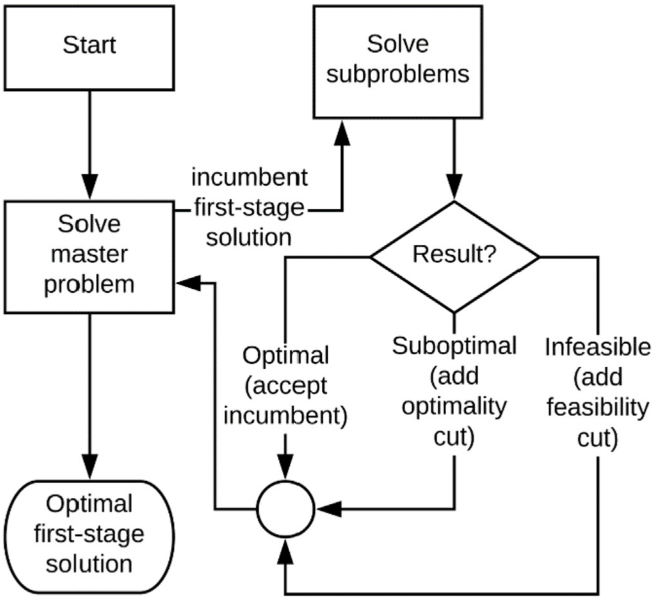

Fig. 2. A flow chart describing the Benders decomposition with lazy constraints.

(CPLEX, 2019). The MIP gap parameter was set at 1.5%, which was decided to be sufficiently low for this application. The individual subproblems in the second stage were solved by the primal-dual simplex method, calling the GUROBI 7.5 solver (GUROBI, 2019). This combination of solvers and algorithms achieved the best overall performance – the scheme reached the 1.5% optimality gap for the problem formulation with 1000 scenarios within 24 h for each considered value of the scalarization parameter λ. The computations were carried out on an ordinary computer (3.2 GHz i5-4460 CPU, 16 GB RAM).

6. Results and discussion

The results of the computations for 7 different values of λ are summarized in Table 2 – the mean and standard deviation (Std) for both objectives and the number and total capacity of transfer stations is presented. The trade-off between the overall costs and the total travelled distance, based on the value of the scalarization parameter λ, is best exemplified by the Pareto frontier graph in Fig. 3. The decisions based only on one of the objectives (corresponding to $\lambda = 0$ and $\lambda = 1$) are rather "extreme" to be used in as a support for decision making. Instead they serve as very useful reference points for comparing the possible trade-offs. A very important feature of the results is the "very steep" and "very shallow" slopes of the graph near the extreme values of λ (close to the single-objective optimal decisions). This means that for a very small compromise in one objective, large gains can be achieved in the other objective. This can be clearly seen, for example, on the solution for $\lambda = 0.05$, that is just very marginally worse in terms of costs than the decision that focuses solely on costs (for $\lambda = 1$, results for this setting were basically the same as the ones obtained by Kůdela et al. (2018)) but has 8.7% lower total travelled distance. For practical purposes, the best trade-off solutions seem to be obtained between $\lambda = 0.001$ and $\lambda = 0.03$. For $\lambda = 0.03$, the costs are only 0.3% higher than the best possible and the total distance travelled is 42.2% higher than the best possible. For $\lambda = 0.001$, the costs are 3.97% higher than the best possible and the total distance travelled is 1.35% higher than the best possible.

Another interesting aspect of the decision is the variability in the values of the two objectives. The more "focus" is shifted towards one of the objectives, the lower are the standard deviations in this objective and the higher are the standard deviation in the other objective. This can be clearly seen in Fig. 4. For $\lambda = 0$, the resulting plan was the same for all the considered scenarios which means Std $= 0$. It is caused by the considered random variable, which was the cost of waste treatment at the different facilities. Thus, the only objective was to use the operating decisions (transfer and treatment) with least amount of total travelled distance.

The planning decisions on the placement and capacity of the transfer stations are rather similar, ranging between 75 and 90 for the number of stations, and between $4.25\cdot10^6$ t to $5.06\cdot10^6$ t in terms of the installed capacity. This signifies that the use of the transfer stations is preferable for both objectives. There is, however, no apparent simple relationship between the optimal number/capacity of the built transfer stations and the values of λ, which indicates that the optimal decisions are rather complex (as opposed to a straightforward "higher λ means more capacity" or similar ones). Many of the optimal decision for placement of the transfer stations for different values of λ overlap, which can be seen in Fig. 5 (with $\lambda = 0$, focusing on distance), Fig. 6 (with $\lambda = 0.01$, describing a trade-off between distance and costs), and Fig. 7 (with $\lambda = 1$, focusing on costs). These places can be seen as the best potential candidates for the construction of transfer stations, regardless of the particular objective.

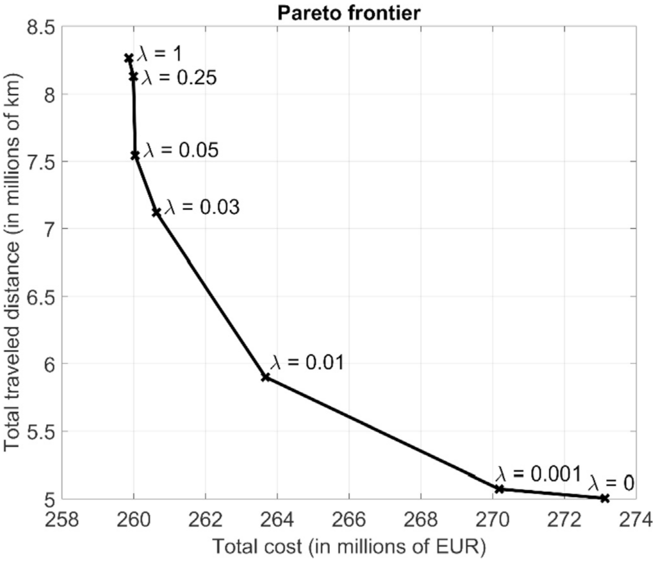

Fig. 3. Pareto frontier describing the trade-off between cost and distance for different values of λ.

The operating decision, however, depend on the value of λ to a much higher degree. As can be seen in Fig. 5, Fig. 6, Fig. 7, and, in more detail, in Fig. 8, the transport of waste from different municipalities to transfer stations and waste treatment plants naturally divides the map into (mostly unconnected) areas of influence. These areas change just slightly depending on the values of λ, where the biggest differences are caused by decision on building additional/different transfer stations, illustrated in Fig. 8. Additionally, the areas of influence also depend on the particular scenario, as the flow on both of the transport networks can vary (but the layout of transfer station network for a selected value of λ remains fixed).

The decision that depends on the desired trade-off between the overall costs and total travelled distance the most is the transport

Table 2
The results of the evaluation with 10,000 scenarios.

λ	Total cost		Total travelled distance		Stations	
	Mean (in EUR)	Std (in EUR)	Mean (in km)	Std (in km)	number built	Capacity (in t)
0	$273.13\cdot10^6$	$6.036\cdot10^6$	$5.006\cdot10^6$	0	90	$5.06\cdot10^6$
0.001	$270.18\cdot10^6$	$5.909\cdot10^6$	$5.074\cdot10^6$	$0.108\cdot10^5$	84	$5.02\cdot10^6$
0.01	$263.67\cdot10^6$	$5.468\cdot10^6$	$5.901\cdot10^6$	$2.519\cdot10^5$	75	$4.45\cdot10^6$
0.03	$260.63\cdot10^6$	$5.238\cdot10^6$	$7.119\cdot10^6$	$6.571\cdot10^5$	83	$4.25\cdot10^6$
0.05	$260.04\cdot10^6$	$5.196\cdot10^6$	$7.543\cdot10^6$	$7.533\cdot10^5$	81	$4.38\cdot10^6$
0.25	$259.99\cdot10^6$	$5.157\cdot10^6$	$8.131\cdot10^6$	$8.953\cdot10^5$	79	$4.43\cdot10^6$
1	$259.86\cdot10^6$	$5.158\cdot10^6$	$8.267\cdot10^6$	$9.084\cdot10^5$	79	$4.68\cdot10^6$

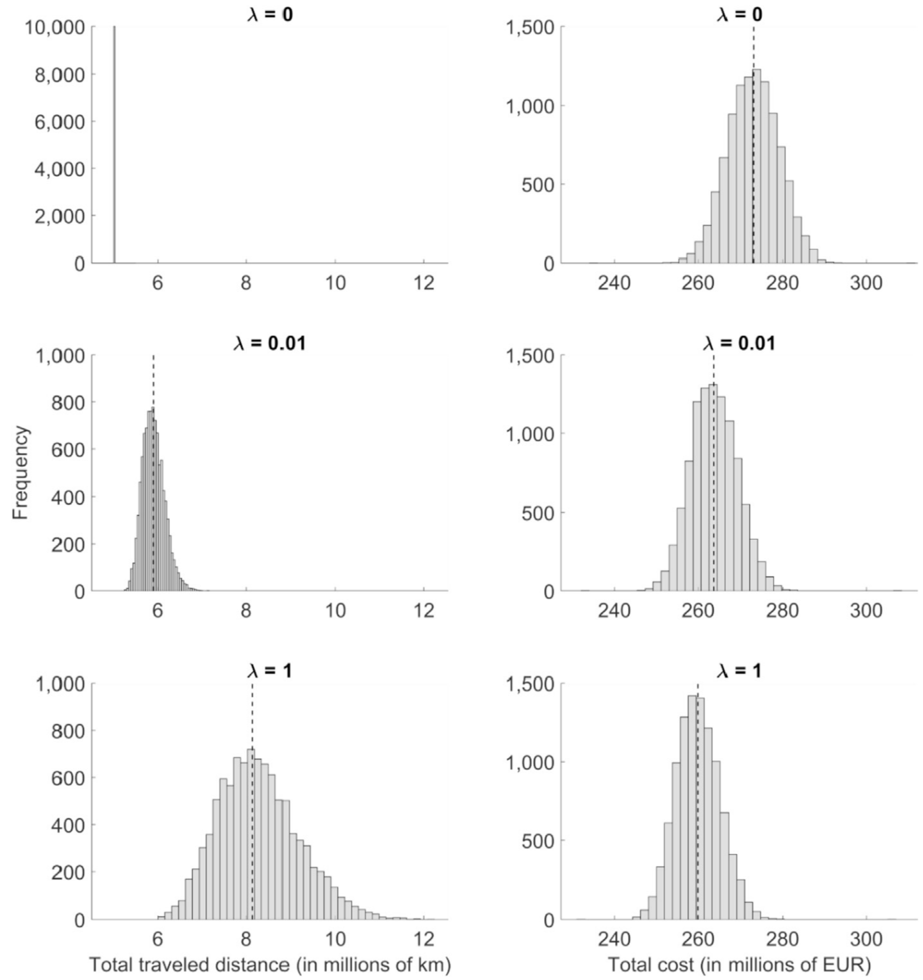

Fig. 4. Histograms of total travelled distance and total cost for different values of parameter λ. Mean values are denoted by a dashed line.

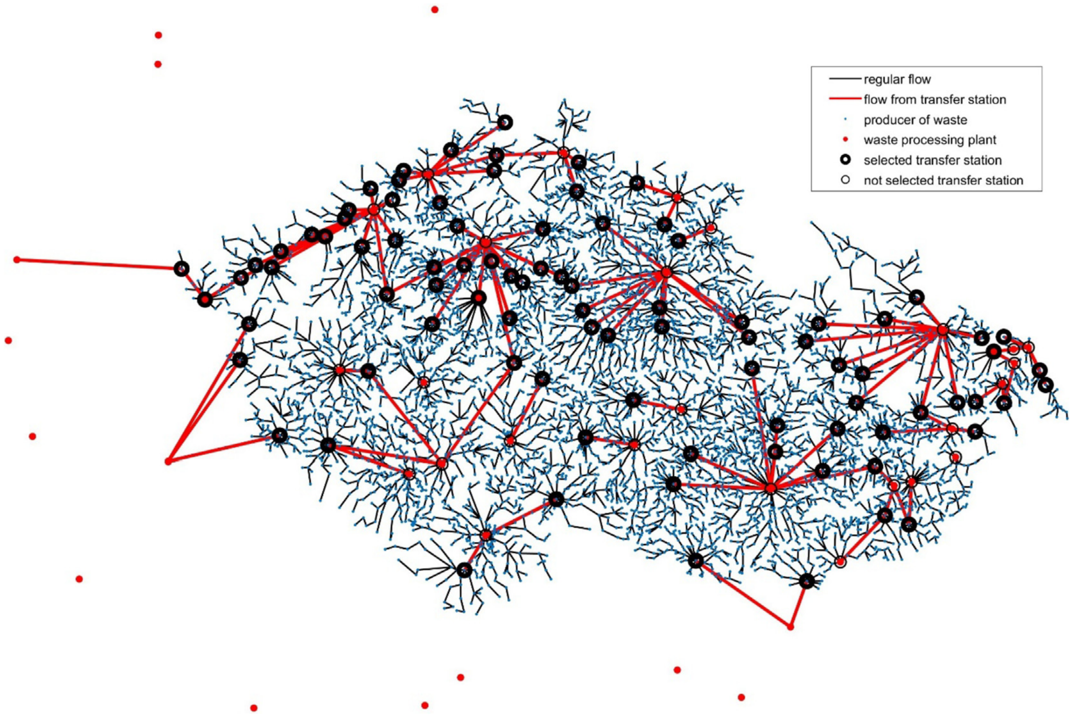

Fig. 5. A map showing the results for a baseline scenario. $\lambda = 0$.

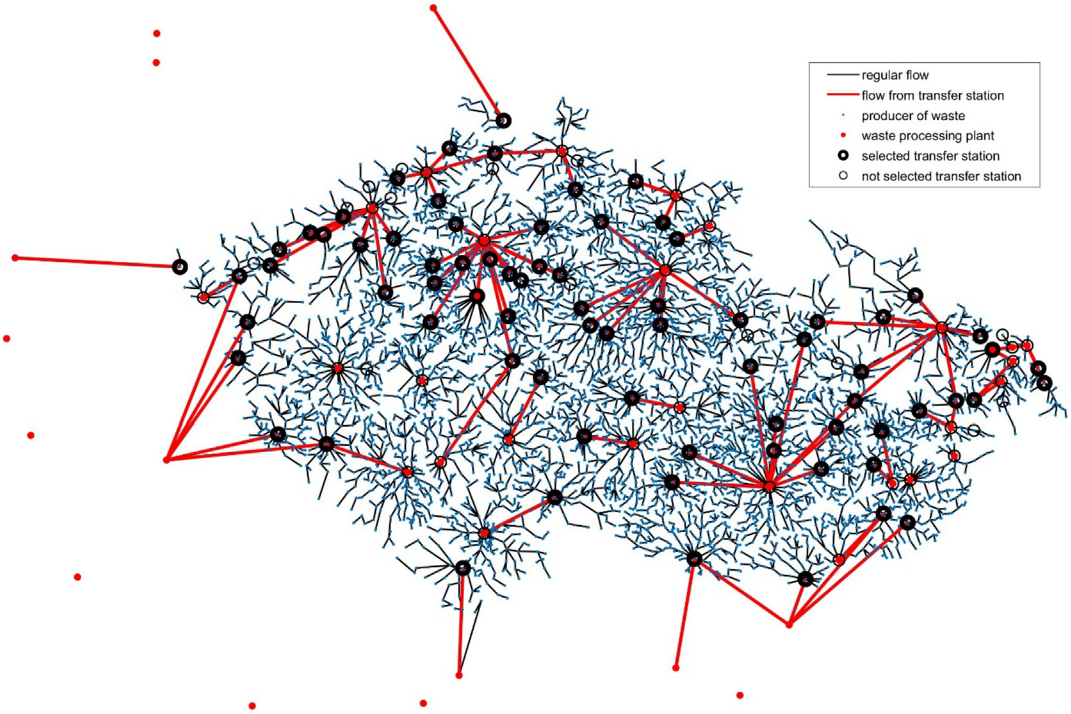

Fig. 6. A map showing the results for a baseline scenario. $\lambda = 0.01$.

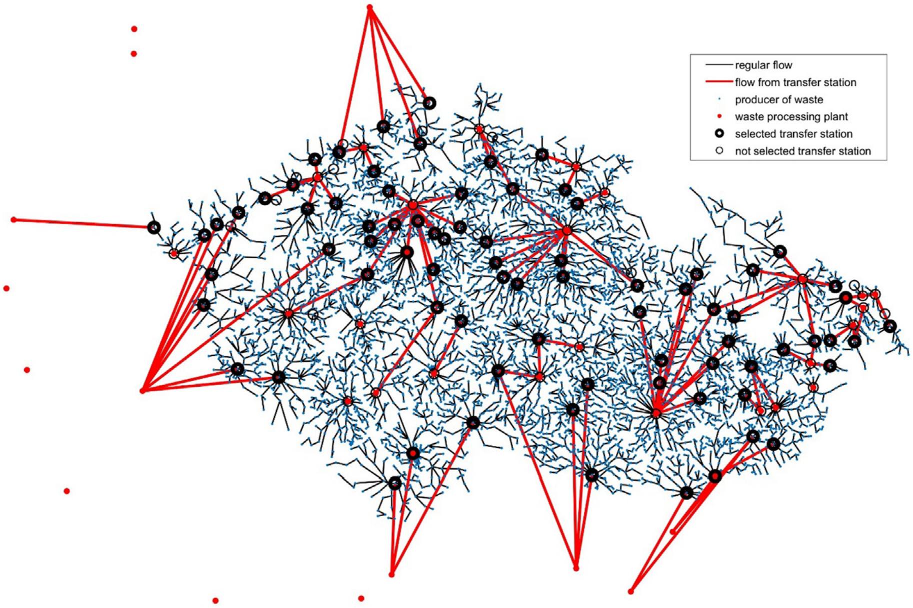

Fig. 7. A map showing the results for a baseline scenario. $\lambda = 1$.

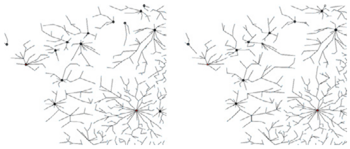

Fig. 8. A close-up on the map (western part) showing the transport only on the first network. The map naturally decomposes into areas of influence. $\lambda = 0$ (left) and $\lambda = 1$ (right).

from the selected transfer stations to the waste treatment plants. For lower values of λ (exemplified in Figs. 5 and 6), this transport is much more regionally focused, preferring the nearby waste treatment plants that have more expensive treatment costs. For higher values of λ (Fig. 7) the solution shifts towards the utilization of much more of the further placed and the foreign waste treatment plants that offer lower waste treatment costs.

The results suggest that each municipality has its preferred “transport destination” – either a transfer station or a waste treatment plant that the municipality utilized for most scenarios. In

Fig. 10, the percentage utilization of the most used transport destination for the municipalities is depicted for λ = 0.01. Over 34% of the municipalities had a singular transfer destination that did not change over the 10,000 scenarios. For 86% municipalities, the most used transfer destination was used at least 91% of the time — or, to rephrase, the claim: “This municipality uses the same transfer destination in at least 91% scenarios”, was true for 86% municipalities. For 97.5% municipalities, the most used transfer destination was used at least 70% of the time. For the municipalities, this analysis can serve as a foundation for their support of the

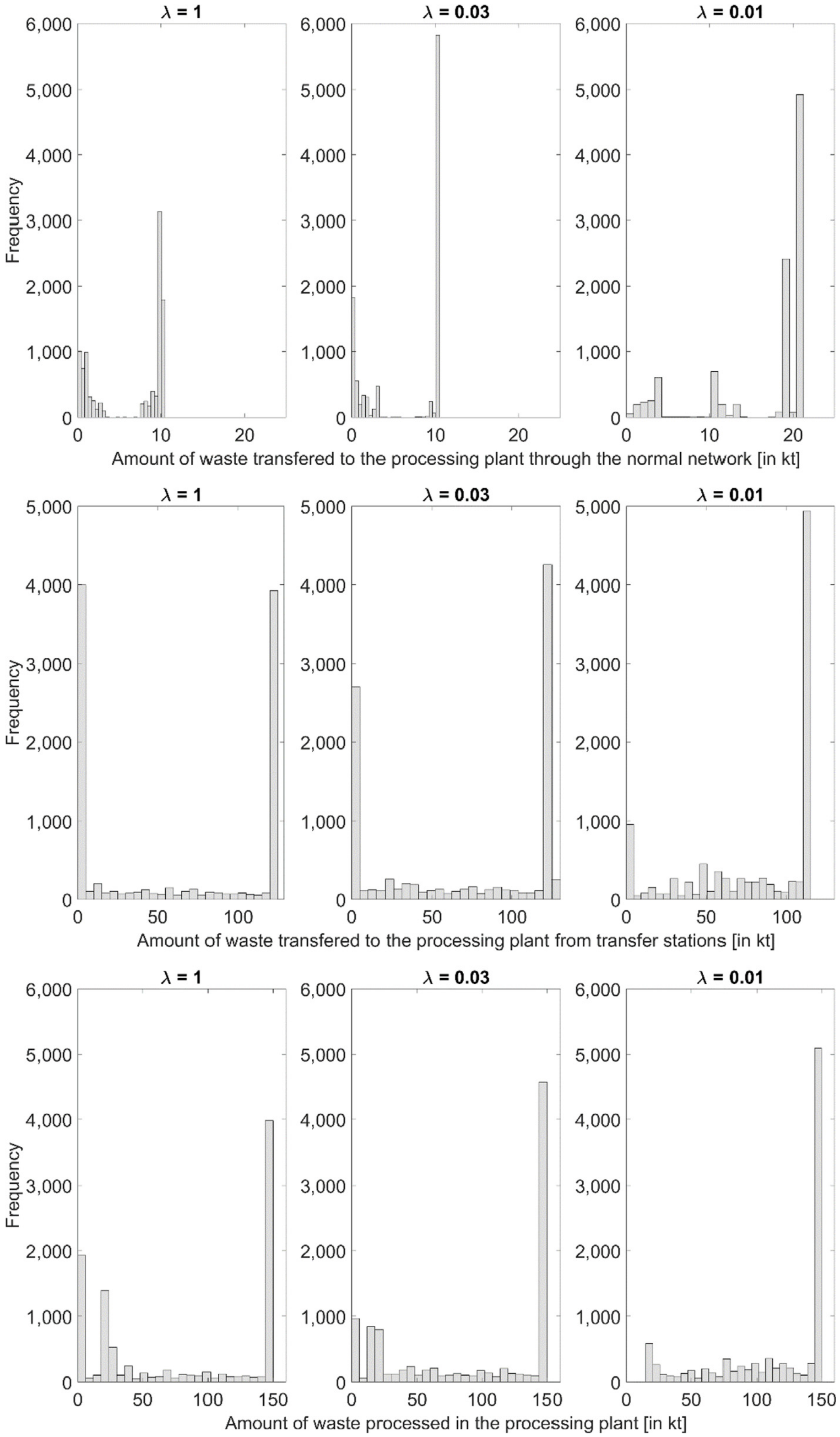

Fig. 9. Histograms of waste processing and transportation in processing plant in “Most”.

plan to build a particular transfer station.

An additional perspective can be gained by analysing the effect of choosing λ on individual waste processing plants. In Fig. 9 are the histograms for the transportation and processing of waste in the processing plant in a municipality called "Most". This municipality is the capital city of the "Most District" located in the northwest of the Czech Republic. It has approximately 67 thousand inhabitants, and the waste processing plant located there has a capacity of 150 kt. As the value of the parameter λ decreases and the optimal waste processing plan gets more locally focused, the utilization of the processing plant in "Most" increases. This can be clearly seen in the histogram of amount of processed waste – for $\lambda = 1$ the plant in "Most" is not used in almost 20% of the scenarios, while for $\lambda = 0.01$ the plant is always in use. The percentage of times the plant runs at full capacity also increases from almost 40% for $\lambda = 1$ to over 50% for $\lambda = 0.01$. However, the increase in the utilization of the plant naturally increases the traffic from both the normal network and from the transfer stations. The overall effect on the traffic situation in individual municipalities should be carefully analysed.

7. Conclusions

Decision making in an uncertain environment is always a delicate task and requires proper handling and careful consideration. In this paper, a mathematical model for an optimal transfer station grid is developed, taking into account the uncertain development in the waste processing costs, caused by the unknown future development in legislation and technology. The multi-objective nature of the model provides a ground for evaluation of the advantages and disadvantages of the trade-off between the environmental aspects and the economic viability attained by the different solutions.

A case study demonstrating the applicability and scalability of the model is presented. This study describes in high detail (considering over 6,000 municipalities) the mixed municipal waste management situation in the Czech Republic. The results show a range of viable option and strategies for the planning and managing the transfer station grid.

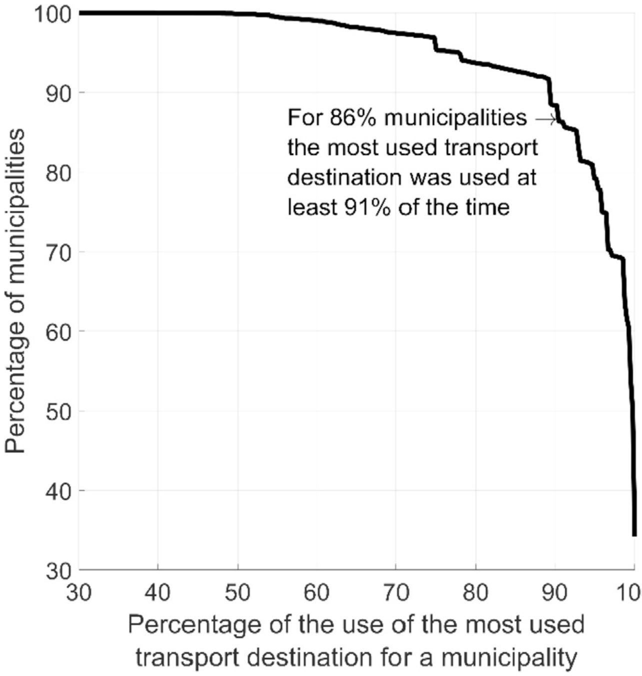

Fig. 10. Utilization of the most frequently used transport destinations (transfer stations and waste treatment facilities).$\lambda = 0.01$.

Because of the large scale of the resulting model, a suitable optimization algorithm was needed to process and solve the problem. The Benders decomposition algorithm with the utilization of lazy constraints and warm start cuts was chosen, as it is highly scalable and relatively straightforward to implement. A high-level description of the algorithm was presented.

From the macro-level perspective, the mathematical model can be used for the assessment of the optimal strategies (both tactical and operational), exemplified in Figs. 3, Fig. 4, and Fig. 10. It also provides means for the micro-level analysis of the impacts of the selected strategies on the individual municipalities and waste processing plants.

However, the most difficult task is still left for the specific decision maker (possible investors, municipalities and/or stakeholders from the field of waste management). The proposed results serve as the support and recommendation. The optimal trade-off probably lies between values 0.001 and 0.03 of the scalarization parameter λ. For λ equal to 0.03, it is possible to save 1.148 mil of travelled kilometres with only 0.77 mil EUR as extra costs. It corresponds with establishment of 83 transfer stations with total capacity 4.25 mil tones. There can be suggested locations for transfer stations, which are robust both with regards to the objective functions and uncertainties. These transfer stations can represent the first step for stakeholders in supporting sustainable waste management. The consideration of the environmental and economic aspects of the different solutions must be further examined in a much broader context. Another factor that could improve the model in the future is the addition of more decision stages, providing the possibility to plan the opening/closure of the transfer station alongside with the development of the waste processing infrastructure. Also, it is possible to merge the transfer station planning model with a model for the planning of the waste processing infrastructure, which would offer a more holistic view. However, such a model is likely to cause severe tractability/computational issues, that need to be addressed by the development of appropriate algorithms.

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ORIGINAL PAPER

Logistic model-based tool for policy-making towards sustainable waste management

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Jiří Kropáč · Ondřej Putna · Vít Procházka

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Abstract The aim of this paper is to introduce a novel approach which supports facility planning in the field of waste management. Only 23 % of municipal solid waste (MSW) was thermally treated in the EU 27 in 2011. The increased exploitation of its potential for energy recovery must be accompanied by massive investments into highly efficient and reliable incineration technologies. Therefore, the challenge is to be efficient and use the technology to its optimal level. Feasibility studies of all plants providing a service for a region create a large and complex task. Gate fee (the charge for waste processing in the facility) represents one of the most crucial input parameters for the assessment. The gate fee is driven by configuration of the technology, competition, market development, environmental taxation and costs of waste transport to satisfy the plant's capacity. Valid prediction of the gate fee thus presents a demanding task. In this paper, first, an advanced tool called *NERUDA* is introduced, which addresses logistic optimization and capacity sizing. The key idea is to focus on the problem of competition modelling among waste-to-energy plants, landfill sites, and mechanical–biological treatment plants producing refuse-derived fuel. Then, the main theoretical concepts are discussed, followed by the development of a suitable mathematical model. The goal is to obtain a minimized cost of MSW treatment for waste producers (municipalities). The application of the developed tool is demonstrated through a case study, where uncertain parameters entering the calculation are handled by a repetitive Monte Carlo simulation based on real-world data.

Keywords Supply chain · Optimization · Waste-to-energy · Monte Carlo · Gate fee · Waste management · Waste management plan

List of symbols

CEE	Central and Eastern Europe
CZE	Czech Republic
DH	District heating
EU	European Union
IRR	Internal rate of return
LCA	Life-cycle assessment
MBT	Mechanical and biological treatment
MSW	Municipal solid waste
R1	Energy efficiency, R1 factor
RDF	Refuse-derived fuel
WM	Waste management
WMP	Waste management plan
WTE	Waste-to-energy (plant)

Introduction

This paper deals with the recent salient issues of the municipal solid waste (MSW) management facility planning, and by facility planning, we mean proposing processing capacities and waste logistics optimization, which both play an important role. Individual Member States of

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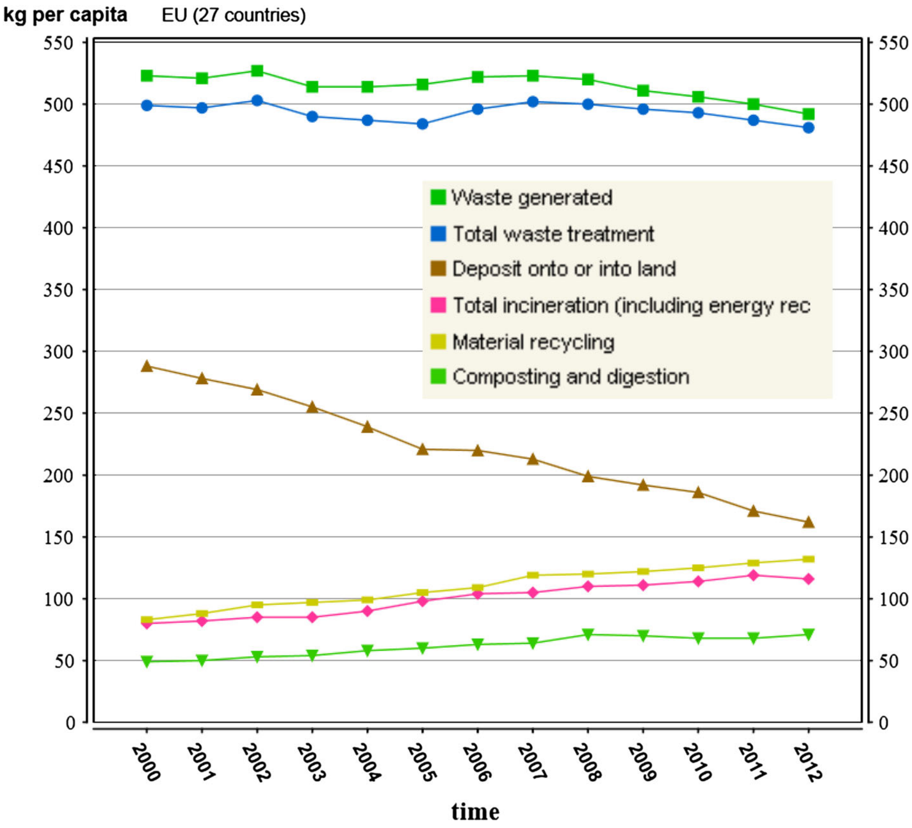


Fig. 1 Trends of municipal waste generation and treatment in the EU, by type of treatment method (Eurostat 2012)

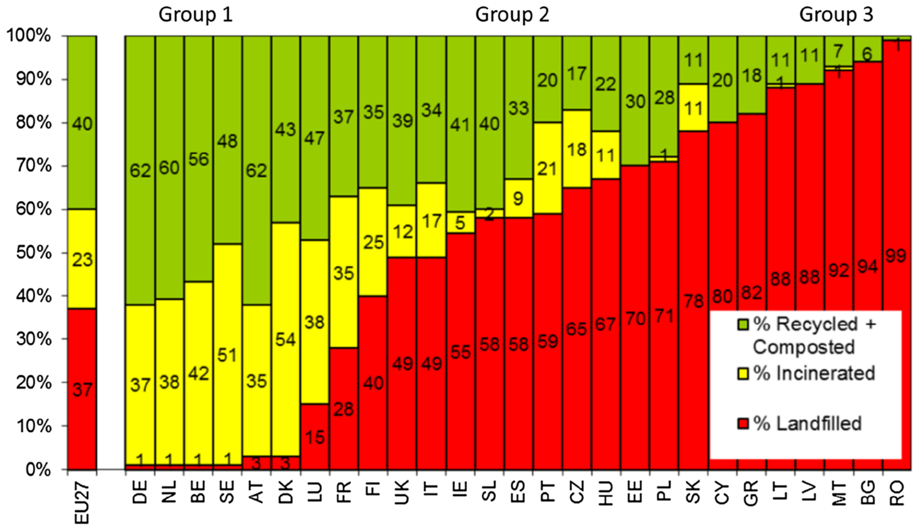


Fig. 2 Municipal waste treated in 2011 in the the EU 27, by country and treatment category (% of municipal waste treated) (CEWEP 2013)

the European Union (EU) are committed to reducing the ratio of landfilled waste, and at the same time, to treating the waste in an efficient way. Specifically, the EU issued Directive 2008/98/EC on waste and the hierarchy of waste management (WM). Waste prevention is a priority of the Directive, followed by a decrease in waste production. The reuse of certain products should also be promoted. Material recovery is at the third level in the Directive hierarchy. If all the previously mentioned levels of WM are fully exploited, energy recovery from waste should then be preferred to waste disposal, e.g. landfilling and incineration, which has no energy recovery.

In order to demonstrate the contemporary situation in the EU, a short summary of how WM is currently handled will now be given. The graph in Fig. 1 shows that the generation of MSW in the 27 Member States of the EU (EU 27) has been moderately falling. The current average of waste generation is slightly below 500 kg per capita per

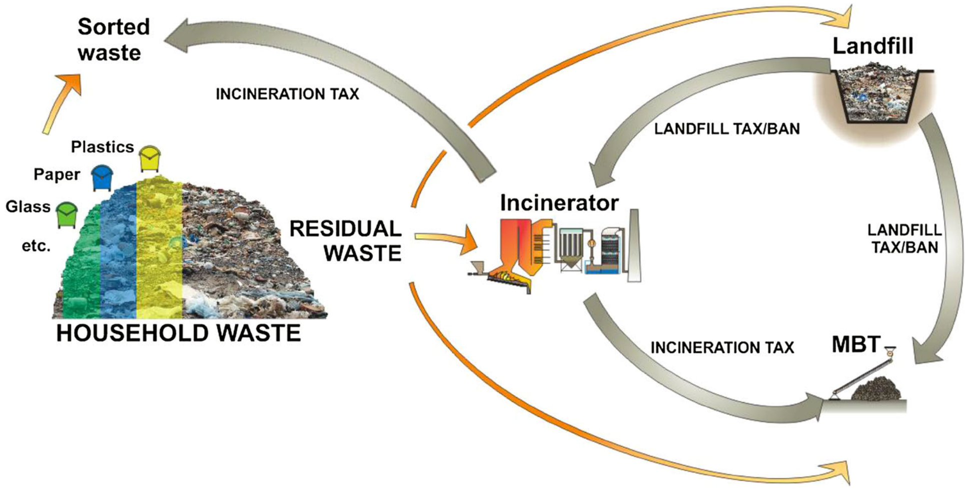


Fig. 3 Impact of landfill tax/ban and incineration tax on waste flow among key elements of MSW processing system

year. One may also notice a progressive tendency to prefer material and energy recovery to landfilling (Eurostat 2012). The latest data on the proportion of MSW processing methods (recycling, incineration, composting and landfilling) in the EU Member States in 2011 are given in Fig. 2.

Figure 2 clearly shows that the current situation and efficiency of WM vary greatly across Europe. We may distinguish between three groups of countries in this paper. Yet, there is no rigid boundary among particular groups:

Group 1 (Fig. 2 left)—we can identify countries with well-developed WM, where landfilling has been nearly eliminated. The majority of MSW is recovered for material reuse. These successful countries focus on sophisticated and effective waste collection which encompasses dozens of recyclables. The amount of residual waste, which cannot be recycled, has seriously decreased. Landfilling of this untreated and biodegradable MSW is forbidden, and therefore it is incinerated. The amount of incinerated waste is high and ranges between 30 and 40 % of the total waste generation. Incineration plants, therefore, play a significant role in these countries' WM, and the promotion of recycling is reinforced by incineration taxes (see Fig. 3). Waste prevention policy combined with demographic development may create overcapacities in the following years, and there is an ongoing discussion whether intensive recycling is sustainable for the future (Velis and Brunner 2013).

Group 2 (Fig. 2 middle)—countries where the changes towards more sustainable WM are in progress. Here, legislation is already in place, and policy is implemented in the waste management plan (WMP). There is a sufficient processing capacity but, unfortunately, processing capacity commonly refers to landfill sites, and a great share of biodegradable waste is still landfilled. These countries do not forbid waste landfilling, but they do impose landfill taxes to redirect some waste from landfilling to material recovery and/or WTE (Fig. 3). Countries in this group are experienced in waste-to-energy (WTE) plant operation. However, material recovery is insufficient, and there is still potential for its further enhancement in these countries. Overall, in these countries, more WTE projects are being prepared, and new WTE plants are being built or have building permission confirmed. The United Kingdom (UK) may serve as an example of a country on the borderline between the first and the second groups. The UK exported almost 868 kt of mechanical–biological treatment (MBT) products in 2012 (see below) (CHIWM 2013). Currently, the UK has around 18,900 kt/y of residual waste treatment capacity either 'operating' or 'under construction', which includes 44 dedicated incineration facilities and 57 other facilities. The capacity of prepared/designed projects is equal to 24,200 kt/year (Eunomia Research and Consulting 2013).

Group 3 (Fig. 2 right)—Countries awaiting the transformation of WMPs. These have insufficient capacity for processing waste, even concerning landfilling sites. Landfilling is not restricted, a low amount of waste is recycled and no WMPs are in place.

For more information about the current state in the individual EU Member States, see a detailed study issued by BiPRO (BiPRO 2012). It aims to evaluate Member States in terms of their compliance with the above mentioned hierarchy, existence and efficiency of economic tools for WM promotion, number and stage of development of waste treatment facilities, and planned projects and fulfilment of the targets for the diversion of biodegradable waste from landfilled sites.

As mentioned above, one of the key economic drivers towards efficient WM is a landfill tax or total ban on landfilling untreated waste. These restrictions influence the economy of key system elements (landfill sites, WTE, MBT, separated collection followed by material recovery, etc.) and thus the waste flow as well. This impact is summarized in a graphical form in Fig. 3.

The general relationship between the price of treating waste, landfilling, and recycling, including an analysis of correlations between the implementation stages of these strategies, is studied in (European Commission 2012). Further comments on the issue can be found in the paper (Van de Wiel 2010), where the impact of introducing these taxations for the transfrontier shipment of waste is reviewed. The recent phenomenon of overcapacity for WTE in certain countries, accompanied by legislation allowing cross-border transport of waste and different processing prices, has created a competitive environment within the EU. According to the report (Eunomia Research and Consulting 2013), if all currently planned projects in the UK, with a capacity of roughly 24,200 kt/year, are successfully implemented, there will be approximately 13,800 kt/year of overcapacity. By 2020, Germany expects incineration overcapacity to be 3,000 kt/year (Dehoust et al. 2010). Therefore, the import of waste into countries suffering overcapacity will become an important issue. Any possible imports are conditioned by energy recovery in the target country. Incineration facilities must comply with R1 (Energy efficiency, R1 factor) stipulated by the EU legislation, which allows the MSW incinerators to be classified in R category ('Use principally as a fuel or other means to generate energy') (2008/98/EC) and thus profit from this classification. An analysis and comparison of R1 factors can be found in Grosso et al. (2010) and Reimann (2012). Pavlas and Touš (2009) evaluated particular systems of MSW incinerators in terms of energy utilization and their impact on various operation modes on the R1 value. Since R1 is strongly dependent on the rate of energy generation, it has a direct relation to primary energy savings. Pavlas et al. (2010) proved that energy generated in MSW incinerators contributes to primary energy savings, as well as energy from biomass, whereas the release of emissions and pollutants is significantly lower.

Waste today has more denotations than it traditionally used to have. It is a valuable commodity—a source of energy and a source of raw materials at the same time (e.g. ferrous and non-ferrous metals). These factors lead to situations where it is beneficial to transport the waste even over long distances. This initiates the development of a unified market which is then divided into regions with insufficient processing capacities (sources of waste, groups 2 and 3) and regions where free processing capacities are available (sinks of waste, group 3). In such an environment, countries are supposed to plan, build and operate new capacities in the near future in order to meet obligations to reduce the amount of landfilled biodegradable waste (European Commission 2012). These new capacities will include not only WTE, but also MBT.

MBT spread to several EU countries in the 1990s. The process incorporates the mechanical grinding and separation of waste followed by biological processing (anaerobic decomposition and/or aerobic composting). This technology separates the input waste flow into utilizable parts. For more information about this method, see (Department for Environment, Food and Rural Affairs 2013). One MBT product is the refuse-derived fuel (RDF) with sufficient calorific value for subsequent use as fuel in combustion plants (power plants, cement plants, etc.). Finding end-users for RDF and local conditions at a particular site is vital for an efficient processing chain incorporating MBT. This line of argument is supported by various studies looking into Life Cycle Assessment (LCA) in WM. In addition, this method helped us find several general insights into the suitability of the MBT. Consonni et al. (2005) showed that when assessing all potential impacts, the direct incineration of untreated waste in an up-to-date incinerator is the most preferred strategy. Münster et al. (2013) stressed the need for the development of scenarios for the assessment of projects researching both WM and energy issues not only in the case of LCA; but Ma et al. (2010) discussed also the increased risk of corrosion due to chlorine presence in RDF. MBT was an important topic in WM debate in the 1990s and has been increasingly utilized in some countries, e.g. in Italy and Germany. Today this concept is proposed as a tentative solution for countries in groups 2 and 3.

Since the two concepts (i.e. direct combustion of MSW in WTE and RDF production in MBT) correspond to the overall balance in significantly different ways, we have summarized the key figures related to each concept in Fig. 4.

Although the sustainability of each concept should be evaluated based on both financial and environmental criteria, the final decision about pushing a specific project into realization is made by the investor. In this decision, the prediction of a competitive gate fee plays an essential role as an important economic parameter Šomplák et al. (2012a). They investigate the economy of scale related to specific WTE. They also mention the positive effect of falling per ton capital costs with increasing capacity. The cost of waste transport should be included as well, as it increases with the capacity and waste can be shipped even over long distances. At the same time, the supply chain, comprising all operations following the route of the waste from the place of its origin to its final processing place, becomes more and more complex (collecting vehicles, waste transfer stations, rail and truck transport, loading/unloading mechanisms, etc.).

In this complicated situation, it is useful to have a computational tool which can support decisions related to the following activities: (1) feasible location screening for WTE and/or MBT sites and their sizing based on residual waste availability; (2) waste flow simulation between waste

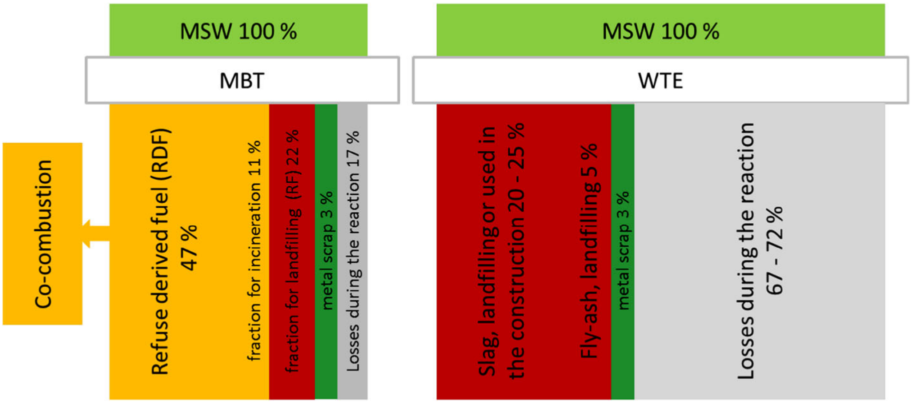


Fig. 4 A comparison of overall mass balance for WTE and MBT facilities (based on data provided by Thiel 2011)

sources and waste sinks in a rapidly extending EU waste market as an approach towards waste-availability modelling in a specific region; (3) support on supply chain planning and infrastructure improvement to remove expected bottlenecks; (4) project feasibility evaluation (risk analysis) focused on the prediction of competitive processing price (Šomplák et al. 2012a); and (5) impact evaluation of regulation and legislation (landfill taxes or ban).

Following from an extensive review published by Ghiani et al. (2013), many papers have contributed to the phenomena of WM modelling. However, the theoretical concepts and models have thus far focused on specific fields (e.g. collection itself, the exploitation of capacities of different types of technologies, transport cost minimization). In addition, they have considered some limitations and presumptions, e.g. fixed or linear cost, one technological concept included, limited number of nodes. Optimum solutions have been proposed, but a discussion about the project's feasibility, from the point of view of potential investors, is missing, and this restricts their practical application.

Therefore, our team has developed a computational tool called *NERUDA* which supports the aforementioned activities related to a new WTE project in its early stage of development (conceptual development phase). The benefits of using such a tool for analysis including hundreds of sub-regions and tens of plants is demonstrated in this paper through a case study aimed at a specific region (the Czech Republic—CZE).

The basic idea behind the *NERUDA* tool is as follows: the producer of waste (a municipality in case of MSW) makes a decision about its future MSW treatment strategy. The objective function addresses expenses in terms of cost for waste processing at individual facilities and the overall cost of the transport of waste to the facilities. Environmental taxation is included as well and reflected in the gate fee (environmental externalities can be included in the same way if necessary). For a discussion on the potential problems in the creation of models for WM planning and price estimates, see Parthan et al. (2012). The basic idea is the minimization of costs, which is presented in Fig. 5.

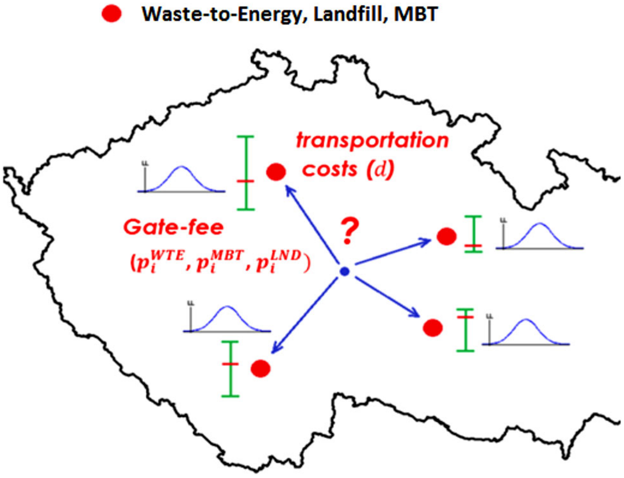


Fig. 5 A visualization of the basic ideas of transportation problems behind the developed tool

Although the idea presented in Fig. 5 looks simple, as soon as it is spread into the simultaneous calculation of many sub-regions, it turns into a comprehensive model (see "Mathematical model" Section) dependent on gathering and processing of real-world data. The sets of inputs can, of course, differ depending on the level of detail in the investigation. In general, the sets include information about: (1) *existing logistic infrastructure*—routes and their quality, taxation, railway corridors and their loading, distances, and expected transport times; (2) *waste-management statistics*—specific waste production, waste lower heating value, availability of separate collections systems for recyclables and their efficiency, demand for secondary raw materials, etc.; (3) *facilities*—existing landfill sites, incineration plants, new projects under consideration and/or erection; (4) *prices*—energy prices (heat, electricity, fuels), landfilling taxation, etc.

Mathematical model

First, we have to mention papers relevant to the topic, and solution methods. There are several inspiring texts dealing with sustainable supply chains design (Young et al. 2012), energy network solutions for regions (Kettl et al. 2012), descriptions and simulations by p-graphs (Süle et al. 2011), and multiple-criteria reduction in biomass energy supply chains (Varbanov et al. 2012). Concerning useful sources related to logistic models, we have to mention Ghiani et al. (2004) and Williams (2009) concerning indicator-variable integer programming techniques. There have also been several attempts to tackle the topic using an operational research approach, see (Lang et al. 2003). However, no paper has yet dealt with as an extensive case study which also assesses profitability and risks as that we shall present later in "Practical application in a selected region" Section.

We have successfully dealt with a decision-making process related to the specific WM strategy and built a specialized transportation optimization model. The key idea is to study the disposal of waste produced in villages and towns (sources of waste) and to model an approximate competitive environment. We denote sources of waste as nodes, and roads are represented as edges. Thus we minimize the overall costs as follows:

$$\begin{aligned}\min \sum_j dv_j x_j + \sum_i \sum_j a_{ij} x_j \left(p_i^{\mathrm{WTE}}\left(C_i^{\mathrm{WTE}}\right) + p_i^{\mathrm{LND}}\right) \\ + \sum_j ev_j l_j + \sum_i \sum_j a_{ij} l_j p_i^{\mathrm{MBT}}\left(C_i^{\mathrm{MBT}}\right)\end{aligned} \tag{1}$$

subject to (constraints are valid for all nodes i representing sources of waste):

$$\sum_j a_{ij} + o_i + \delta_i^{\mathrm{MBT}}\left(\sum_j a_{ij} l_j + \sum_j b_{ij} t_j\right) \le C_i^{\mathrm{WTE}} + C_i^{\mathrm{LND}} \tag{2}$$

$$\sum_j a_{ij} l_j \le C_i^{\mathrm{RDF}} \tag{3}$$

$$-\sum_j a_{ij} l_j \le C_i^{\mathrm{MBT}} \tag{4}$$

$$\delta_i^{\mathrm{MBT}} \sum_j a_{ij} l_j = \delta_i^{\mathrm{MBT}} \sum_j b_{ij} t_j \tag{5}$$

$$\delta_i^{\mathrm{LND}} \sum_j a_{ij} x_j + \sum_j b_{ij} t_j \le C_i^{\mathrm{LND}} \tag{6}$$

where x_j is an amount of MSW transported by arc j, l_j is the RDF amount transported by edge j, t_j is the TF amount transported by edge j, a_{ij} is an incidence matrix for MSW and RDF transportation graph, b_{ij} is an incidence matrix for RF transportation graph, d is the MSW unit transformation cost for 1 ton, e is the RDF transportation cost for 1 ton, and v_j is the length of edge j (distance between related nodes), p_i^{WTE} (C_i^{WTE}) is a gate fee for 1 ton of MSW in WTE in node i, p_i^{MBT} (C_i^{MBT}) is a gate fee for 1 ton of MSW in MBT in node i, p_i^{LND} is a gate fee landfill for 1 ton of MSW in node i, o_i is an amount of MSW production in node i, C_i^{WTE} is a WTE capacity in node i, C_i^{LND} is a capacity of landfilled site in node i, C_i^{MBT} is a capacity of MBT in node i, C_i^{RDF} is a capacity for RDF incineration in node i, δ_i^{LND} is equal to 1, if node i is of landfill type, and equals 0 otherwise, and δ_i^{MBT} is equal to 1, if node i is a village with MBT, and equals 0 otherwise.

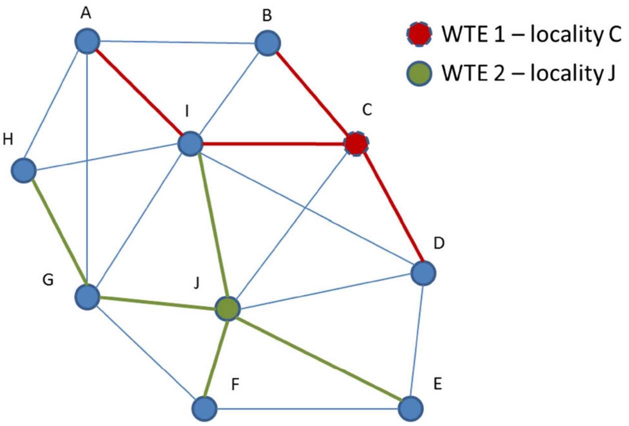


Fig. 6 Visualization of transportation network for simplified task

Calculation, simplified task

In order to provide an easy explanation of the model, we will first demonstrate the principles of calculation on a simplified task. The example here considers only a small number of nodes and edges (10 nodes, 21 edges) and does not account for the processing of waste in a MBT plant or its landfilling. Only two WTE facilities (C and J nodes in Fig. 6), which have a fixed annual processing capacity of 300 kt/year each, are considered. The overall capacity 600 kt/year slightly exceeds the total generation in all the selected nodes A to J, which is 570 kt/year (see Table 1). The gate fee is constant and amounts to 74 EUR/t and 81 EUR/t for facilities in C node and in J node, respectively. The objective function and all constrains are linear. Therefore, the solution is global. Figure 6 presents a transportation network with relevant data for this simplified optimization task. Data related to infrastructure model are summarized in Table 2.

Only road transport is considered, and the transportation price is constant, regardless of distance, amounting to 0.15 EUR/(km t). The compression of waste in transfer stations and relevant transportation price optimization are not

Table 1 Waste generation as considered in simplified task

Node	A	B	C	D	E	F	G	H	I	J
Waste production (kt/year)	50	80	85	55	75	45	35	70	35	40

considered either. Waste generation at particular nodes of the transportation task is given in Table 1.

The mathematical model is simplified to the subsequent objective function (7) and one constraint (13).

$$\min \sum_j dv_j x_j + \sum_i \sum_j a_{ij} x_j p_i^{\mathrm{WTE}} \tag{7}$$

provided that (constraint applies to all nodes and edges)

$$\sum_j a_{ij} x_j + o_i \le C_i^{\mathrm{WTE}} \tag{8}$$

Results may be easily checked, and the validity of the mathematical model may be proved thanks to the simplicity of the task. The results of the example are given in Fig. 7 and Table 3.

It is obvious that a real situation, where hundreds of subregions are optimized simultaneously, with necessary nonlinearities, makes the verification of results essentially impossible. Such an application of our tool is presented in the next section.

Practical application in a selected region

Now, we would like to introduce the benefits of our tool through its more practical real-world data-based application.

Introduction to the case study

We follow on from the discussion about future WTE potential capacities in CZE as mentioned in Šomplák et al. (2012b) and Pavlas et al. (2010). Based on the classification above, CZE falls into the second group. There are 10.2 million inhabitants in CZE, and current waste generation reaches 2.93 million tons, i.e. the specific generation per capita amounts to 287 kg/year, which is below the EU average. There are three incinerators in operation with an overall processing capacity of 645 kt/year, another incinerator is under construction, and several more are planned to be built in the future. The recent WM concept presented by Pavlas et al. (2012) proposes up to 11 new WTE projects with an overall capacity of 2,200 kt/year after 2020 (see Table 4; Fig. 8). A small number of MBT plants and plants co-incinerating RDF are included as well. The total technical potential—of waste-based net power and heat production of 800 GWh/year and 14 PJ/year, respectively—is predicted for all WTE plants. The figure of 800 GWh/year may be compared with current power production from biomass, which reached approximately 1,500 GWh in 2012. The expected heat delivery may reach 16 % of the current heat delivered to end-users via district heating (DH) systems (2012 data).

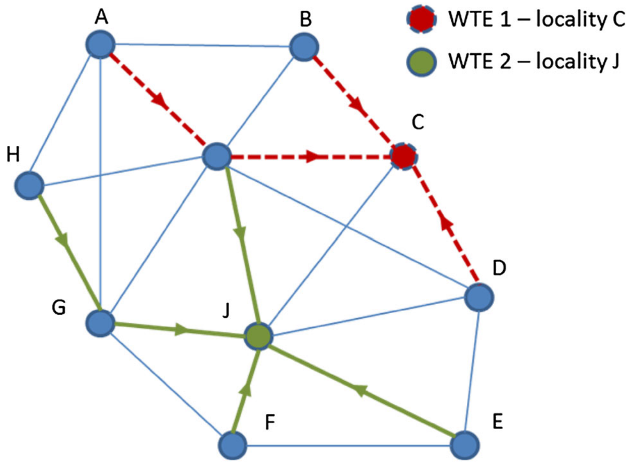


Fig. 7 Graphical representation of results of the simplified optimization task

In this paper, we are planning to go one step further in the analysis. We simulate the performance of this concept from an economic point of view with the help of our tool *NERUDA*.

Note: The country is characterized by a large amount of heat delivered by DH systems (88 PJ in 2012). Currently, heat is mainly supplied by coal-fired heating plants. New locations for WTE are associated with large cities where sufficient DH systems exist.

Calculations and Monte Carlo simulation

Since gate fee is the crucial input parameter in the model, we start this section with some comments on the methodology used for its generation. Constant values of gate fees are often considered in published papers and thus were also

Table 2 Definition of transportation network for simplified task–distance matrix

Edge defined by nodes	A B	A G	A H	A I	B C	B I	C D	C I	C J	D E	D I	D J	E F	E J	F G	F J	G H	G I	G J	H I	I J
Distance (km)	30	42	25	25	25	23	28	28	38	26	40	34	35	34	27	20	25	34	25	29	33

Table 3 Results of the simplified optimization task

Edge defining nodes	A B	A G	A H	A I	B C	B I	C D	C I	C J	Node with WTE plant	C	J
Amount of waste transported (kt/year)	30	42	25	25	25	23	28	28	38	Amount of waste treated (kt/year)	300	270

Table 4 Values of survival function for projects with capacities considered in the concept (scenario Sc2)

	X	**Y**	A	B	C	D	E	F	G	H	I	J	K	L
Planned capacity (kt/year) Pavlas et al. (2012)	**150**	**150**	171	220	285	96	190	180	270	95	452	220	140	163
Survival function $R(c)$ [%]	**2**	**43**	35	100	88	97	17	98	79	31	86	97	13	85

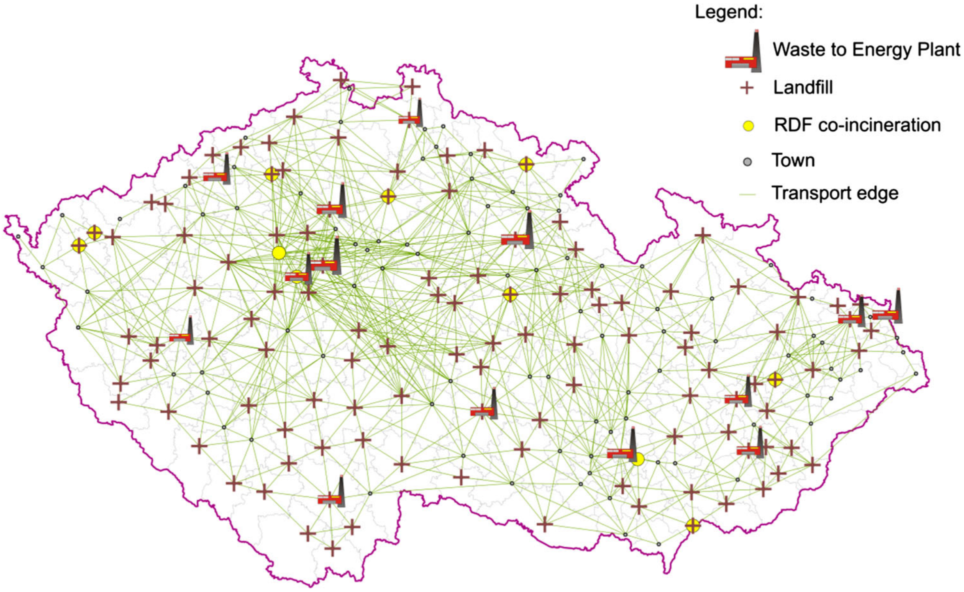


Fig. 8 Transportation infrastructure of the model with key elements for assessed concept

considered in our simplified task. In this case study, we take into account the economy of scale (see $p_i^{\mathrm{WTE}}(C_i^{\mathrm{WTE}})$ in Eq. 1), where the effects of falling specific capital costs with increased capacity can be observed. The gate fee function is generated separately for each project included in the assessment by external techno-economic models. The specific conditions in the locality (e.g. heat demand, heat price, existing infrastructure reducing capital cost) are taken into account as well. An example of capacity-dependent gate fee function is depicted in Fig. 9. The prices are projected onto 2020 (year of calculation) considering an annual inflation of 3 %. Let us briefly explain the meaning of parameter IRR in Fig. 9.

The sustainability and financial attractiveness of each new project are determined by many uncertain parameters (energy prices, waste quality, maintenance, unexpected power outages, etc.). All of these parameters have their own positive or negative effects on the project's cash flow and subsequently on the project's profitability, which is often expressed by internal rate of return—IRR. The sensitivity of IRR (under varying futures in uncertain parameters) can be tested under the assumption of a fixed gate fee with the use of complex techno-economic models. Vice versa, if IRR is fixed, we can investigate the sensitivity of the gate fee. We considered the same average IRR of 10 % for each competitive project in our case study, which is considered to be adequate revenue related to this industrial sector and expected by a private investor. To address the uncertainty, we as well set its minimum and maximum values to 8 and 12 %, respectively. The corresponding gate fee intervals are determined in the next step (see Fig. 9 as an example).

The optimization of the aforementioned objective function (Eq. 1) was repeated thousands times for varying combinations of gate fees at individual facilities. The gate fee for each calculation was generated by the Monte Carlo

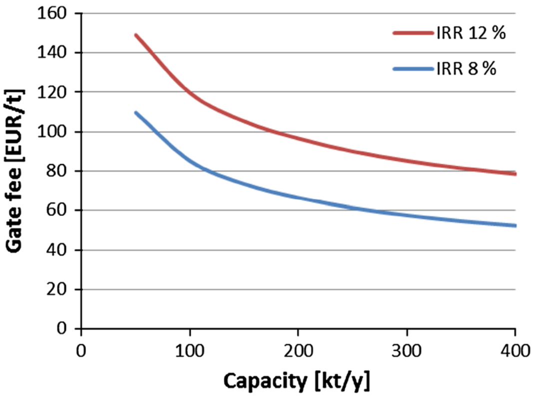


Fig. 9 An example of capacity-dependent gate fee function generated for one specific project. Uncertainty of future development in key economic parameters is addressed by varying internal rate of return (IRR)

method using the gate fee interval with the truncated normal probability distribution function. This stochastic approach, which may be considered a wait-and-see approach by terminology of stochastic programming (Birge and Louveaux 2011), allows for the subsequent statistical analysis of results.

Results

There is too limited space here to give a detailed description of all benefits of our *NERUDA* tool, and therefore we will now present only few examples of our results.

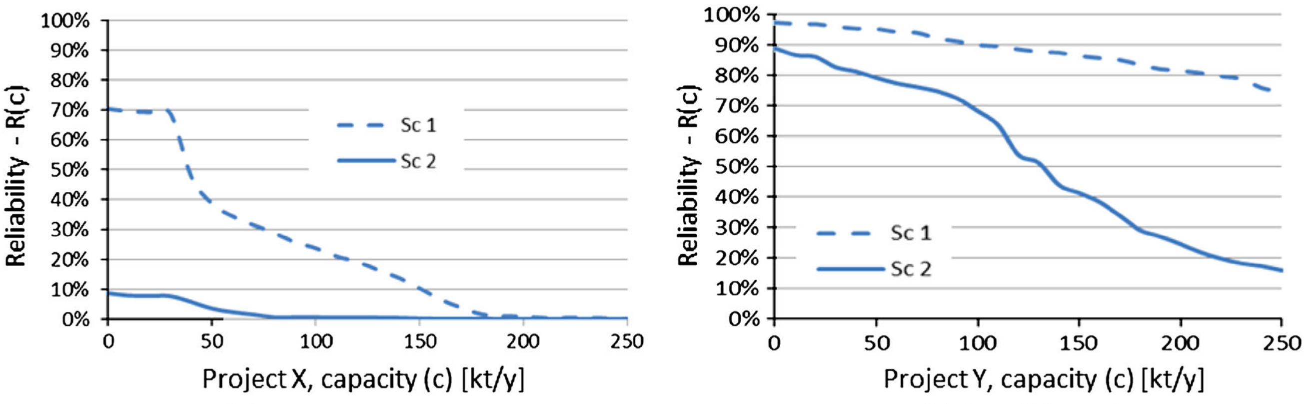
The first result is related to risk analysis, where two WTE projects to be located in different locations (denoted as X and Y) are compared. Figure 10 shows that they perform in a manner completely different from each other. The risk is expressed by survival function (see Fig. 10):

$$R(c) = P(\{C > c\}) = \int_{c}^{\infty} f(u)\mathrm{d}u = 1 - F(c). \qquad (9)$$

where $F(c)$ is the cumulative distribution function, and c is plant capacity. Function $F(c)$ is obtained from the results of a Monte Carlo simulation. In each run, one capacity c for the project was proposed as optimally reflecting the current gate fees of all competitors. The survival function $R(c)$ (complementary cumulative distribution function or reliability function) then expresses the percentage of experiments resulting in a capacity higher than capacity c. Moreover, two different scenarios related to legislation development were included (Sc1—promoting WTE only; Sc2—promoting both WTE and MBT). Under the assumption that the same capacity of 150 kt/year for both projects was proposed by the concept specified in Table 4, we conclude that project Y is less sensitive to future competitors, whereas project X is very risky and probably feasible only under specific circumstances resulting in a lower gate fee and subsequently in lower IRR.

One can speculate about the effect of an even higher landfill tax 80 EUR/t expected in our calculation in Sc1 and Sc2. This situation is depicted in Fig. 11 where the relationship between the risk and landfill tax is shown. The project in locality X remains high-risk even under conditions of a high landfill tax. Other methods to enhance its competitiveness have to be investigated (e.g. establish if it as a municipal project with lower return on investment expectations).

The survival function $R(c)$ was evaluated for each plant. The results for one scenario are presented in Table 4. The calculation also proposes collection areas for each facility, and therefore, maps the expected future flow of waste in



(a) High-risk project **(b)** Feasible project

Fig. 10 Risk-analysis related to the reliability of capacity fulfilment performed on two projects in different locations for two different scenarios of future legislation development

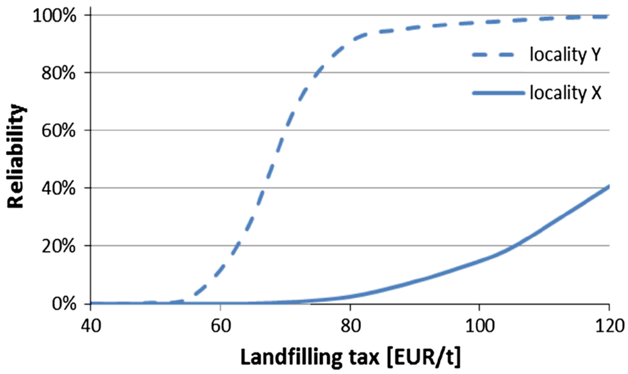


Fig. 11 Risk-analysis related to the reliability of capacity fulfilment performed on two projects under different landfill taxation rates

the region. This information is crucial for a survey of the traffic load and missing infrastructure planning. A graphical illustration of collection areas is depicted in Fig. 12. The layout fully corresponds to the proposed concept of WM; almost all WTE facilities are in operation. The majority of waste is incinerated directly; only a small portion goes through a MBT process and/or is landfilled. These streams are excluded to keep Fig. 12 clear.

The results prove the complexity of the task which has to deal with all locations simultaneously. We have demonstrated a sensitivity analysis of environmental taxation (Sc1 and Sc2). In the same way, waste calorific value, fuel prices, transportation costs and limitation, the situation in neighbouring countries (cross-border transport of waste) and other uncertain parameters can be included as well. There are two approaches available. We can model scenarios, or we can generate values from an interval. The first method was used for Sc1 and Sc2, the latter for gate fee modelling in our case study. For the each of further applications, the task can be adjusted with respect to the required targets of the calculation.

Further research and other *NERUDA* applications

Previous sections presented a logistic task and application of the model on a specific region and one type of waste. The task must be interpreted as motivational. The model is universal and may be modified depending on the assignment. Modifications include various locations and types of waste (the so-called multi-commodity problem), discussed in detail in (Ghiani et al. 2004). In general, the model may be applied to altogether different commodities. Several potential subjects may benefit from the developed tool, and they are given in Fig. 10. It is clear that end-users of the results (e.g. state administration, representatives of government, potential investors interested in new plants, operators of existing plants) will differ in their motivation and objectives and that the application must be always tailored to their needs. Future development of our tool (reflecting current demands) is expected as follows:

- Previous parts of the paper discussed a stochastic approach based on repeated calculations with adjusted input data according to defined scenarios. Reliability functions are generated subsequently (see Fig. 10). Obtained functions indicate risky and/or attractive

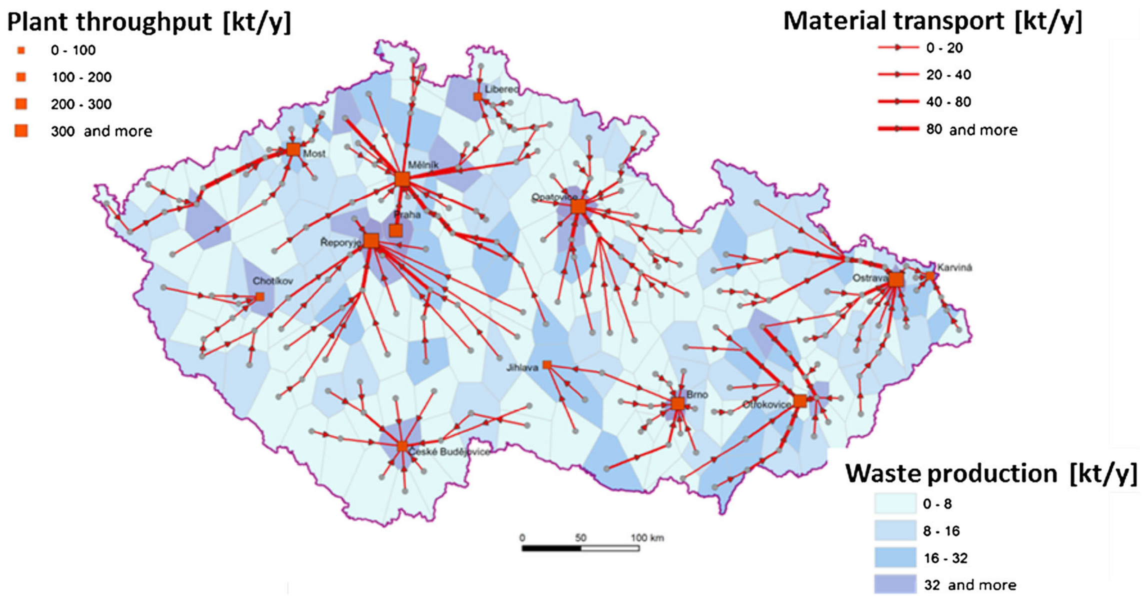


Fig. 12 Visualization of results of the transportation model for one particular scenario—high landfill tax introduced, energy produced in WTE supported by subsidies

projects. This approach is called a wait-and-see approach. We further plan to focus on the generalization and modification of our model to involve uncertain parameters in a more complex way, see (Huang et al. 2001; Birge and Louveaux 2011). This will lead to an improved methodology for risk assessment under uncertain future conditions.

- The calculation model described in this paper allows for simulation only for a single time-frame, i.e. a year. Our new and improved model will include sequences for several years, where calculation results from previous years constitute inputs and constraints for future years. Therefore, particular years of the simulations interact. This also enables modelling of long-term contracts between producers and operators.
- In all the previous points, the tasks are related to analyse waste flow on an annual basis. Such a calculation provides us with a conceptual insight into the problem. Once the promising patterns of the sender and the receiver are identified, a detailed analysis is expected. The whole logistic chain is optimized in terms of selecting the best transportation system and sizing it. The result is sensitive to many local aspects (fluctuation in waste production, local infrastructure, transport routes, loading and an increase in freight transport duration times due to transport accidents). These local factors must be considered in a task simulating a short time-frame (shipment on a daily basis). A typical application includes finding a location for transfer stations within metropolises and/or regions.

Conclusion

In the paper, the tool *NERUDA* for conceptual planning of new WTE capacities was introduced. By using the calculations results, WM policies can be implemented through legislation amendments. In addition, it is also possible to determine the attractiveness of potential sites for the construction of new facilities. Therefore, the proposed optimization model contributes to effective WM.

The model represents a transportation problem implemented in WM. Its practical application was demonstrated through a case study related to a specific region (the Czech Republic). A risk analysis of two WTE projects located in different areas was performed.

Another challenging task is the application of our tool for simulation and/or optimization of a developing and ever-growing EU waste market. The introduction of the model in large areas exceeding the borders of one country will inevitably increase the requirements/demand for input data.

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Příloha 8: Publikace [A28] – A waste-to-energy project: A complex approach towards the assessment of investment risks.

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Research paper

A waste-to-energy project: A complex approach towards the assessment of investment risks

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HIGHLIGHTS

- Some regions of the EU will have to invest into thermal treatment in the coming years.
- Feasibility studies with risk analysis are major parts of the pre-project phase.
- New methodology for risk analysis based on a competition modelling proposed.
- Waste availability is one of the most important risk factor.

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ABSTRACT

This paper presents a complex methodology towards investment risk quantification in a waste-to-energy (WTE) project. It focuses on risks related to the supply of waste. A novel approach is proposed, where waste availability is assessed based on a complex simulation of future competition in the waste market.

The methodology takes advantage of complex calculation performed by the system NERUDA. NERUDA is a logistic-based optimization tool, which allocates processing capacities and proposes waste flows between producers and processors within modelled region. One original feature of the methodology is how the assessment is formulated, whereby the optimum collection areas are compared with a project's capacity. The new term waste availability factor is defined and used in the assessment. The practical implications of such an approach are demonstrated through a case study.

The results of this work support decision-making processes involved in new WTE projects. Since one of the major risks is a lock of waste availability, its evaluation represents an integral part of feasibility studies for WTE projects.

1. Introduction

Waste production, and its environmentally-friendly treatment, has become a worldwide challenge. The European Union (EU) has established a hierarchy of waste management based on the classification of various waste treatment methods with the prevention of waste is the foremost aim. Recycling methods and material recovery fall next in the waste treatment hierarchy. However, these methods are rather costly and do not allow for processing all municipal waste. Furthermore, the higher are the yield of these methods, the higher are the costs. Energy recovery from waste, i.e. recovery through incineration with subsequent use of the energy for production of electricity and heat, is employed if the above mentioned methods cannot be applied. Waste disposal without energy recovery and landfilling are the last resort.

It has been estimated that approximately 1.7–1.9 × 10^9 tonnes of municipal solid waste is produced annually worldwide. Only about 70% of this amount is actually collected within organized waste management (WM) systems, and only 20% is utilized (through energy or material recovery) in compliance with the EU waste treatment hierarchy [1]. However, some countries in Western Europe, such as Germany, Switzerland, the Netherlands, and Belgium, rank highest in the share of waste utilization, with numbers reaching as high as 80–90% [2].

WM in the EU has and will undergo major developments. Many countries have experienced a positive trend in the so called process

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of decoupling, when an economy is able to grow without burdening the environment [3]. However, individual EU Member States are at different levels in their approaches to waste treatment.

Many EU countries, especially from Central, Southern and Eastern Europe, have agreed to decrease the amount of landfilled biologically degradable waste by 2020. This represents 50–60% of municipal solid waste produced in an area, and an increase in the share of material recovery from waste. The shift towards more efficient utilization requires the design of intelligent regional strategies together with investors' willingness to build and operate new incineration plants.

1.1. Modelling approaches toward efficient waste management systems

Many studies have discussed the topic of how sustainable particular WM solutions are, and compared them extensively.

One subsection of studies commonly deals with conditions in specific regions, and their conclusions are therefore locally-dependent. Evaluation methods for various WM technologies include supply-cost curves analyses [4] or life cycle assessments (LCA). Beccali in Ref. [5] applied LCA on a comparison of three WM systems; Kočí and Trečáková in Ref. [6] compared seven model systems using the LCA method. Margallo in Ref. [7] then introduced normalization and weighting procedure for the results of LCA studies.

Another group of the published studies present theoretical models and procedures aimed at finding the optimum arrangements integrating more technologies. An extensive review of modelling optimization techniques was published in Ref. [8]. Waste treatment optimizations are often calculated for large regions, and then try to propose the best location for WM facilities in a given area. However, this effectively tackles only waste transportation and the only criterion is the cost. An example of a multi-criteria objective function is given in Ref. [9] where two approaches are presented, which deals with sustainable system synthesis. Another example is using multi-objective mathematical calculations for decision making support in Ref. [10]. Interesting multi-objective optimization of WM in Mexico is used in Ref. [11] where it is used to maximize the net annual profit and minimize the environmental impact.

From a practical point of view, the currently available models dealing with these issues are often insufficiently interconnected, and very limited in their practical implementation. Researchers are now facing the task to make the computational methods more sophisticated and simpler. Lam et al. [12] reduced the connectivity in a biomass supply chain in order to lower the computational time. In a similar manner Ng [13] presented a clustering approach for optimizing industrial resources.

The recycling targets of the EU, should they be applied to all EU countries, are rather ambitious. The aim of the EU is to move all Member States up the waste treatment hierarchy, which is above all costly and of course unwelcome by the general public, especially if they should bear the costs. However, acceptance is one of the pillars of sustainability, as was resolved at the World Summit on Sustainable Development in Johannesburg 2002. In this context, WTE is a sustainable solution for many regions (in low-income countries) as it presents less ambitious targets and may be the first step in moving higher up the waste treatment hierarchy. WTE systems may bridge the gap in WM in Eastern European countries as well as create the chance for developing markets worldwide [14]. Even though those future obligations exist, it looks as though the current motivation driving investors' activity to move the projects from planning to their implementation phase is missing.

1.2. A successful waste-to-energy project – the basic requirements and feasibility studies

The construction of a WTE plant is a rather costly, complicated, and prolonged endeavour. Investment costs of a WTE plant and technologies range from 700 to 1000 EUR/t of annual capacity [15]. The preparation phase lasts 5 years at best but is usually longer [16]. Moreover, the life cycle of these plants lasts 20–30 years. To help future investors, several guides and manuals have been issued e.g. the World Bank presented general guide for evaluation of WTE plant [17] or more specific guide from Themelis [18] that deals with situation in Latin America. Despite the fact that the manuals were drafted for various countries over different periods, the basic principles and conditions remain the same, and are as follows:

- A stable planning environment (15–20 years), relatively stable and preferably foreseeable cost of spare parts, consumables, etc.
- Energy delivery contracts
- A relatively stable market and energy costs
- A reliable supply of suitable waste for the waste incineration plant
- The annual mean lower heating value of the waste cannot drop below 7 MJ/kg
- The support of stakeholders
- The acceptance of the plant from the general public and municipalities – good public awareness
- Support from the Government/legislators – landfill taxes/bans, bonuses, tax relieves, etc.

If all of these conditions and principles are met, a situation for the building of a WTE project is ideal. If any of these needs fall short of what is required, the project team has to rely on a detailed analysis that will prove the economic and technical feasibility of the project from the investor's point of view. The project has to be acceptable from the stakeholders' point of view.

Prefeasibility and feasibility studies are major parts of the pre-project phase. The contents of both of these studies are basically identical, but differ in input data and structure (see Table 1). The prefeasibility study is drafted using generally available data and references. The feasibility study must work with accurate information and data from a given location so that the project team may estimate relevant factors, evaluate project financing and identify a financing strategy as accurately as possible.

The risk analysis is one of the most important parts of the feasibility study. The risk analysis refers to the identification of the greatest risk sources, the risk's impact on the project's stability and financing, and/or measures taken to minimize the risk. An extensive risk analysis for WTE, established and run as a PPP project, is given in the study by Song [19] who identified various associated risks and classified them in ten major groups. These are: government decision-making risk, government credit risk, legal and policy risk, technical risk, contract change risk, environment risk, public opposition risk, waste supply risk, payment risk and revenue risk. Song [19] further describes a potential correlation of risks when a poor governmental decision-making process results in the selection of an inadequate plant location. This in turn may cause a failure to comply with environmental requirements, the dissatisfaction of local authorities, and the rescission of certain contracts.

1.3. Identifying and assessing investment risk

The basic structure of expenses and income given in Fig. 1 gives us a clear idea what the risk analysis should focus on. The particular parameters affecting expenses and income of the project significantly change throughout the life of the plant, and each parameter

Table 1
Content of WTE pre-feasibility and feasibility studies [18].

Pre-feasibility study	Feasibility study
• The potential location of the plant • The outline of waste collection areas, and basic information about the average composition of waste coming from different producers • Basic demographic information • Basic information about plant size, capacity and technology • A basic environmental assessment • An estimate of investment and operational costs and gains • Project organisation	• The potential location of the plant • The identification of the waste collection area, and detailed information about the composition of the waste • Demographic data for the given location • A stakeholders' analysis • Detailed energy market research: consumption, cost, competition • Plant design (size, capacity, technologies, etc.) • Full environmental assessment • Project organization – others • The identification of the plant's organization and management • Risk analysis and control

has a different impact on the final return on investment (ROI) of the project.

Expenditures do not usually fluctuate much and there is little risk unless the plant encounters a serious accident or has to face unexpected expenses. Risk is therefore associated with the revenue of a plant. Revenue includes income from the sale of electricity and heat (supplies into a system of central heat source or integration of the WTE facility with other commercial facilities). These sales are affected by price trends, and by the amount of the produced and exported commodity. However, the processing of waste is the most important income. This main revenue is then set by the gate fee price.

Song [19] discusses only information about the mere existence of the risks. Unfortunately, his work provides no quantification data on particular risks and/or the quantification of the risk's impact on the project returns indicators, e.g. the internal rate of return (IRR) and payback (PB) [20]. Pereira [21] and Li [22] both present quantitative data related to the risk, and analyse the risks using a Monte Carlo method applied on photovoltaics and wind farms, respectively. Various indicators help assess the quality of an investment project [20]. The outcome of the first article [21] is a net present value (NPV), and dynamic payback period (T_d) and IRR in the second article [22]. In both cases, energy is converted from renewable resources of energy (wind, sun). However, the availability of wind and sun is rather random, which affects production costs and interferes with the competitiveness of the plant. Therefore, statistical planning and scenario analyses must be employed in the assessment. A similar analysis of a WTE was outlined by Ferdan [23] who modelled the gate fee (price for waste processing) using variable input parameters; see Section 3.

1.4. The objective of the paper

High investment costs, uncertainty of profit (the availability of waste, price of waste processing, energy cost, etc.) along with competition from landfills, make WTE projects an ideal area for utilizing advanced simulation and evaluation techniques. Such a tool could provide the investor and stakeholders with all the necessary information for their decisions. All studies dealing with project planning and constructing WTE plants (e.g. the aforementioned Refs. [17–19]) list particular risks but do not mention any methodology for calculating input data for the risk analysis.

This paper presents the required methodology for a complex assessment of an investment project risk associated with future waste delivery and waste processing price. Regarding the gate fee, the intended project has to be competitive with the current treatment method. Future environmental taxation is also taken into account. In addition to this, the plant has to be competitive with any other intended projects in the area. With increased plant capacity, the collection area becomes larger and it can interfere with the collection areas of other projects (see Fig. 2). To secure the waste available within the collection area a competitive price should be proposed.

The objectives of the paper are: (1) evaluate the availability of waste – a key aspect in the project's success, (2) identify risks associated with waste shortage and assess. The proposed methodology contributes to resolving questions such as: the size of the waste collection area, and availability of the waste and its cost.

2. Methodology based on a competition modelling approach

The methodology proposed in this paper is focused on waste availability modelling and its evaluation. It is based on an innovative computational approach involving complex simulations of future competitive environments. For this a network flow optimization tool NERUDA is used. The approach comprises three interconnected steps (see Fig. 3). Step 1 and step 2 exploit the findings of our previous work which was recently published (see Sections 2.1 and 2.2). The main objective of this paper is step 3 – a newly developed simulation analysis focused on quantifying risks from a limited supply of waste (Section 3). The new term *waste availability factor* is defined within the framework of our methodology and used in the assessment. Competition modelling concerns several competing plants, whereas the subject of this analysis is one particular WTE plant.

Since the methodology takes advantage of the repetitive use of the NERUDA tool, let us first summarize its main features and

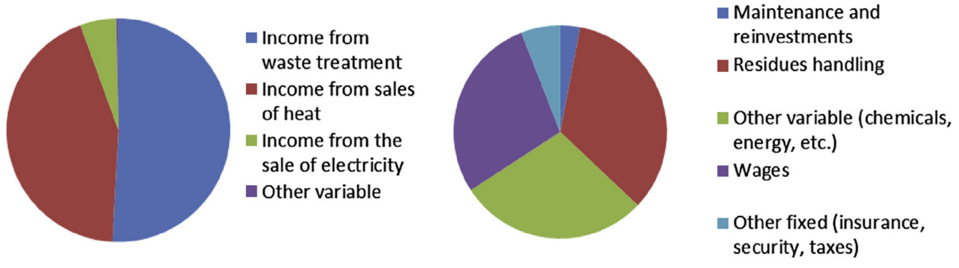

Fig. 1. An example of structure of incomes (left) and expenses (right), [%] [15].

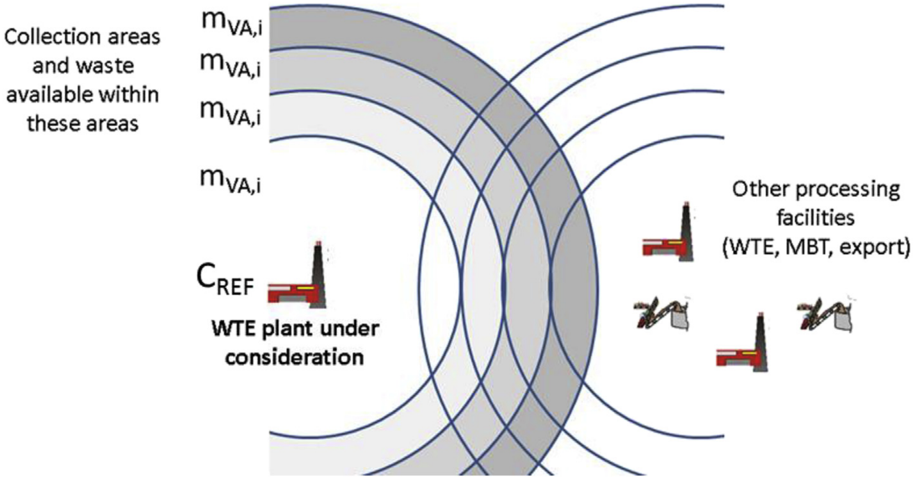

Fig. 2. Interference of collection areas resulting in a limited waste availability.

provide more details for predicting gate fees in relation to the objective of this paper.

2.1. NERUDA introduction and its basic features

NERUDA is a network logistic-based computational tool which simulates and optimizes waste flow from waste producers to processing facilities within a particular geographical area (region, country, etc.). These regions are then divided into many sub-regions represented by nodes. A detailed description of the tool, its main principles and equations forming the mathematical model, is provided by Šomplák et al. [24]. In the same paper, the model is first explained with a simplified example covering only a few nodes and then an extensive case study with more than 200 nodes is solved.

The tool contains data about basic waste producers (municipalities) within the sub-regions, the waste transportation network between nodes, and existing plants processing waste. The calculation is performed for all nodes (producers) simultaneously. The results of the calculation provide information about waste flows and allocate processing capacities. The tool is currently able to compare three types of waste treatment methods – WTE, mechanical-biological treatment, and landfilling, and the tool is open for further extensions. Moreover, the simulations take into account transfer stations where waste volume is reduced by pressing into containers. This decreases the costs of transportation over long distances. So far, road and rail transportation has been integrated in the software.

The tool further allows for us to evaluate investment projects and the competitiveness of new and existing waste processing facilities. NERUDA helps producers (municipalities) in a given region optimize waste treatment by employing the basic principle of minimizing the cost of waste treatment in this region. Generally, the application potential of NERUDA (see Fig. 4) is as follows:

- The design and optimization of waste management concepts at various levels of public administration

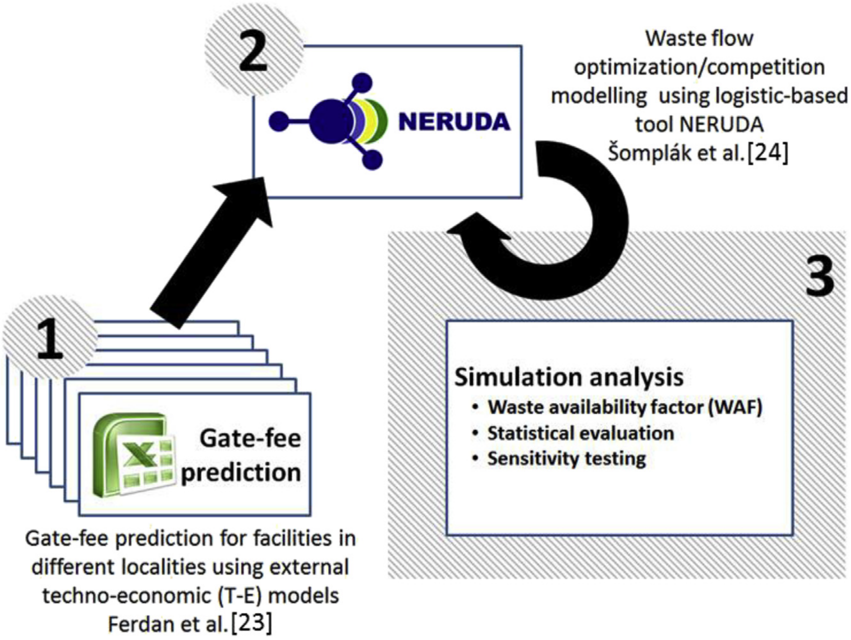

Fig. 3. The components of our waste delivery risk analysis methodology.

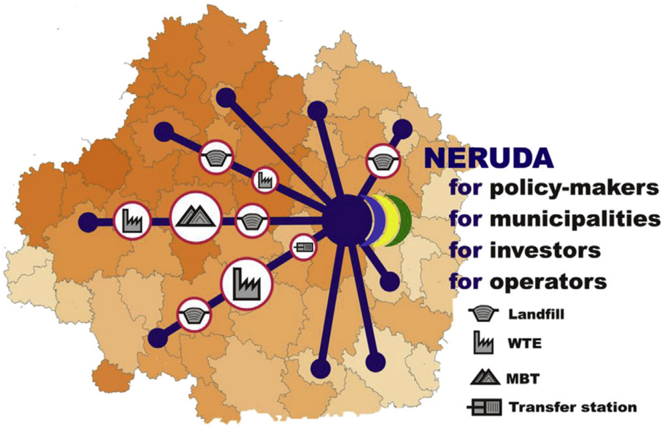

Fig. 4. Scheme of NERUDA software and components included.

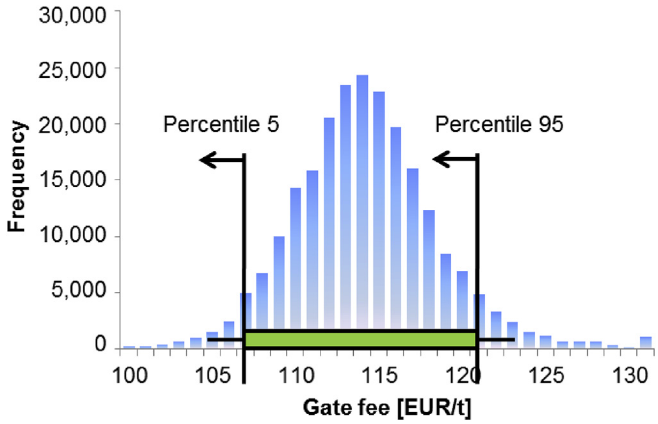

Fig. 5. A histogram of the gate fee distribution for a given capacity C_{REF} [23].

- A feasibility study of plant investments
- The optimization of waste transportation
- The complex modelling of waste market.

Calculations in NERUDA are influenced by a number of uncertain parameters which can be predicted only with difficulty. However, these parameters influence waste availability, plant economy, plant competitiveness and energy production, and therefore have to be considered and integrated in the simulations. This is done with a stochastic approach and scenario generation.

Following Fig. 3, calculations in the NERUDA software are an intermediate step in our methodology. Before the calculation, an interval of a suitable fee at a WTE gate is identified for all facilities included in the assessment. The desired return on investment is considered as well. Since we deal with the project preparation phase and future predictions, changes in key parameters, which affect the project economy, should be considered. This phase is called the "gate fee prediction" and it is introduced in the next section.

2.2. Gate fee prediction

Estimating the facility gate fee, using the desired returns given by IRR, is the foremost part of the whole methodology. We developed a "Flexi model" to help us here. A flexi model is a technical-economic model of a WTE plant which integrates an adjustable balance model of technology and a complex economic model. The flexi model allows us to set various configurations of technologies employed in modern incinerators, and then simulate the economic outlook for the whole duration of the project, see Ref. [23].

In order to identify the dependency of gate fee vs capacity, it was useful for us to apply a scenario-based approach. We used various scenarios to outline the development of major parameters which affect the project economy (energy costs, maintenance costs, etc.). The scenarios are generated using geometric Brownian motion. Real historic data, relevant to the location of the planned plant, are used for the scenario generation. Individual parameters are assumed to correlate with each other. We performed that many simulations to guarantee convergence. It was measured by several characteristic parameters of probability distribution (mean value, variance, kurtosis, skewness). Results were used to construct a histogram which displays the gate fee distribution. Fig. 5 gives a concrete example for a particular capacity.

The results of most of the proposed and simulated scenarios ($C_{REF} = 150$ kt/y) show that the gate fee ranges from 107 to 121 EUR/t. These values correspond with 5 and 95 percentile, and are displayed in Fig. 5.

The simulations were repeated for various C_{REF} capacities ranging from C_{MIN} to C_{MAX} (e.g. 50–400 kt/y in Fig. 6). A dependency graph of gate fee vs capacity is constructed using point estimates (Fig. 6).

The decreasing gate fee, together with an increasing capacity, reflects lower specific investments cost per ton of processed waste. This positive effect outweighs the negative effect of falling income from heat delivery (if measured in GJ per ton of waste incinerated). Our simulations in NERUDA also have to consider zero capacity (i.e. the NERUDA tool will not recommend building the plant). Problems with integer programming (switching between zero capacity and C_{MIN}–C_{MAX} interval) are overcome by an extrapolation close to zero capacity with extremely high gate fees. Therefore capacities in the range of 1–50 kt/y are never proposed.

Whereas two gate fee values related to 5 and 95 percentile for specific C_{REF} and IRR were presented in Fig. 5, these points are converted into two capacity-dependent curves in Fig. 6. There is a relationship between the gate fee and project profitability. Therefore, we present two sets of results. One result where the lower IRR of 8–10%, represented by the value 9%, is requested by a public investor (e.g. municipal project), and the other for meeting a private investor's requirements (IRR of 10–12%), represented by the value 11%.

The results presented are valid for one location (one facility). In order to simulate the competitiveness of the plant, the gate fee of competing plants must be specified, i.e. a similar prediction must be done for all locations. We introduced a financial plan for each location, considered specific local aspects, and then generated the gate fee curves. These enter the NERUDA calculation later on, when we incorporate additional payments and fees, such as landfill tax

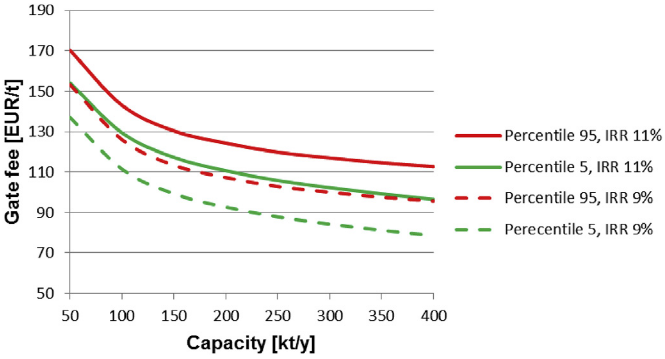

Fig. 6. The dependency of the gate fee and capacity–gate fee curves.

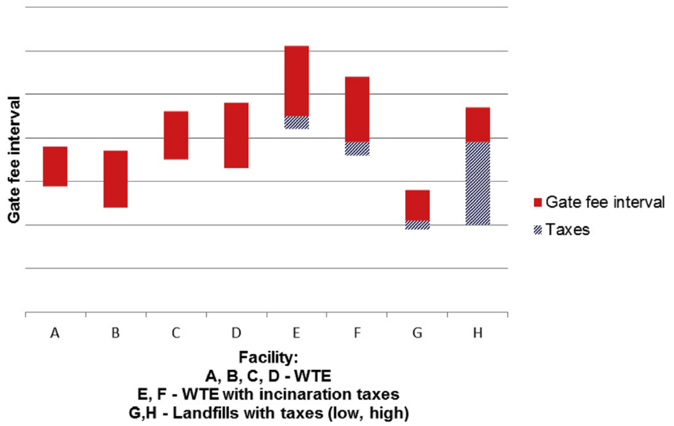

Fig. 7. Gate fees at various locations and environmental taxation – basic inputs for the NERUDA tool.

and incineration tax (see Fig. 7), by which market competition in waste management is simulated. The dependency of the gate fee against the capacity is a result of the first step and serves as an input for the competition modelling phase.

3. A simulation analysis for evaluating waste availability

Previous sections discussed conditions for the sustainable operation of a WTE plant and gave an overview of associated risks. One of the major risks is an adequate and constant supply of municipal waste, i.e. waste availability. Waste availability is mentioned in every paper which deals with risk analyses and WTE project evaluation. However, none of these papers actually present a principle for determining waste availability. This is obviously a precondition for a quantitative risk assessment and any identification of a risk's impact on the project's finances (using, for example, an IRR indicator).

3.1. Waste availability and waste availability factor

We decided to formulate a new criterion called *waste availability factor (WAF)*, and to incorporate it in our methodology. This new criterion helps quantify and display the effect that changes to various parameters (such as capacity, landfill fee, and IRR) have on waste availability.

Before we proceed to explain the calculation of the WAF, we want to clearly define the parameters which are evaluated by the NERUDA software:

- C_{REF} – reference capacity. The capacity of the plant which is subject to a risk analysis.
- C_{MAX} – maximum project capacity. The maximum capacity is identical with the value of CREF before individual iterations, and is relaxed during the simulation analysis described in the following section.
- C_{OPT} – optimum capacity – the calculation result obtained in every calculation step. This is the sum of waste transported to the plant from several subregions.
- m_{WA} – waste availability – amount of waste produced within a specific geographical area. This amount may be a subject-matter of future negotiations between producers and processor. Both the producer and the waste processor must agree on the cost of waste processing (the gate fee), and only then can they enter into a contract. The facility operator offers the cost of waste processing, and the waste producer opts for the best price on the market. In other words, waste availability is a sum of municipal waste production in the municipalities which find the proposed gate fee as the cheapest alternative.
- Waste availability factor (WAF) – the ratio between waste availability and planned reference capacity C_{REF}; defined by equation (1). The calculation of WAF is discussed as a simulation analysis in the following section.

$$W_{AF} = \frac{m_{WA}}{C_{REF}} \tag{1}$$

An example of the calculation is shown in Section 3.3 in addition to a graphical representation of the parameters used to calculate the WAF. The capacity C_{REF} is set before the calculation and the capacity C_{OPT} is the optimum obtained from the NERUDA calculation for each scenario.

3.2. The basic principles for determining WAF

The simulation analysis is based on the tool NERUDA and provides us with a quantification of waste availability and/or WAF criterion. Šomplák [24] gives the basic principle of calculations in NERUDA. A shortened description is as follows: The capacity of existing projects is given. The optimum capacity C_{OPT} of all new projects in locations (i) must be identified; the gate fee is related to capacity via functions similar to Fig. 6. This principle is presented in Fig. 8. The capacity of individual projects may be limited by C_{MAX}.

We slightly modified the basic principle to accommodate the risk assessment. Waste availability is analysed for a given capacity (C_{REF}). The basic principle is governed by the following maxim: waste is available if the waste producers have no cheaper alternative for processing their waste.

Calculations are commonly carried out as a stochastic simulation, but for now we will not consider any scenarios. We present a procedure for a simulation run (further marked as a point in Fig. 10) which consists of the following steps:

- The capacity of an evaluated location is given as $C = C_{REF}$. The gate fee (GF_{REF}) is assigned to this capacity. The fee is fixed throughout the calculation.
- The gate fee is dependent on capacity ($GF = f(C)$) in other locations (competing projects). Capacity C_{OPT} is unknown (it is a variable) and the gate fee is given by a gate fee curve as in the basic calculation (see Fig. 6). The waste processing cost was estimated using a technical-economic model for all waste processing projects (see Section 2.2).
- Waste availability at a fixed cost GF_{REF} is analysed later. For now, the capacity is unknown, the C_{MAX} limit is relaxed (the capacity is theoretically unlimited), and we search for the optimum amount of waste mw that is available at this price. This optimum

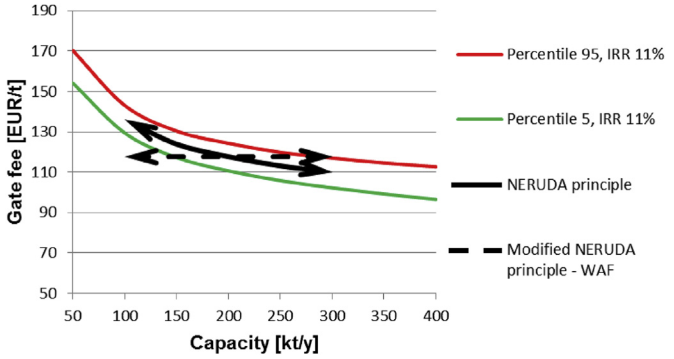

Fig. 8. NERUDA principles.

amount is then defined as waste availability m_{WA}. The calculation scheme is illustrated by horizontal arrows in Fig. 8.

- The WAF is evaluated using equation (1).

If the waste availability m_{WA} is higher than the reference capacity (C_{REF}), the project is sustainable and complies with the requirements for profitability, and the WAF is higher than 1. If the waste availability is lower than the reference capacity, the facility does not have an adequate amount of waste at GF_{REF} fee (WAF is lower than 1, see Fig. 9 and for more details Table 2). In order to obtain enough waste, investors should expect a lower gate fee, which decreases their income and consequently the returns too (IRR). We calculated WAF for various IRRs so that we can demonstrate the dependency of waste availability on project returns. This solution allows us to simulate various types of ownership arrangement.

3.3. An example of WAF calculation

To clearly demonstrate how the calculation of WAF works with NERUDA, we present a simple case study. The whole geographical region (country, state, etc.) is divided into 41 nodes (municipalities, cities, etc.), see Fig. 9. Each sub-region is characterized by its residual waste production, which at the same time represents waste available for thermal treatment with WTE. The plant (the subject of the risk analysis) is placed in node 8 in this particular case, see Fig. 9. Its competitors are not displayed for simplicity. The computation in NERUDA was carried out and we obtained results from 500 simulations (various gate fees for other projects). We present the results for two particular scenarios, see Fig. 9. The data for those 2 scenarios are presented in Table 2.

In each scenario, the NERUDA tool proposed a collection area (see Fig. 9). Waste from other sub-regions is treated in different facilities. Following this, we the amount of waste transported to the facility. This is amount is identical with the optimal capacity C_{OPT}, which was provided by NERUDA. The WAF is then calculated using the equation (1). The total waste transported to the facility in scenario 1 is lower than the reference capacity, therefore WAF is equal to 0.80. In the other scenario the amount of waste exceeds the reference capacity and WAF is 1.28. The results are displayed in Table 3.

3.4. A stochastic simulation to determine WAF

Compared to the previous simplified example, we now wish to present a more complex analysis here which incorporates various

Table 2
Input data for calculating WAF as received from the simulation analysis using NERUDA tool.

Node	Waste delivered to the facility		Transportation cost	Scenarios		
	Amount [t/y]	Price [EUR/t]	[EUR/t]			
1	1,742	67.72	7.4	Scenario 1	Reference capacity C_{REF}	Scenario 2
2	10,620	67.72	4.9			
3	2,783	67.72	3.1			
4	7,801	67.72	6.1			
5	10,470	67.72	2.9			
6	5,323	67.72	6.2			
7	4,120	67.72	5.6			
8	12,521	67.72	0.2			
9	5,398	67.72	4.5			
10	51,384	67.72	3.7			
13	4,534	67.72	6.7			
15	2,825	67.72	10.7			
11	1,827	67.72	10.1			
14	5,678	67.72	10.3			
16	1,523	67.72	10.8			
17	5,225	67.72	11.4			
19	14,350	67.72	11.9			
20	1,874	67.72	12.5			
12	3,898	67.72	10.5			
18	5,347	67.72	12.5			
21	4,674	67.72	12.6			
22	599	67.72	13.3			
23	6,946	67.72	12.6			
24	17,210	67.72	14.8			
25	3,120	67.72	12.0			

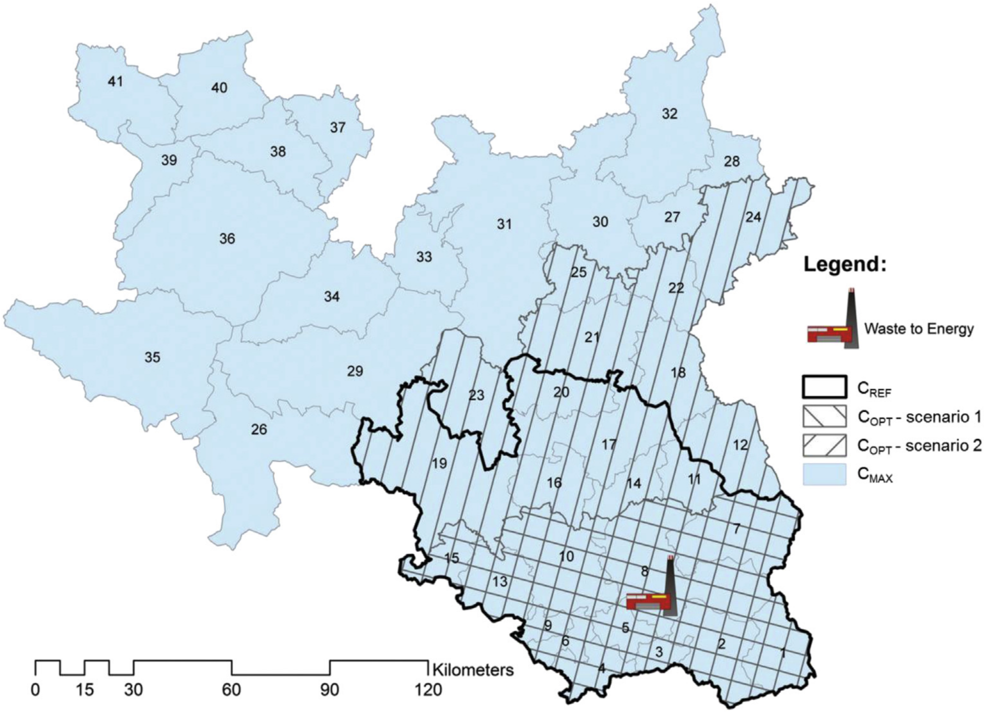

Fig. 9. A graphical illustration of two proposed collection areas for two different scenarios.

Table 3
Waste availability factor calculation.

Parameter	Total waste [t/y]	Reference capacity [t/y]	WAF [−]
Scenario 1	119,522	150,000	**0.80**
Scenario 2	191,795	150,000	**1.28**

uncertainties embodied in the scenarios. The capacity of the project may not be decided at this stage of the project development, and, therefore, it may be useful to analyse WAF for different reference capacities C_{REF}. We simulated the scenarios where C_{REF} ranged from 100 to 350 kt/y (six scenarios, each with a 50 kt/y increment). Likewise, legislation trends on landfill fees are also unclear as the fees may range from 37 to 81 EUR/t (seven scenarios, each with an 8 EUR/t increment). In total, we simulated 42 scenarios (i.e. combinations of various capacity solutions and various landfill fees). We simulated 500 situations for a particular scenario; the gate fee from a predefined interval was randomly generated for all projects (see Section 2.2).

Fig. 10 displays the sensitivity of average WAF to the changing capacity C_{REF}. The results are valid for a 75 EUR/t landfill fee. Two options for desired returns were evaluated: IRR ranging from 10 to 12%, and 8–10%. The results are presented further.

The project with lower IRR requirements (an IRR of 8–10%) produced better results for all capacities compared to requirements for higher returns (an IRR of 10–12%). The waste availability factor rises along with the rising capacity for both IRRs, see the graph in Fig. 10. The project has enough waste, obtained at a gate fee corresponding to 8–10% IRR, if capacities exceed 150 kt/y. However, a further increase in capacity does not result in an increase in WAF. The advantages of higher gate fee are outweighed by the need for a larger waste collection area and higher transportation costs. Competition from other plants also becomes fiercer as the waste collection area enlarges. Compared to the reference capacity (C_{REF}), the project has a capacity reserve of roughly 25–30% for capacities exceeding 150 kt/y. If the investors require higher returns (IRR of 10–12%), the analyses prove that the waste availability at a given reference capacity (C_{REF}) is inadequate for all scenarios. A facility with capacities exceeding 200 kt/y has only 80% of the required waste available.

Since the calculations were carried out in a stochastic model, we may analyse the results in greater detail. Let us now focus on capacity $C_{REF} = 150$ kt (see the black points in Fig. 10). Fig. 11 displays a histogram of the amount of available waste (m_{WA}) which was calculated in particular simulation runs. The results of waste availability at IRR = 10–12% clearly show that most of the simulations (95%) estimate that the waste availability for C_{REF} of 150 kt/y will be lower than the reference capacity; only 5% of simulations estimate sufficient amounts of waste. These values correspond with an average waste availability factor of ca. 0.4 (see Fig. 10).

We constructed a similar histogram for IRR = 8–10% (see Fig. 12). Most of the simulations (81%) proved that there is enough waste available. The rest of the simulations (19%) showed a lack of available waste. Incidentally, the two scenarios mentioned in

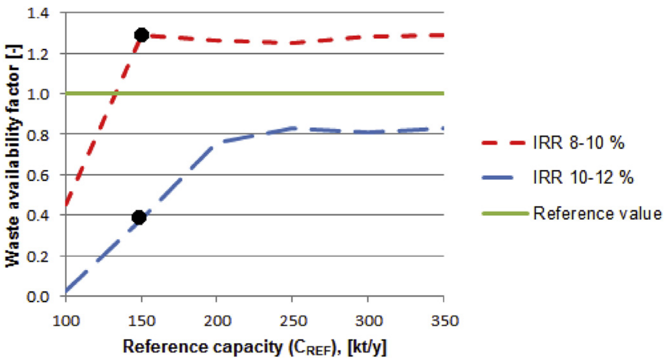

Fig. 10. The dependency of average WAF and reference capacity.

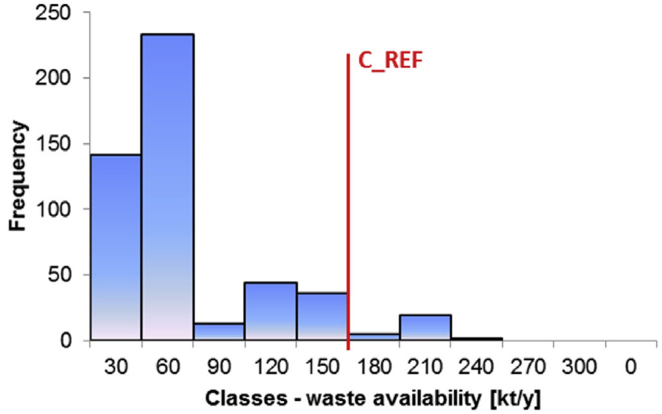

Fig. 11. A histogram of waste availability for IRR of 10–12%.

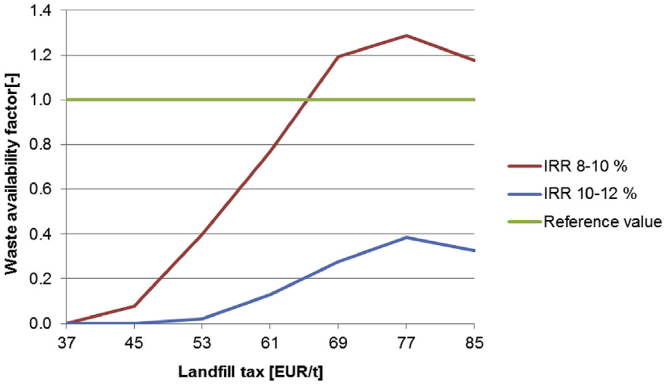

Fig. 13. The dependency of WAF and landfill tax.

Section 3.3 are displayed in Fig. 9 as well. Here we may analyse risk factors and/or a set of boundary conditions affecting the results.

The results proved that if the plant had insufficient amounts of waste (WAF lower than 1), a relatively small decrease in gate fee (lower requirements on return of investments) significantly increased the probability of meeting the capacity (i.e. having sufficient amounts of waste). This gate fee – waste availability dependency is unique for each project, and reflects concrete locations and competition in the close vicinity of the plant.

3.5. The impact of other parameters on WAF

An assessment into the impact of a particular parameter is a different type of simulation results analysis. Fig. 13 displays the dependency of waste availability and landfill tax. The results were calculated for a reference capacity (C_{REF}) of 150 kt/y. Again, we analysed two options for potential returns: an IRR of 10–12%, and IRR of 8–10%. The decrease in waste availability for 81 EUR/t landfill tax is caused by tough competition from other projects, especially those based on mechanical-biological waste treatment technologies. The results presented in Fig. 13 are average values of all simulations with relevant boundary conditions (scenarios).

For returns higher than 10%, waste availability is very low (max. factor of 0.4) even for a landfill tax fee of ca. 75 EUR/t. If returns drop below 10%, waste availability is satisfactory for a landfill tax rate of ca. 63 EUR/t. If the landfill tax equals 75 EUR/t, the project has a ca. 30% waste reserve above the reference capacity C_{REF}. The results may again be analysed in greater detail (as for Figs. 11 and 12). We may identify the factors which impose a risk on waste availability and economic sustainability. We shall deal with these issues in the following section.

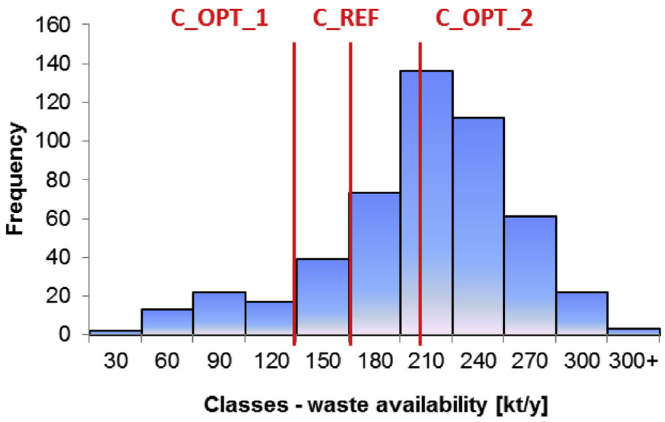

Fig. 12. A histogram of waste availability for IRR of 8–10%.

The previous parts of the text discussed the relationship between the gate fee and waste availability. Many other risks are associated with the gate fee. The project must be successful, and for example an increase in operational costs must be compensated with an increase in income. The gate fee, therefore, reflects a certain scenario and must provide the project with a sufficient amount of waste. The scenario is a combination of developing parameters (risk factors) which may impose a risk on the project.

4. Conclusion

In this paper a novel methodology was proposed for a complex analysis of risks associated with limited waste delivery. The formulated methodology comprises three steps, which are logically linked and make up a thorough system.

The first step in this methodology is identifying the dependency of the gate fee in relation to the capacity for several facilities. These are derived from complex techno-economic models addressing technology- and locally-dependent parameters.

A major element and important computational tool is the software NERUDA, which is used for simulating waste flows, allocating processing capacities and determining collection areas (step two). The subject of the calculation is a particular region. Regarding its application, the basic features of NERUDA were introduced.

The last step in our proposed methodology comprises a simulation analysis. The algorithm of the analysis was formulated in Section 3. It is based on the repetitive use of NERUDA tool in order to properly simulate the waste market competition. The collection areas were proposed for relaxed project capacity. The new term waste availability factor was defined, which is later used as the main criteria for risk evaluation. The evaluation of this factor is first comprehensively demonstrated for two particular scenarios. Finally, the results of a complex stochastic-based analysis are provided which incorporated various uncertainties embodied in the scenarios. This was done in order to justify the practical implications of this approach.

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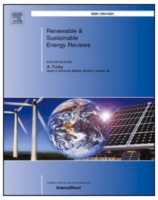

Legislation-induced planning of waste processing infrastructure: A case study of the Czech Republic

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ABSTRACT

Trends in the treatment of municipal solid waste are changing worldwide. In the European Union, one of the largest economies in the world, the waste treatment and management among the member states vary significantly. To support and promote environmentally friendly waste management, the European Union issued directives commonly called the Circular Economy Package. This legislative is designed to accelerate the transition to a cleaner future. It gives an obligation to member states to meet specific landfilling and recycling targets. To reach these ambitious goals will be a challenging task, especially for the member states with less developed waste management systems. An approach using multi-stage stochastic programming is suggested for solving such a problem. The developed model considers current material recovery rates and trends in municipal waste, while uncertain waste production is forecasted by possible scenarios. The model enables sequential decision-making and assessment of various strategies for different future scenarios with specific years, locations, technologies and capacities for the establishment of the waste processing infrastructure. The utilization of the model and its computational tractability is demonstrated in a case study of the Czech Republic.

1. Introduction

Sustainability of human activities is evaluated by three basic aspects: economical, environmental and social. Sustainable development is highly influenced by municipal solid waste (MSW) treatment [1]. In the European Union, the preferred ways of waste treatment are defined by *Waste hierarchy*, which is anchored in the directive [2]. Waste management is a very complex task, which encompasses the whole process of waste handling: waste collection, transportation, eventual adjustment and final treatment. Different phases of waste handling are linked with a great variety of technological options and waste management methods.

Population growth, urbanization, and the changing lifestyle of people in developing countries are connected with an increase in the production of waste worldwide [3]. If the waste cannot be recovered materially, the next preferred way of treatment is energy recovery [4]. Waste management sustainability can be supported by the utilization of hidden potential in waste, which is one of the most significant future renewable energy source [5]. It presents one of the alternatives for fossil fuels which still cover most of the global energy production [6]. Waste incineration is not available in many developing countries (except in countries with fast-growing economies such as China, Malaysia, etc.) for the following reasons [7]:

- high initial and operating costs,
- unfavorable waste composition,
- lack of technical knowledge,
- availability of easy landfilling.

In developed countries (EU, US and Japan), the waste incineration for energy production is one of the common waste treatment options [8]. The Waste-to-Energy (WtE) facilities have quite lower emissions compared to electricity production facilities from fossil fuels (except natural gas), and help to reduce further greenhouse gases emissions from landfills [9]. The increase in the utilization of WtE plants in the EU is expected in the view of strict limitations of waste landfilling that should follow from the passed legislation.

In order to reinforce interventions that change currently

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List of abbreviations, units and nomenclature

Abbreviation	*Definition Notes/Case study values*
MSW	municipal solid waste
EU	European Union
US	United States
WtE	waste-to-energy
CEP	Circular Economy Package
MBT	mechanical biological treatment
BAU	business as usual
EUR	Euro
kt	kilotonne
s, z	Indices for scenarios $s, z \in \{1, \ldots, 27\}$
i	Index for cities $i \in \{1, \ldots, 206\}$
j	Index for routes between the cities $j \in \{1, \ldots, 1898\}$
t	Index for periods $t \in \{1, \ldots, 11\}$
τ	Index for decision stages $\tau \in \{1, 6, 11\}$
o^i_{WtE}	Set of possible options for WtE plants in city i; For every city i, there are 9 options (these can differ between cities). These options have different capacities and treatment costs, based on the analysis of the candidate locations in the individual cities
o^i_{MBT}	Set of possible options for MBT plants in city i; For every city i, there are 9 options (as in the WtE case discussed above)
$k^i_{o^i_{WtE}}$	The capacity of the options for the WtE plant in city i
$k^i_{o^i_{MBT}}$	The capacity of the options for the MBT plant in city i
${}^{WtE}c^i_{o^i_{WtE}}$	Treatment cost of the options for the WtE plant in city i
${}^{MBT}c^i_{o^i_{MBT}}$	Treatment cost of the options for the MBT plant in city i
c^i_L	Landfilling cost in city i; Assumed static (not developing in time), around 70 EUR/t
c^j_R	Shipping cost on arc j; Assumed static, 0.12 EUR/(t·km). The cost of fuel did not show any significant trend in the past years. If it were the case, the augmentation of the model by adding time-dependent shipping costs would be quite straightforward.
$\xi^i_{t,s}$	Amount of produced MSW that requires treatment in city i, the time period t, scenario s; The most important stochastic parameter that was considered in this study. The scenario branching considers possible demographic and societal changes that affect the MSW production in individual cities
$\xi^i_{[t],s}$	Progression of MSW production up to time period t, city i, scenario s, i.e. $\xi^{\mathrm{i}}_{[\mathrm{t}],\mathrm{s}} = (\xi^{\mathrm{i}}_{1,\mathrm{s}}, \xi^{\mathrm{i}}_{2,\mathrm{s}}, \ldots, \xi^{\mathrm{i}}_{\mathrm{t},\mathrm{s}})$; "Dummy" parameters used in the nonanticipativity constraints
$A^{i,j}$	Incidence matrix of the road network
pen_{WtE}	The penalty for unused WtE capacity $pen_{WtE} = 0.8$; This rather high penalty value ensures that the installed waste treatment facilities are properly utilized
pen_{MBT}	The penalty for unused MBT capacity $pen_{MBT} = 0.8$; Same as above
κ	The ratio of MBT treated MSW that needs to be landfilled $\kappa = 0.4$; Assumed static (no significant technological breakthroughts during the planning period) and independent of the MBT option
$MSW_{t,s}$	The total amount of MSW generated in the whole region/country in time period t, scenario s
p_s	The probability of scenario s; In the case study, all the scenarios had the same probability
g_1, g_2, g_3	Target values for the amount of landfilled MSW $g_1 = 0.3$, $g_2 = 0.2, g_3 = 0.1$
$x^j_{t,s}$	Flow on the arc j, time period t, scenario s; Real nonnegative variable
$w^{i,o^i_{WtE}}_{\tau,s}$	Building the WtE plant in city i, with option o^i_{WtE}, in decision stage τ, in scenario s; Binary variable
$m^{i,o^i_{MBT}}_{\tau,s}$	Building the MBT plant in city i, with option o^i_{MBT}, in decision stage τ, in scenario s; Binary variable
${}^{WtE}r^{i,o^i_{WtE}}_{t,s}$	Amount of MSW treated in WtE in city i, with option o^i_{WtE}, in time period t, in scenario s; Real nonnegative variable
${}^{MBT}r^{i,o^i_{MBT}}_{t,s}$	Amount of MSW treated in MBT in city i, with option o^i_{MBT}, in time period t, in scenario s; Real nonnegative variable
${}^{L}r^i_{t,s}$	Amount of MSW landfilled in city i, in time period t, in scenario s; Real nonnegative variable
${}^{WtE}u^{i,o^i_{WtE}}_{t,s}$	Amount of unused capacity in WtE in city i, with option o^i_{WtE}, in time period t, in scenario s; Real nonnegative variable
${}^{MBT}u^{i,o^i_{MBT}}_{t,s}$	Amount of unused capacity in MBT in city i, with option o^i_{MBT}, in time period t, in scenario s; Real nonnegative variable
f	Index for waste fraction
RR_f	recycling rate for waste fraction f
MAT_f	amount of materially recovered waste fraction f
SEP_f	amount of separated waste fraction f

unsustainable practices, the existing policies and legislation need to be reformed [10]. The trend in developed countries leads from the linear economy system to a circular economy. The impact of these legislative changes is an essential factor in waste management models. For example, the legislation induced changes on the gate-fee of and WtE plant were investigated in the paper [11]. To ensure the smooth transition to the circular economy in waste management, it is necessary to solve the complex tasks taking into account the different ways of waste handling and production forecasts. This contribution presents a multi-stage stochastic model as a support tool for the decision-making process. The approach is presented on the real data from the Czech Republic, which represents the country in the transition process from linear to the circular economy.

2. Literature review and theory

Waste management is a dynamically developing area that is currently subject to several changes that were outlined above. Within waste management, it is necessary to address the strategy of waste collection, waste transport and finally its treatment. The sustainability is measured along the triple bottom line [12]: economic, environmental and social impact. The following text is devoted to the literature review, which is divided into thematic parts with the final evaluation of the research gap.

2.1. Circular economy

In recent years there has been an effort to move from a linear economy to a circular economy. These tendencies arise worldwide, mainly because of the limited capacities of primary sources and environmental pollution. The study [13] pointed out that current trends in the circular economy are built on research into resource efficiency [14]. The paper [15] formulated ten common circular economy strategies: recovery, recycling, repurpose, remanufacture, refurbish, repair, re-use,

Table 1
The targets anchored in the Directives within CEP.

Action	Source	Waste stream	2025	2030	2035
Recycling/reuse (minimum)	Directive (EU) 2018/851 [18];	Municipal solid waste	55%	60%	65%
	Directive (EU) 2018/852 [19];	Packaging waste	65%	70%	
		Packaging paper	75%	85%	
		Packaging plastics	50%	55%	
		Packaging glass	70%	75%	
		Packaging ferrous metals	70%	80%	
		Packaging aluminum	50%	60%	
		Packaging wood	25%	30%	
Landfill (maximum)	Directive (EU) 2018/850 [20];	Municipal solid waste			10%
Reduction (minimum)	Directive (EU) 2018/851 [18];	Food waste	30%	50%	

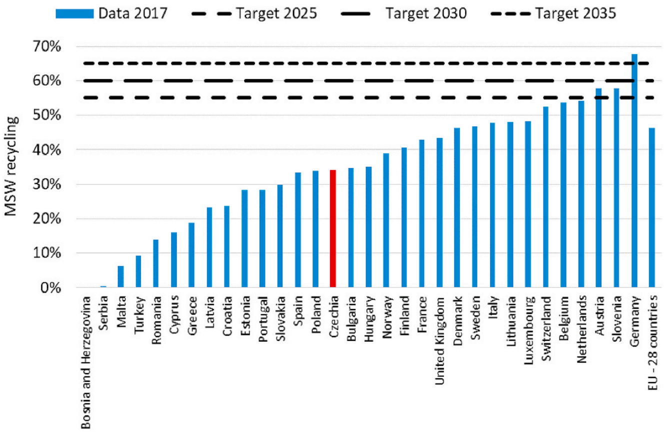


Fig. 1. Municipal waste recycling in the year 2017 and recycling targets (Eurostat, 2019 [21]).

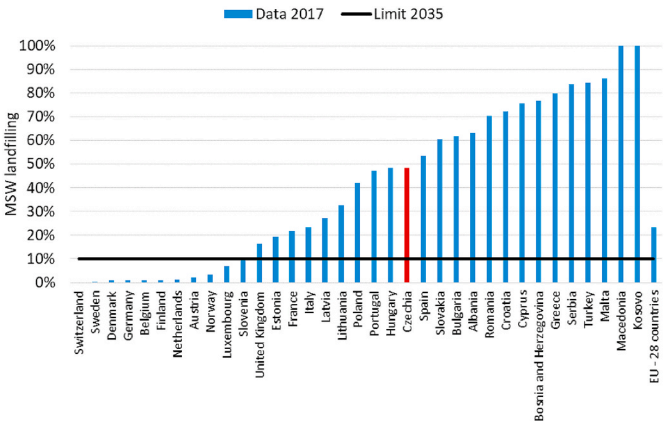


Fig. 2. Municipal waste landfilling in the year 2017 and the landfilling limit [21].

reduce, rethink, refuse. The aim is to maintain the value of the product for as long as possible to exploit its maximum utility. The principle is in the closing loops of products, product parts and materials. The transition from a linear to a circular economy brings with it a range of practical challenges for policies and companies. The paper [16] developed a framework of strategies to guide designers and business strategists in the move from a linear to a circular economy. The transition to a circular economy will be reflected throughout the production chain. Three basic principles characterize the circular business model: closing, slowing and narrowing resource loop. However, the measurement and assessment of circularity performances are not yet a common practice in companies.

The transition to a circular economy requires actions and legislative intervention. Turning waste into a resource is an essential part of increasing resource efficiency and closing the loop in a circular economy. In 2018, the European Commission accepted the Circular Economy Package (CEP) with the stated goal of "closing the cycle" of the product life cycle. It seeks to establish an action program with measures covering the whole cycle from production and consumption to waste management and the secondary raw materials market [17]. According to the CEP, the aim is to minimize waste so that once a product reaches the end of its life, its materials will be kept within the economy for as long as possible. What was previously considered as "waste" is therefore transformed into a valuable resource. The EU member states must incorporate directives included in the CEP into national legislation.

The targets included in the CEP are summarized in Table 1. The recycling targets set a minimum percentage of recycled or reused wasted, and they deal with both general municipal solid waste and particular packaging waste. The next important milestone is landfill restriction at maximal 10%, which will come into force in 2035. CEP also addresses the issue of prevention by means of food waste reduction.

The assessment of the current situation (in 2017) for European states is illustrated in Fig. 1 and Fig. 2. Fig. 1 shows the current waste recycling of 32 states in relation to the desired targets. On average, only 46.4% of MSW is recycled by the 28-EU Member States. The only country that currently meets the strictest target set for the year 2035 is Germany. Unfortunately, most countries are not very close to these recycling targets at present. The Czech Republic, as a representative of countries in the transition process from linear to the circular economy, recycles approximately 34% of MSW (red color in Fig. 1).

Alongside the recycling targets, the member states also have to react to the landfilling restrictions. A total of 11 countries already meet the landfilling limit, see Fig. 2. On average, EU-28 Member States landfill currently 23.4% of waste.

It is important to consider the different levels of development of individual EU member states and their starting position. In some cases, which are specified in the relevant Directives, a member state may request that the deadlines be postponed. The Czech Republic ranks in both the recycling and landfilling somewhere in the middle of the EU-28 countries. There has been a lack of financing in the Baltic countries to promote and operate waste incineration. Their first goal after joining the EU was to avoid dumping at uncontrolled sites and to meet the EU standards. Later on, Estonia has become the most advanced of these countries in terms of waste avoidance and recycling in the capitals, and it is ranking top even in the whole EU. The construction of WtE and MBT plants has shifted total landfilling drastically [22]. On the other hand, Poland, which is the neighbor of the Czech Republic, still has problems securing the real values of waste production. It is caused by existing gaps in landfill weighting or illegal dumping. Poland is also in the middle of the EU countries regarding landfilling, but its WtE sector has been evolving dynamically in the recent years in contrast to the Czech Republic, where new projects are waiting for greater legislative support.

Croatia, as the southern country from the EU, still landfills a significant amount of the MSW. Even though it has recently adopted the national Waste Management Plan 2017–2022, its implementation is delayed. Reaching the targets from the CEP will require substantial investment in waste infrastructure. So far, the investments and plans have not been efficient, causing the future overcapacity of MBT plants. The waste hierarchy has not been properly followed, and responsibilities among authorities were not in line with each other. One of the proposed changes is to focus on bio-waste, its composing and separation at source. Waste management centers in operation are costly and not the best option available since it only increases landfilling and produces low

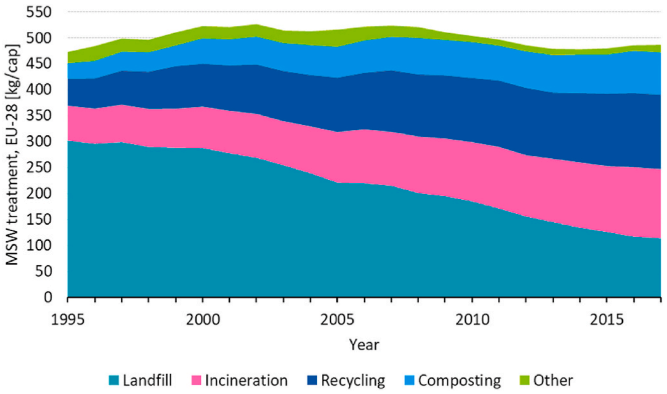


Fig. 3. Municipal waste treatment, EU-28, (kg/capita) (Eurostat, 2019 [21]).

quality refuse-derived fuel [23]. The performance of the EU-28 countries has been compared in detail [24]. The degree of transition to the circular economy is measured by defined indicators considering waste production, material reuse or recycling and their correlation with Growth Domestic Product has been proven.

In response to CEP, EU member states will make efforts to reduce the amount of landfilled MSW. Where possible, MSW is used for material or energy recovery. MSW treatment methods over the period 1995–2017 are illustrated in Fig. 3 for the EU-28 countries. Waste prevention is not reflected in historical data, although it is the most preferred method by *Waste management hierarchy* [2]. There is a clear trend in landfill reduction in the long-term. Despite the objectives of maximizing recycling, a direct transition from landfill is not possible without intermediate steps in the form of WtE, which plays a not negligible role in the circular economy [22]. Different WtE processes were clearly assigned to options in the waste hierarchy ladder [25]. However, there are concerns about undermining the waste hierarchy with respect to new incineration plants.

2.2. *Waste management tasks*

Waste management is concerned with adapting existing infrastructure to create a satisfactory and sustainable system. Most tasks from waste management can be classified into the following categories:

Waste collection and transport play an important role in the processing chain. Waste collection routes are the output of vehicle routing models. Because of the computational complexity, heuristic solutions are often used [26]. Most often, the minimum travel cost is the aim of optimization [27].

Location problems search for the optimum placement of new waste treatment facilities [28]. Also, the optimal location of transfer stations [29] and the deployment of waste collecting bins in the cities [30] fall into this category. There are several methods used to solve the location problems, among which are the overlay technique [28] and mixed-integer programming approaches [31].

Allocation problems deal with waste streams from producers to processing sites [32].

Facility design addresses all technological obstacles of individual subsystems. The aim is to dimension the facility so that it can process waste from the appropriate collection area [33].

The collection of MSW is highly dependent on the development level of the country in question [34]. While informal recycling and manual labor for collection and transportation of MSW are common practices in developing countries [35], in developed countries mechanical collection systems [36] of segregated MSW are more commonly practiced [37].

An extensive review of models for supply chain systems was presented by Ref. [38]. Collection and transportation represent a considerable part of the cost within the waste management system. For example, in India, which represents developing countries, the collection and transportation cost is estimated at 70–85% [39]. But collection and transportation costs are significant also for developed countries, e.g. in Sweden, they amount to 50–75% of waste management cost [40].

Transfer stations are often used to support waste transportation for long distances. Approaches for selection of appropriate transfer station locations include spatial multi-criteria analysis [41], interval optimization [42], multi-objective stochastic programming [43], and GIS-based

Table 2
Waste management tasks, data types and solution methods of the selected works.

	Task				Data type		Solution method
	Collection	Location	Allocation	Design	Deterministic	Uncertain	
Badran et al., 2006 [31];		✓			✓		MIP
Benjamin et al., 2010 [59];	✓				✓		Heuristic
Boonmee et al., 2018 [55];		✓	✓		✓		Heuristic
Cebi et al., 2016 [57];		✓				✓	Hybrid model
Chatzouridis et al., 2012 [45];	✓	✓			✓		MIP
Cheng et al., 2003 [32];		✓	✓			✓	MIP
Das et al., 2015 [27];	✓				✓		Heuristic
Gambella et al., 2019 [63];			✓			✓	MIP
Ghiani et al., 2012 [30];		✓	✓		✓		Heuristic
Ghose et al., 2006 [39];	✓				✓		Energy consumption
Hrabec et al., 2019 [65];		✓	✓			✓	MIP
Hu et al., 2017 [49];		✓				✓	MIP
Jin et al., 2019 [33];			✓	✓		✓	Fuzzy linear programming
Kim et al., 2005 [58];	✓				✓		Heuristic
Kudela et al., 2019 [43];		✓	✓			✓	MIP
Li et al., 2008 [66];			✓	✓		✓	Fuzzy MIP
Li et al., 2009 [67];			✓	✓		✓	Inexact fuzzy stoch.
Li et al., 2012 [64];			✓			✓	Fuzzy-stoch. Quadratic programming
López et al., 2008 [56];		✓			✓		Metaheuristic
Randazzo et al., 2018 [62];		✓			✓		GIS, multi-criteria analysis
Sonesson, 2000 [40];	✓				✓		Mechanistic approach
Tung et al., 2000 [26];	✓				✓		Heuristic
Yadav et al., 2016 [68];		✓			✓		MIP
Yadav et al., 2018 [29];		✓				✓	Interval programming
Yousefi et al., 2018 [28];		✓			✓		Index overlay method
Zhao et al., 2016 [53];	✓	✓			✓		MIP
this work		✓	✓			✓	MIP

Table 3
Optimization criteria and decision stages of the selected works.

	Criteria			Optimized part of the waste management chain	Objective function		Stage	
	Economical	Environmental	Social		Single	Multi	One	Multi
Badran et al., 2006 [31];	✓			Collection stations	✓		✓	
Benjamin et al., 2010 [59];	Number of vehicles			Collection	✓		✓	
Boonmee et al., 2018 [55];	✓	✓		Composting, recycling, land.		✓	✓	
Cebi et al., 2016 [57];	✓			MBT	✓		✓	
Chatzouridis et al., 2012 [45];	✓			Transfer station	✓		✓	
Cheng et al., 2003 [32];	✓	✓	✓	Landfill		✓		two
Das et al., 2015 [27];	✓			Transfer station, treatment facility, recycling, composting	✓		✓	
Gambella et al., 2019 [63];	✓			Treatment facility	✓			two
Ghiani et al., 2012 [30];	Number of collection sites			Bins	✓		✓	
Ghose et al., 2006 [39];	✓			Collection	✓		✓	
Hrabec et al., 2019 [65];	✓			Waste reduction	✓			two
Hu et al., 2017 [49];	✓	✓		WtE		✓		two
Jin et al., 2019 [33];	✓	✓		WtE, land.		✓	✓	
Kim et al., 2005 [58];	Traveling time, number of vehicles			Collection		✓	✓	
Kudela et al., 2019 [43];	✓	✓		Transfer station		✓		two
Li et al., 2008 [66];	✓			Unspecified ways of treatment	✓			two
Li et al., 2009 [67];	✓			Composting, recycling, land.	✓			✓
Li et al., 2012 [64];	✓	✓		Composting, recycling, land.		✓		✓
López et al., 2008 [56];	✓			Biomass power plant	✓		✓	
Randazzo et al., 2018 [62];	✓	✓	✓	Land.		✓	✓	
Sonesson, 2000 [40];	Energy consumption			Collection	✓		✓	
Tung et al., 2000 [26];	✓			Collection	✓		✓	
Yadav et al., 2016 [68];	✓			Transfer station	✓		✓	
Yadav et al., 2018 [29];	✓			Transfer station	✓		✓	
Yousefi et al., 2018 [28];		✓		Land.			✓	
Zhao et al., 2016 [53];	✓	✓		MBT		✓	✓	
this work	✓			WtE, MBT, land.	✓			✓

technologies [44], which can also be used together with binary optimization [1].

Based on the *Waste hierarchy*, landfilling is the least desirable way of waste treatment. Yet it still prevails in many countries, even in developed EU countries (as depicted in Fig. 2). However, current trends are gradually reducing landfilling and waste is largely used for material or energy recovery. A recent review of the WtE technologies can be found in the studies [46], which considered bio-waste, and [47], where the authors also consider the utilization of landfill gas for power production. The paper [48] reported that energy recovery from waste is an integral part of an environmentally sustainable waste management strategy. The contribution [49] developed the model for WtE location based on stochastic parameters considering economical and environmental criteria.

Recent studies [50] emphasized other advantages of incineration (apart from volume reduction and electricity generation) such as the utilization of bottom and fly ash of incineration plants in road construction and cement production, and recovery of ferrous and non-ferrous substances. This suggests that the technological development in metal recovery from dry bottom ash of incineration plants will enhance the acceptance of WtE facilities [13]. The study [51] reported on the average recoverable energy contents (in terms of electrical energy efficiency) of the different components of MSW using different WtE technologies. It was found that anaerobic digestion is the best-suited WtE option for food and yard wastes, while gasification is the best WtE option for treating plastic wastes. Incineration was found to be an attractive option amongst all the waste streams, as it can be used for energy recovery from all the reported waste streams. Other types of wastes, such as inert, metals, glass, etc., were not considered in the abovementioned study.

The study [52] focused on a Life cycle assessment of four waste management strategies in the municipality of Rome (Italy): landfill without biogas utilization; landfill with biogas combustion to generate electricity; sorting plant which splits the inorganic waste fraction from the organic waste fraction; and direct incineration of waste. Results, which they claim to be useful for most of the big European cities, show landfill systems as the worst waste management options and significant environmental savings at the global scale are achieved from undertaking energy recycling. Furthermore, waste treatments finalized to energy recovery provide an energy output that could meet 15% of Rome electricity consumption (in one of the considered case scenarios).

In the United States, for example, about 13% of power is generated from alternative electricity-production sources; of this fraction, approximately 11% of the alternative production is the contribution of biomass [53]. However, the high costs of biomass power generation, as well as the unreasonable distribution of biomass power plants [54] have led to an insufficient feedstock supply and some of the environmental issues hindering this industry from further development. Models can be targeted to exceptional situations such as in post-disaster waste management [55].

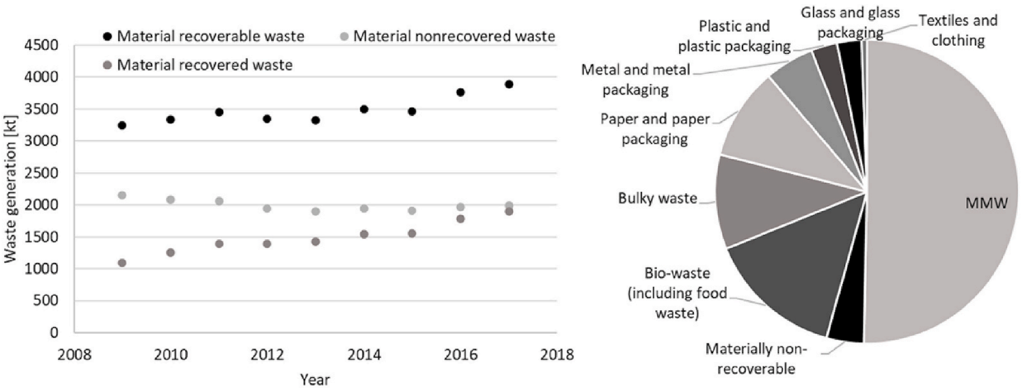
The types of waste management tasks for contributions mentioned in the literature review text are summarized in Table 2.

2.3. Optimization models

2.3.1. Single-criteria vs. multi-criteria models

When solving waste management tasks, models are often limited to just one criterion, in most cases total costs. The contribution [56] dealt with a suitable location for biomass power plant with minimum cost, where the model was solved using metaheuristic. Also [57] searched the location for a biomass power plant but with the fuzzy input information. The study [26] presented modified Solomon's insertion algorithm to solve the vehicular routing problem. The objective function sometimes minimizes other value, such as traveling time [58] or vehicles number [59].

The multi-criteria models consider not only the costs but also the environmental problems and social affairs that correspond to the different decisions [60]. The public acceptance of MSW treatment facilities can be largely driven by the social and cultural perception of the positive impact of resource recovery processes and facilities in the community. If they are perceived to foster climate change mitigation, and address local deficiencies or inefficiencies, such as employment, energy and fertilizer shortages, these are highly accepted by the community (especially in rural areas where jobs and energy supply are of greater concern) further enhancing socio-economic processes and



a) Material recoverable waste and its utilization 2009–2017, the Czech Republic

b) The MSW composition in 2017, the Czech Republic

Fig. 4. Material recoverable waste treatment in the Czech Republic.

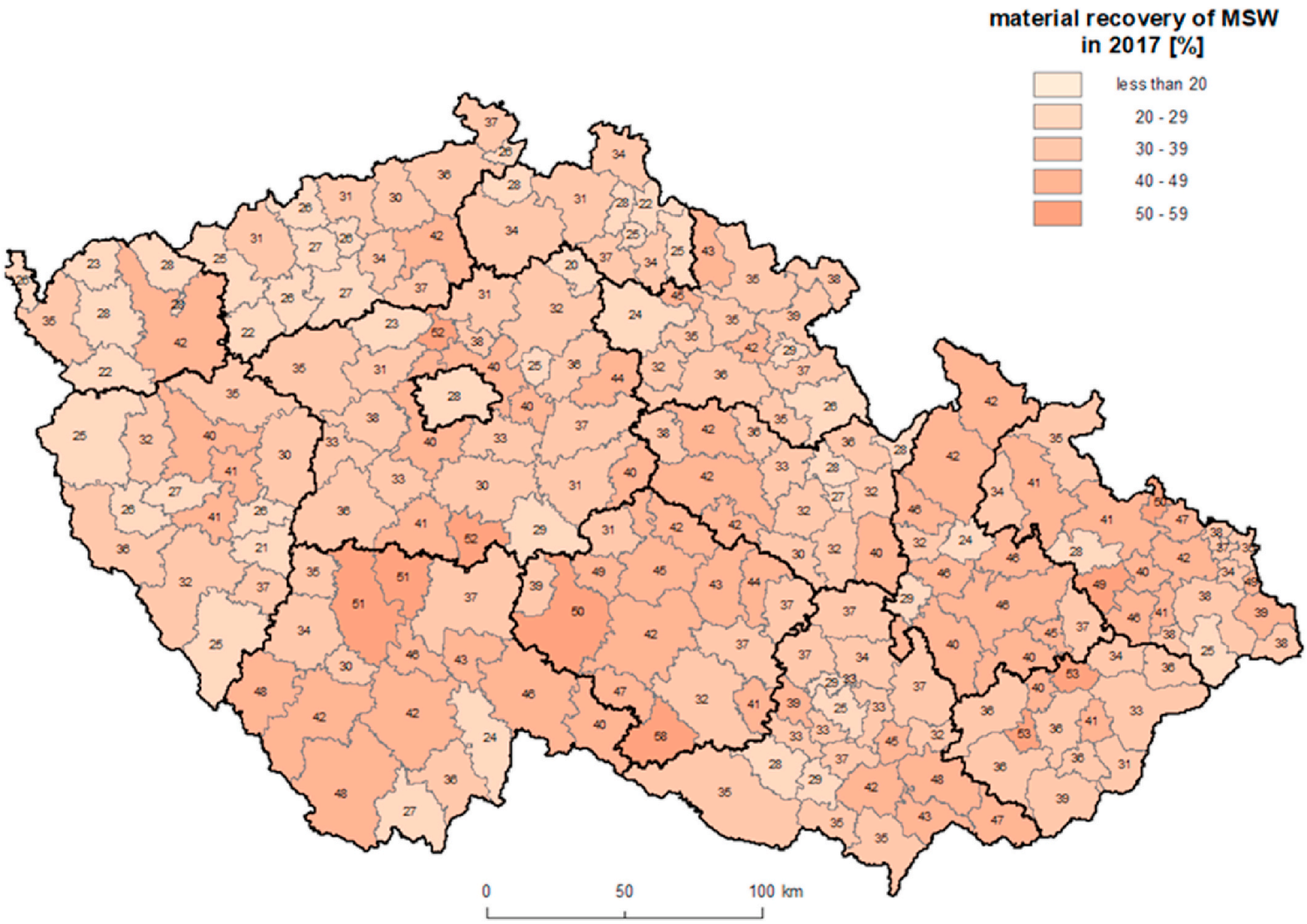


Fig. 5. Material recovery of MSW in the Czech Republic in 2017.

improving the human, social and cultural capital [61]. The operation research perspective on the strategic decision-making that takes place in designing sustainable systems was carried out [38]. The authors found that the economic and environmental aspect of the decision-making outweighed the social aspects in the majority of recent studies. One of the studies [32] that took into account economic, environmental and social impacts, where the authors created a comprehensive approach for landfill location and also dealt with waste stream allocation in the city of Regina (Canada). Similarly, the paper [62] developed an approach for landfill location in Sicily by multi-criteria analysis. The environmental assessment of the site of the landfill was discussed in the study [28] using an index overlay method.

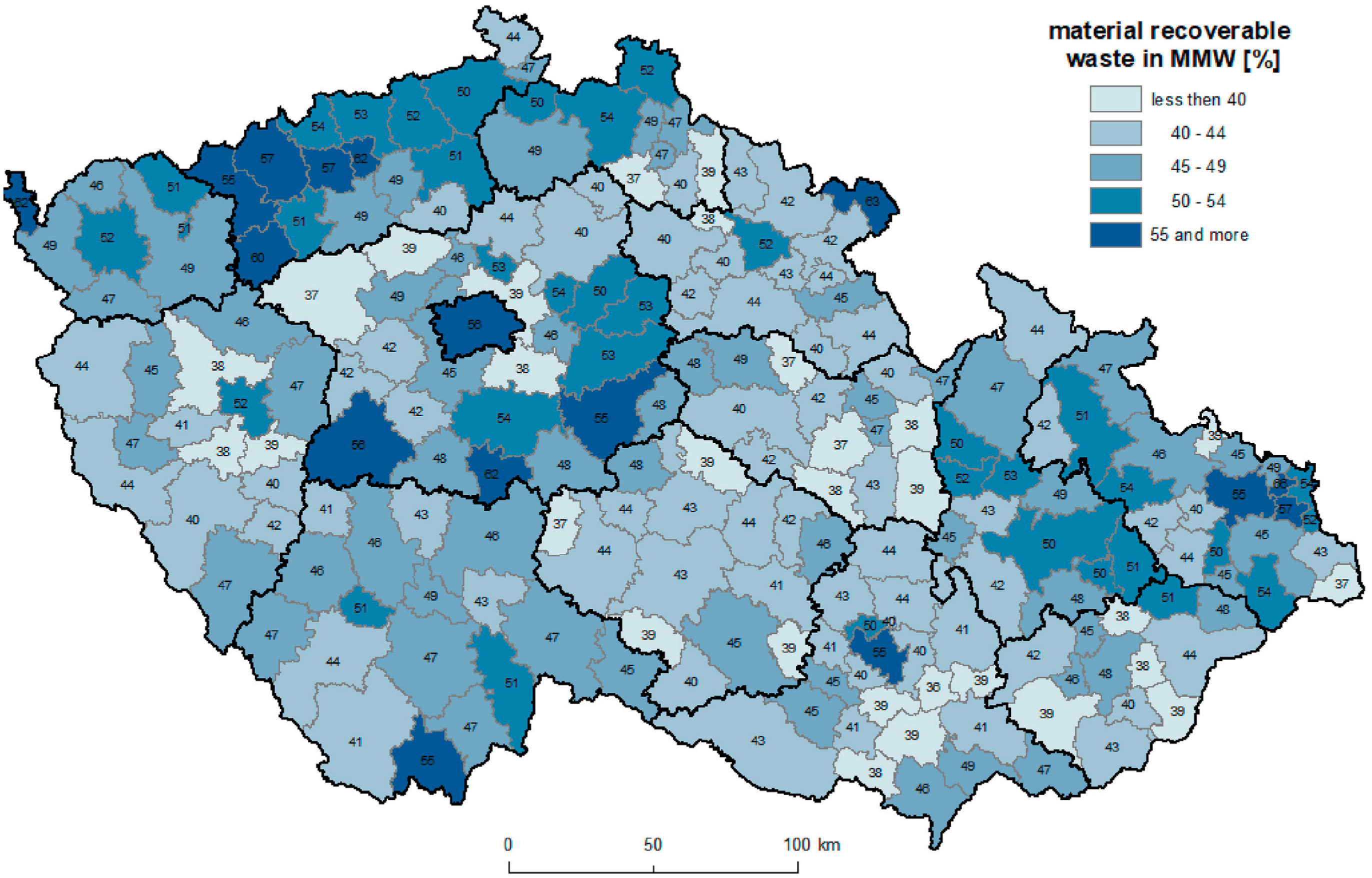


Fig. 6. Proportion of materially recoverable waste if MMW in the Czech Republic in 2017.

Table 4
Recycling rates for the different waste fractions in 2015.

Waste fraction *f*	RR_f
Bio-waste (including food waste)	0.91
Bulky Waste	0.17
Glass and glass packaging	0.90
Metal and metal packaging	0.87
Paper and paper packaging	0.90
Plastic and plastic packaging	0.89
Textiles and clothing	1.00

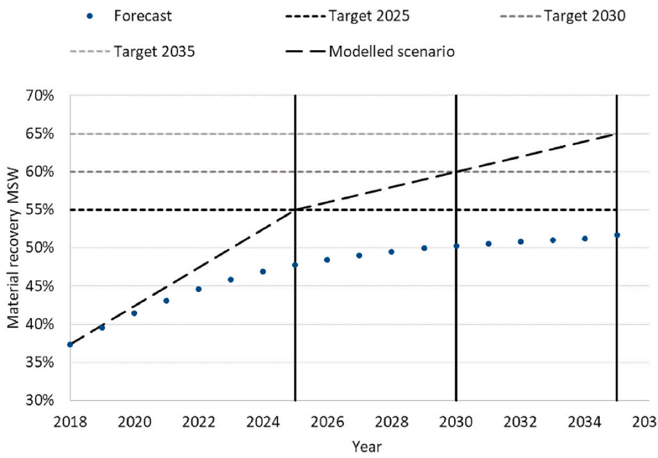


Fig. 7. Forecasting of material recovery in the Czech Republic under current conditions and scenario for targets fulfilling.

2.3.2. *Single-stage vs. multi-stage models*

The dynamic nature of the decision-making process is best captured in the use of models with several decision stages, that correspond to successive instances in time. Whereas single-stage models are best-suited to situations, where the corresponding model data are static (do not change over time), multi-stage models are more appropriate for dynamically changing environments. The difficulty with multi-stage approaches lies in an increase in computational and modelling complexity. As can be seen in Table 3, most of the relevant literature focuses on single-stage models. A sort of an intermediate step between the single-stage and multi-stage models is the two-stage model. In this setting, typically the "important decisions", such as facility locations and their design, are made in the first stage of the model. The second stage than serves to assess the impact that the "important decisions" will have in time. This approach was used in the study [63], where the authors describe a stochastic two-stage multi-period stochastic optimization model for the allocation of waste flows. Similarly, the two-stage model was used in a robust setting for a selection of WtE facilities [49] and in a stochastic setting for a design of a transfer station network [43]. The only work that presents a proper multi-stage model was the one [64] for bi-objective waste allocation in a fuzzy optimization setting.

2.3.3. *Deterministic vs. uncertain models*

A similar dichotomy, as the one between the single-stage and multi-stage models, exists in the approaches to the considered data of the model. When modelling a static situation with very little data variation, the deterministic approaches are the most sensible ones (and the ones most widely used). However, when the system that should be managed is dynamically changing and there are multiple possible paths of development, uncertain models are the most reasonable choice. This naturally means that there are very few contemporary works that are in

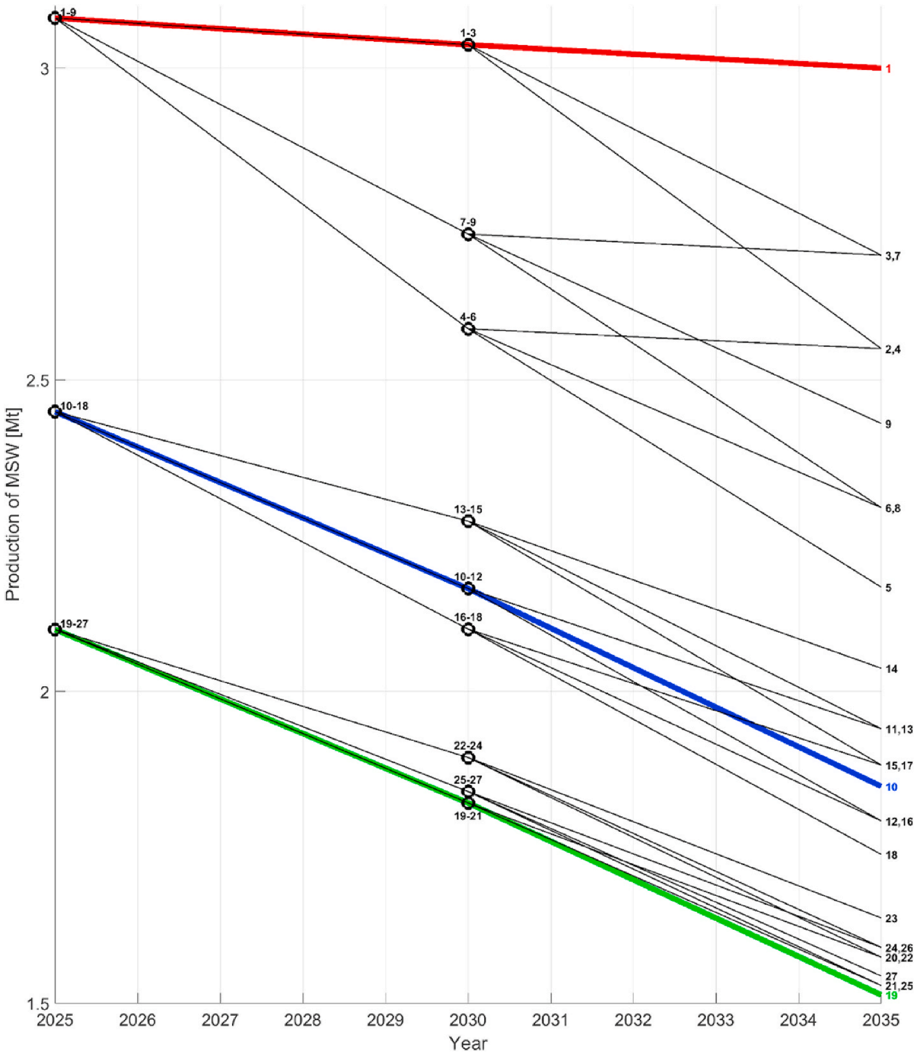


Fig. 8. Scenario branching. Red scenario (1) – BAU, blue scenario (10) – middle, green scenario (19) – on target. Aggregate data for the whole republic. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

a multi-stage setting with deterministic data. Three major approaches try to deal with uncertainty in the data: fuzzy programming, robust programming and stochastic programming. Fuzzy programming was used for waste allocation [33] and facility design [64]. Robust programming was used for waste reduction [65] and a bi-objective selection of WtE facilities [49]. Stochastic programming approaches were used in transfer station planning [43] and waste flow allocation models [63].

2.4. Research gap and novelty

Most contributions deal with setting up individual parts of the processing chain. There are also papers with a comprehensive approach to waste management, but the sequence of steps with regards to time is often disregarded. The dynamical decision-making process that is enabled by the multi-stage models increases the likelihood of a successful deployment of the system, compared to radical changes that correspond to the one-stage models. Since the legislation-induced changes that are coming into effect will significantly alter the production of MSW and its possible treatment options, this dynamic setting is well justified. This paper presents a stochastic multi-period and multi-stage model that captures the planning and decision-making process of selecting the locations and sizes of waste treatment plants, and the subsequent waste flow allocation. Sequential decision-making during the time horizon represents a significant benefit of the model. Despite the complexity of the model, it remains computationally tractable even for real-world instances, which is demonstrated in a case study of the Czech Republic. The approach represents a suitable supporting mathematical apparatus for the “smooth” transition from linear to the circular economy.

3. Multi-stage stochastic optimization model

The presented optimization model falls into the category of multi-stage multi-period stochastic mixed-integer optimization models. There are several monographs dedicated to stochastic programming, with [69] offering the standard more theoretical treatment, and [70] with a more hands-on modelling focus. The goal is to select the optimal locations and sizes of waste treatment facilities in selected cities. Two types of facilities are considered: WtE plants where the waste is incinerated to produce heat and electricity, and mechanical biological treatment (MBT) plants where the MSW is sorted and then either treated with anaerobic digestion or landfilled (the proportion of MBT that needs to be landfilled is denoted as κ). The relationship between the size and cost of treatment in a facility is not simply linear. To model it efficiently, the sizes of the facilities can be chosen only from a predefined set of values. In this way, the linearity of the model can be preserved, although at the cost of introducing new binary variables.

The objective function is purely economical and expresses the ex-

Table 5
The results of the computations. (PG – progressive goals).

	year 2025		year 2030		year 2035	
	with PG	without PG	with PG	without PG	with PG	without PG
max landfilling [%]	29.85	40.15	19.92	38.57	10	10
mean landfilling [%]	21.03	31.61	13.25	26.65	7.35	8.78
max # of new facilities	9	0	6	0	5	16
mean # of new facilities	9	0	2	0	1.89	10.66
mean installed WtE capacity [kt]	981	741	981	741	1099	1074
min used WtE capacity [%]	100	100	100	100	72.31	79.14
mean used WtE capacity [%]	100	100	100	100	97.14	96.69
mean installed MBT capacity [kt]	600	0	883	0	890	822
min used MBT capacity [%]	100	–	100	–	76.30	69.15
mean used MBT capacity [%]	100	–	100	–	96.33	96.80

pected costs of the whole waste treatment system over the considered time period (transportation costs, gate fees at the WtE and MBT plants, penalties for unused capacity, and landfilling fees):

$$\min\sum_{s}p_s\Bigg[\sum_{j,t}c_R^j\cdot x_{t,s}^j+\sum_{i,t}c_L^i\cdot {}^{L}r_{t,s}^i$$

$$+\sum_{i,o_{WtE}^i,t}{}^{WtE}c_{o_{WtE}^i}^i\left({}^{WtE}r_{t,s}^{i,o_{WtE}^i}+pen_{WtE}\cdot{}^{WtE}u_{t,s}^{i,o_{WtE}^i}\right)\tag{1}$$

$$+\sum_{i,o_{MBT}^i,t}{}^{MBT}c_{o_{MBT}^i}^i\left({}^{MBT}r_{t,s}^{i,o_{MBT}^i}+pen_{MBT}\cdot{}^{MBT}u_{t,s}^{i,o_{MBT}^i}\right)\Bigg]$$

The constraints can be grouped into a few categories. The first one comprises of the "conservation of mass" constraints, which enforce that the waste generated in or shipped into city *i* is either shipped away or disposed of (through one of the treatment options):

$$\sum_{j}A^{i,j}x_{t,s}^j-\sum_{o_{WtE}^i}{}^{WtE}r_{t,s}^{i,o_{WtE}^i}-\sum_{o_{MBT}^i}{}^{MBT}r_{t,s}^{i,o_{MBT}^i}-{}^{L}r_{t,s}^i+\xi_{t,s}^i=0,\qquad\forall i,\forall t,\forall s.\tag{2}$$

Another set of constraints restricts building new facilities. If there already is a facility of the given type (WtE or MBT), another one cannot be built:

$$\sum_{\mathrm{o}_{\mathrm{WtE}}^{\mathrm{i}}}\sum_{\tau}w_{\tau,s}^{i,o_{WtE}^i}\le 1,\quad\forall i,\forall s,\tag{3}$$

$$\sum_{\mathrm{o}_{\mathrm{MBT}}^{\mathrm{i}}}\sum_{\tau}m_{\tau,s}^{i,o_{MBT}^i}\le 1,\quad\forall i,\forall s.\tag{4}$$

Next are the constraints that compute the amount of used and unused capacity in the waste treatment facilities in different cities:

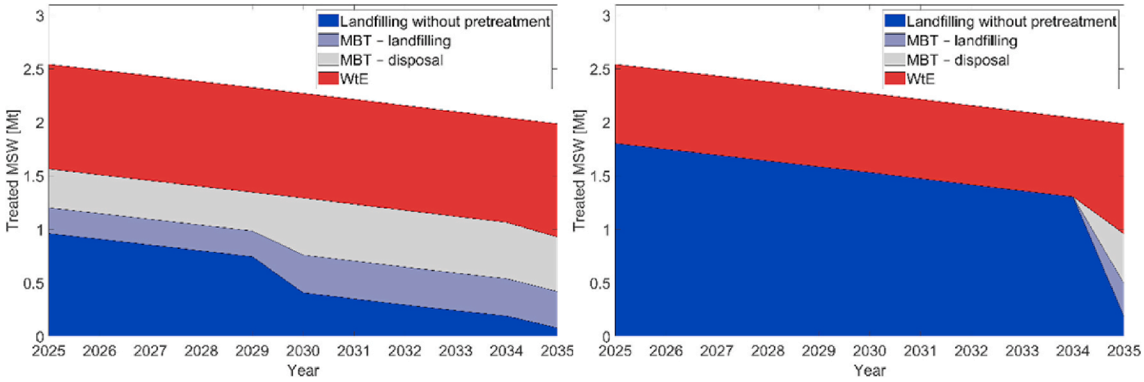


Fig. 9. The volume of MSW treated by the different options in 2025–2035. Solution with progressive goals on the left, the one without progressive goals on the right.

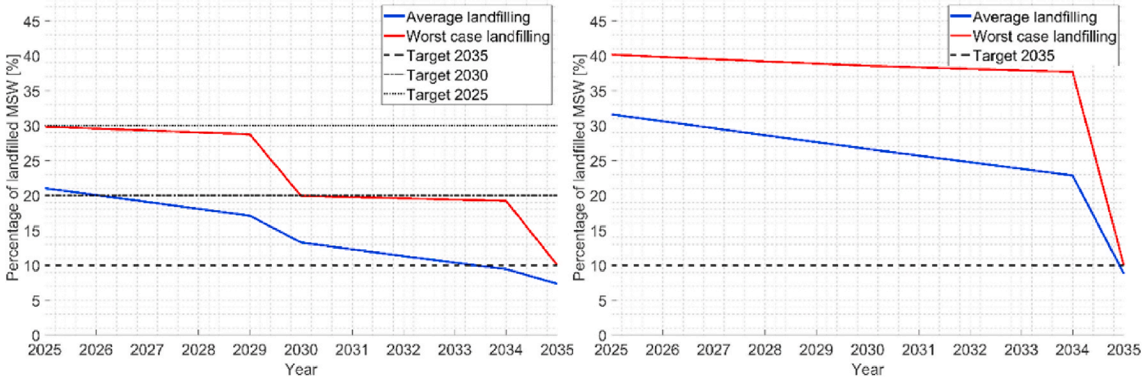


Fig. 10. Percentage of landfilled MSW in 2025–2035. Solution with progressive goals on the left, the one without progressive goals on the right.

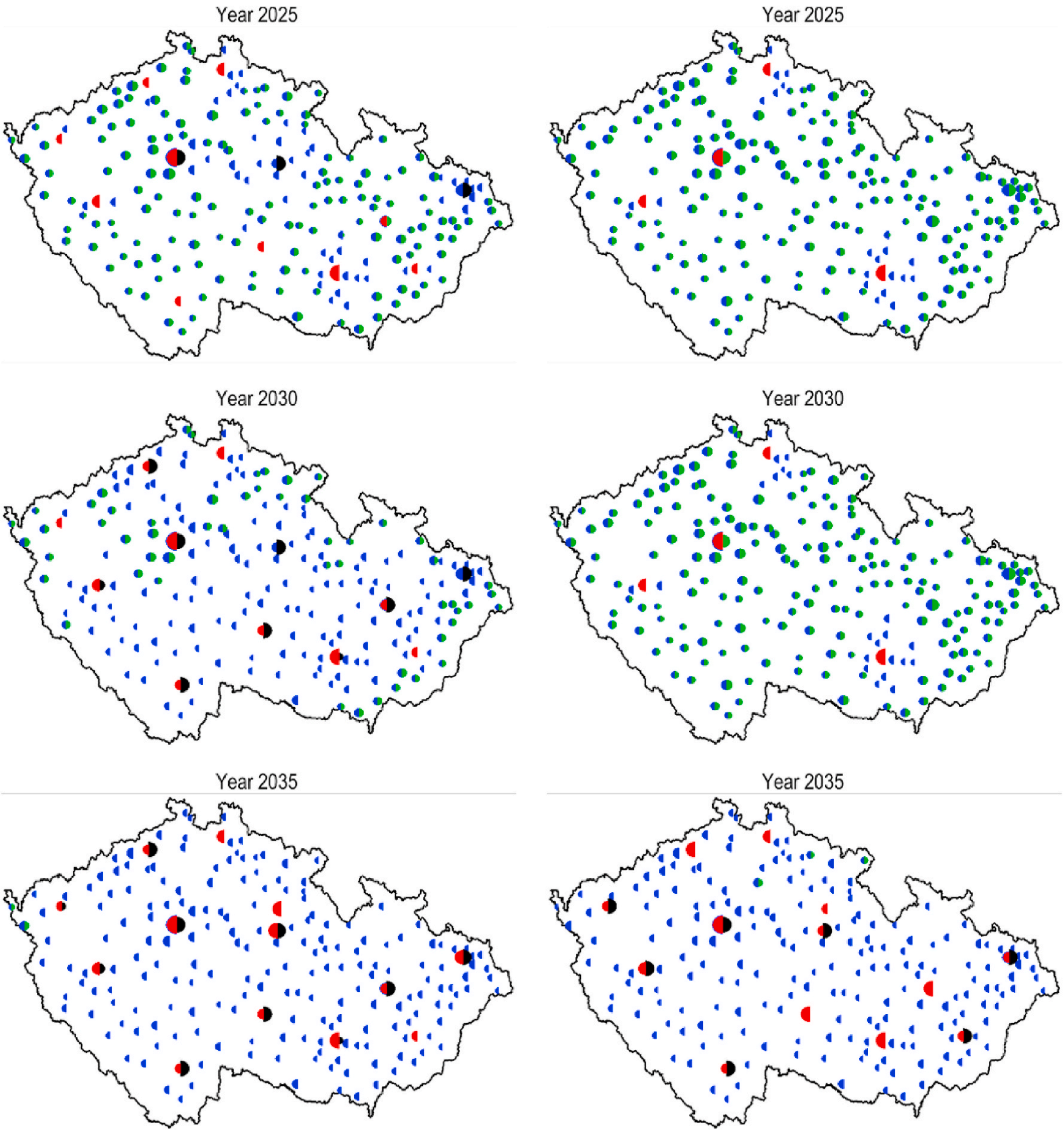


Fig. 11. Scenario 1. Solution with progressive goals on the left, the one without progressive goals on the right. The amount of generated MSW in blue, amount landfilled without pretreatment in green, amount treated in WtE plant in red, and the amount treated in MBT plant in black half-circles. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

$$ {}^{WtE}r_{t,s}^{i,o^i_{WtE}} + {}^{WtE}u_{t,s}^{i,o^i_{WtE}} = \sum_{\tau\le t} k^i_{o^i_{WtE}} \cdot w_{\tau,s}^{i,o^i_{WtE}}, \quad \forall i, \forall t, \forall s, \tag{5} $$

$$ {}^{MBT}r_{t,s}^{i,o^i_{MBT}} + {}^{MBT}u_{t,s}^{i,o^i_{MBT}} = \sum_{\tau\le t} k^i_{o^i_{MBT}} \cdot m_{\tau,s}^{i,o^i_{MBT}}, \forall i, \forall t, \forall s. \tag{6} $$

The penultimate set of constraints consists of the targets for the amount of landfilled MSW:

$$ \sum_j \left({}^{L}r^i_{t,s} + \kappa \cdot \sum_{o^i_{MBT}} {}^{MBT}r_{t,s}^{i,o^i_{MBT}} \right) \le g_1 \cdot \mathrm{MSW}_{t,s}, \quad \forall i, \forall s, t = 1, \dots, 5, \tag{7} $$

$$ \sum_j \left({}^{L}r^i_{t,s} + \kappa \cdot \sum_{o^i_{MBT}} {}^{MBT}r_{t,s}^{i,o^i_{MBT}} \right) \le g_2 \cdot \mathrm{MSW}_{t,s}, \quad \forall i, \forall s, t = 6, \dots, 10, \tag{8} $$

$$ \sum_j \left({}^{L}r^i_{t,s} + \kappa \cdot \sum_{o^i_{MBT}} {}^{MBT}r_{t,s}^{i,o^i_{MBT}} \right) \le g_3 \cdot \mathrm{MSW}_{t,s}, \quad \forall i, \forall s, t = 11, \dots, 16. \tag{9} $$

Lastly, there are the nonanticipativity constraints. These constraints guarantee that the decisions on building the facilities only depend on the information of realized uncertainties up to the present stage:

$$ w_{\tau,s}^{i,o^i_{WtE}} = w_{\tau,z}^{i,o^i_{WtE}}, \cdot \forall i, \forall \tau \text{ for which } \xi^i_{[\tau],s} = \xi^i_{[\tau],z} \tag{10} $$

$$ m_{\tau,s}^{i,o^i_{WtE}} = m_{\tau,z}^{i,o^i_{WtE}}, \cdot \forall i, \forall \tau \text{ for which } \xi^i_{[\tau],s} = \xi^i_{[\tau],z}. \tag{11} $$

It should be noted that the number of cities, scenarios, time periods, decision stages and target values that are present in Table 2 and Eq (1)–Eq (11) are the ones used in a forthcoming case study. These can be readily generalized to take any values depending on the situation at hand.

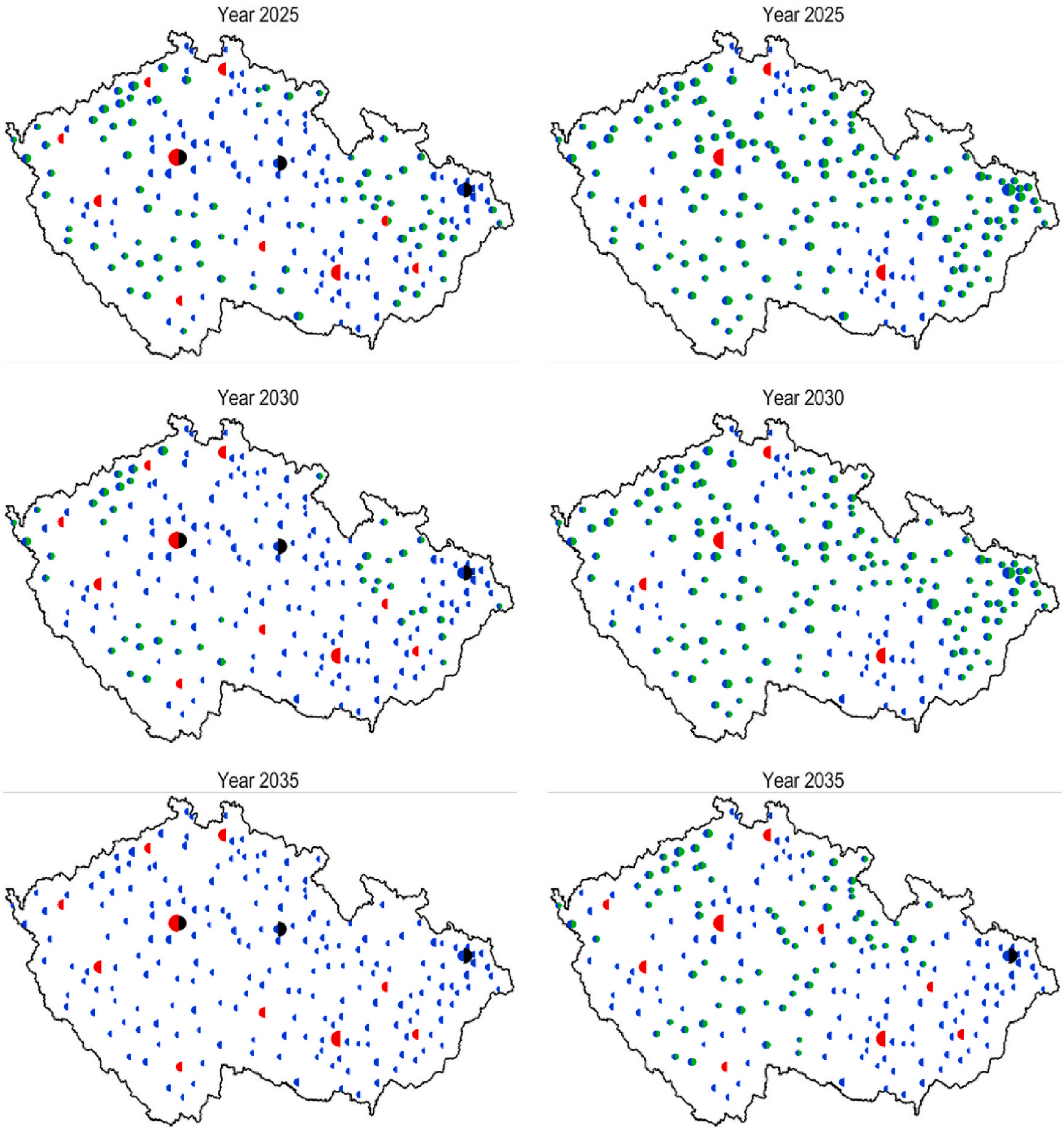


Fig. 12. Scenario 19. Solution with progressive goals on the left, the one without progressive goals on the right. The amount of generated MSW in blue, amount landfilled without pretreatment in green, amount treated in WtE plant in red, and the amount treated in MBT plant in black half-circles. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4. Case study

To demonstrate the strengths of the presented model, it is employed in the assessment of the waste treatment situation in the Czech Republic. The granularity of the case study is the following: 206 cities, connected by a road network with 1898 arcs are considered. Out of the 206 cities, 13 were selected as the most favorable locations for possible WtE and MBT plants. These are the largest cities in their respective regions, which can benefit the most from the electricity and heat generation by the waste treatment facilities and have the largest production of MSW. In 4 of the 13 cities, there already are existing WtE plants with a combined capacity of 741 kt. It is assumed that in these four cities, no additional WtE capacity can be built (although it is possible to build a new MBT facility). There are nine options for possible sizes of the WtE and MBT plants.

The considered planning period covers 11 years, from 2025 to 2035. The reason for the gap between the current year (2020) and the first period is the following – both the WtE and MBT facilities cannot be build overnight. It is assumed that for a facility to be fully operational in a given year, the decision for its construction must be made five years prior. This necessarily means that this decision will be based not so much on the current levels of the MSW production, but on an estimate of the possible levels of MSW production in the upcoming years. The reason for omitting the years 2020–2024 in the analysis is that there are no “substantial” decisions to be made (the model could only manage the system that is currently in place). The 5-year lag between the decision on building the facility and its operation will be achieved through the nonanticipativity constraints Eq (10)–Eq (11) and is discussed further in a forthcoming subsection. In order to make the model computationally tractable (to reduce the number of binary variables), the decisions about building the facilities will be considered only in three decision stages, that corresponds to having the facilities operational in years 2025, 2030, and 2035. Additionally, the costs associated with the year 2035 are multiplied by a factor of 6 to account for the costs that are likely to occur in the years 2036–2040. This should deter the decision that results in building too much infrastructure that will not be efficiently used.

4.1. Data collection and scenario generation

According to the *Waste hierarchy*, energy recovery should be treated if the waste cannot be recovered materially. The rate of waste recycling thus affects the amount of waste for energy recovery.

Waste fractions for material recovery were determined based on the *Waste management plan of the Czech Republic for the period 2015–2024,* which was developed by the Ministry of Environment of the Czech Republic. The following waste fractions were determined as the materially recoverable: glass and glass packaging, metal and metal packaging, paper and paper packaging, plastic and plastic packaging, textiles and clothing. The mandatory waste management records identified other fractions, which are materially recovered: bio-waste and bulky waste. Fig. 4a) depicts the production of MSW fractions, which is material recoverable and its real materially recovery from the year 2009 is still growing. The spatial distribution of the material recovery of the MSW in 2017 is illustrated in Fig. 5.

Mixed municipal waste (MMW) currently accounts for a significant proportion of MSW – about 50% in the year 2017 in the Czech Republic. It is a waste fraction that can be sorted and thus creates the potential for material recovery. Fig. 6 shows the materially recoverable waste in MMW in 2017, which should be separated in the future.

However, the separated waste does not correspond directly to the materially recovered waste. Material recovery of separated waste is mainly dependent on technological and cost conditions. The recycling rate RR_f for waste fraction f, where MAT_f is materially recovered and SEP_f is separated waste f is computed as $RR_f = MAT_f/SEP_f$. The latest available data make it possible to determine the recycling rate RR_f for 2015, these values are summarized in Table 4. The expected development of the material recovery municipal solid waste (if it continues in the current fashion) achieves approximately 47% in the year 2025, as indicated in Fig. 7. But the EU target in 2025, which lies at 55%, necessitates additional steps and effort in order to be reached. The situation for the targets in the years 2030 and 2035 is quite similar, if not more severe.

Material recovery constitutes an extremely important factor as it directly affects the amount of MSW that will be treated in the considered WtE and MBT plants. At present, it is not certain in which direction the production of waste with material recovery will be taken. Three base scenarios for the material recovery are constructed to model this uncertainty:

1. Scenario: BAU – business as usual, depicted as “Forecast” in Fig. 7.
2. Scenario: middle – the EU targets with a 5-year delay
3. Scenario: on target – the “Modelled scenario” in Fig. 7.

These three base scenarios were further “branched”, as depicted in Fig. 8, to more evenly capture the possible developments, resulting in 27 individual scenarios. Alongside the material recovery, other factors went into the construction of the scenarios for the production of MSW that can be treated in the WtE or MBT facilities (denoted as $\xi^i_{t,s}$) in individual cities in the successive time periods. Additionally, demographic changes, i.e. the expected continuation of the trend of higher immigration to bigger cities in the core of the republic (such as Prague or Brno) and the population decline and ageing of the periphery were considered.

With Fig. 8 in mind, the nonanticipativity constraints Eq (10)–Eq (11) that tie certain scenarios together and enforce decisions that can be based only on the current state of knowledge about the uncertain parameters work as follows. As there is currently (the year 2020) no way of knowing which of the 27 scenarios will be the one that comes true, the decision on building the facilities must be made with all 27 scenarios in mind. In other words, for all 27 scenarios, the decision on which facilities will be operational in the year 2025 must be the same. In the year 2025, the situation changes, as one will be able to pinpoint which of the three branches (1–9, 10–18, or 19–27) is the “true one”. This affects the decisions on which facilities to open in 2030, as they will be grouped based on this branching (i.e. one decision for scenarios 1–9, the second one for 10–18, and the third one for 19–27). A similar situation repeats in the year 2030, but with even more branching, as nine possibilities tie the scenarios together.

5. Results and discussion

The optimization model was programmed in the high-performance dynamic language JULIA [71] with the JuMP package for mathematical optimization [72]), that is very well suited for large-scale scientific computing. The solution was computed by the GUROBI 8.0 solver [73]. The optimality gap parameter was set to 1%, which was decided to be sufficiently low for this application. The computations were carried out on an ordinary computer (3.2 GHz i5-4460 CPU, 16 GB RAM) and took about an hour to finish. Two distinct models were considered. The first model has progressive goals ($g_1 = 0.3, g_2 = 0.2, g_3 = 0.1$, in the years 2025, 2030, and 2035, respectively) towards the landfilling target of 10% in the year 2035, to facilitate a “smoother” transition. The second model is without these progressive goals and has only the final goal ($g_3 = 0.1$, in the year 2035). The proportion of the MBT treated waste that still will be landfilled is assumed to be $\kappa = 0.4$. The results of the computations are best summarized in Table 5 and Fig. 9 to Fig. 12

In the model with progressive goals, in the year 2020, the WtE capacity amounted to 981 kt and the MBT capacity to 600 kt (the placements were identical in all scenarios due to the nonanticipativity constraints). In 2025, in the scenarios 1–9 (that stem from the BAU base scenario) additional 850 kt of MBT capacity were built. No other facilities were deemed as needed. In 2030, additional WtE capacity was needed in 15 scenarios (1–15), and additional MBT capacity was needed in 9 scenarios (1–3, 10–15). This leaves 12 scenarios (16–27) in which the initial capacity built in 2020 was all that was necessary to achieve the progressive goals. The differences are exemplified in Fig. 11 and Fig. 12. The optimal objective value was $2.50 \cdot 10^9$ EUR.

In the model without the progressive goal, the results suggest quite the opposite strategy. As there is no pressure to decrease the amount of landfilled waste immediately, the optimal decision is to “wait until the last moment” and act according to the particular scenario path. The optimal objective value in this setting was $2.44 \cdot 10^9$ EUR, which is about 2.4% cheaper than the model with progressive goals.

There is, however, an important issue with this approach, as it requires building a large number of new facilities in the time period between 2030 and 2034 (that can be operating in 2035), in order to reach the 10% landfilling target. For instance, in scenarios 1–9, there are 16 new facilities to be built in this time interval. This would likely put a strain on whatever agency which will be given the task of building these facilities. To find a compromise between the two approaches, one could look at the facilities that are built in both. There are 9 facilities that should be built in 2025 according to the strategy with progressive goals. For the strategy without progressive goals, out of these 9 there are 7 that are built in more than half of the scenarios in 2035, and 5 that are built in more than two-thirds of the scenarios in 2035.

One of the biggest strengths of the model is that it can be used for “rolling-horizon” planning. After analyzing the compromises between possible strategies and deciding on particular facilities to open in the current year (that will become operational in the future) it is expected that the model will be recomputed again after a few years, bringing updated data and trajectories of future development.

The suggested approach has limitations in many ways. The main shortcoming may seem to be the forced link to the material recovery of the waste. Its fair value depends on the capabilities of individual territorial units. Individual regions and micro-regions are different, so their specific potential should be considered. Options for energy recovery should then only be considered for remaining waste in all municipalities. The actual implementation of the new WtE plant is time-consuming and requires the fulfillment of many legislative conditions, including environmental analysis. From the implementer's point of view, the calculation can be applied repeatedly, taking into account new or more accurate information. However, these can only be obtained or changed after binding decisions. Ideally, the options should be analyzed at the lowest possible level of territorial division, i.e. at the level of municipalities (currently around 6250 in the Czech Republic). Calculations on such level are related to the need to make predictions for small areas. However, the results for these areas can be highly variable, and these inaccuracies could affect the credibility of the outputs. Regarding the predictions, it would be beneficial to encompass the demographic development in the population across the Czech Republic. Despite all of this, the feasibility of suggested projects is also highly dependent on the willingness of local authorities and residents to support implementation, where the result of the public referendum can play a significant role.

6. Conclusion

The presented paper reviewed the current state-of-the-art within the waste management of Europe and the possible strategies on how to handle the planning of sustainable processing infrastructure with regards to the circular economy targets. It consists of crucial landfilling and recycling goals that were anchored in legislation. At the same time, the current waste treatment and material recovery were analyzed to define rates and trends used as the baseline point. Scenarios of waste production were generated from forecasts and targets to simulate three scenario trees. These were – business as usual, middle scenario considering 5-year delay and scenario on target. All scenarios were further branched to more evenly capture the possible developments.

The approach was demonstrated within the Czech Republic. One of the main contributions lies in the comparison of models with and without progressive goals. In the model with progressive goals, in the year 2020, the WtE capacity amounted to 981 kt and the MBT capacity to 600 kt. The second model suggests quite the opposite strategy. Since there were no restrictions during the time horizon, the optimal decision suggests to wait until the last moment with changes in processing infrastructure. The strength of the model is that it can be used for "rolling-horizon" planning, which means that it can be recomputed again after a few years and update the upcoming decisions with newly available data.

The future research may incorporate the decision-making regarding material recovery to meet all goals. The current approach requires a steep change from the trend. Also, the detail of the territory level will be analyzed in order to obtain more precise results. The model will identify micro-regions, where there is a potential for more effective waste treatment and management.

Author contribution

Jakub Kůdela: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. Veronika Smejkalová: Investigation, Resources, Data curation, Writing - original draft, Visualization. Vlastimír Nevrlý: Investigation, Resources, Data curation, Writing - review & editing, Visualization. Radovan Šomplák: Conceptualization, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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