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Multiobjective Optimization of Electromagnetic Structures Based on Self-Organizing Migration

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DEPARTMENT OF RADIO ELECTRONICS

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MULTIOBJECTIVE OPTIMIZATION OF ELECTROMAGNETIC STRUCTURES BASED ON SELF-ORGANIZING MIGRATION

VÍCEKRITERIÁLNÍ OPTIMALIZACE ELEKTROMAGNETICKÝCH STRUKTUR ZALOŽENÁ NA SAMO ORGANIZUJÍCÍ SE MIGRACI

SHORT VERSION OF DOCTORAL THESIS

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Contents

1 Introduction

1.1 Multi-objective Optimization

Optimization takes place in almost every engineering discipline. Optimization is a process of finding and comparing feasible solutions until the best solution is assigned. The quality of the solution can be measured by the value of an *objective* (*fitness*, *cost*) function. The objective function expresses requirements on the solution in terms of e.g. reliability, price, dimensions of the final product, efficiency of a manufacturing process etc.

Intuitively, most of the real world problems consider more than one objective. These objectives can be either corresponding or conflicting. In the first case the optimization results in one solution, which is optimal from the viewpoint of all objectives. Considering conflicting objectives optimization leads to a set of solutions. In this case "optimal" solutions represent the trade-off among all objectives.

This set builds in the space of objective functions in the so-called Pareto front named after an Italian economist Vilfredo Pareto (1848 - 1923) who dealt with conflicting objectives in his works about economic efficiency and redistribution of incomes. Members of the Pareto front have to satisfy the Pareto efficiency: improvement of the solution in one objective has to lead to deterioration in quality of all other objectives.

This phenomenon can be easily explained by using the following example from everyday life. When someone travels somewhere, there exist several options to choose: a plane, a car, a bus, a bike etc. Every vehicle has its own traveling time and price. When someone wants to optimize his travel considering both these objectives, Pareto front from Fig. 1.1 can be very helpful for him. It is obvious that using a plane is the fastest option. Therefore, a plane is the best choice from the viewpoint of traveling time. On the contrary, using a bike is the cheapest way so it is optimal from the viewpoint of the amount of spent money. Travelling by bus or driving your own car are the trade-off solutions. But no vehicle beats the other in both objectives.

A designer has two possibilities of choosing the final solution of the multi-objective optimization problem. The first one is to assign a priori importance to every objective, compose an aggregate fitness function and solve the problem as a single-objective one using well-known stochastic single-objective algorithms. This approach assumes that the user knows some extra information about the optimized problem. The trade-off is made with no information about the shape of the Pareto front.

Since it is very difficult to estimate the shape of the Pareto front a priori another way of choosing the final solution can be beneficial. First, the whole Pareto front is obtained and then, trade-off among all objectives is made according to the shape of the Pareto front.

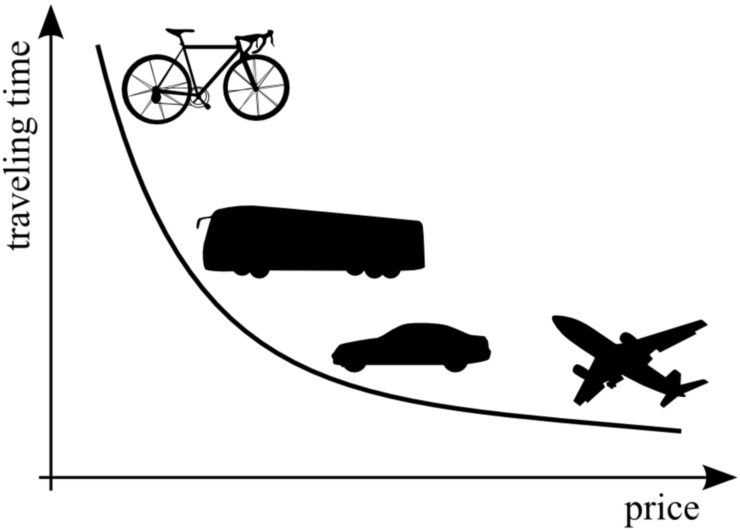

Fig. 1.1: Choosing a vehicle according to traveling time and price.

The first intuitive way how to obtain the Pareto front is to run the single-objective optimizers several times with different settings of importance for individual objectives. Although a great effort was devoted to the development of these methods during the second half of the 20th century some shortcomings lead to the development of “pure” multi-objective optimizers which look for the Pareto efficiency during the optimization process.

It is obvious that an efficient multi-objective optimizer can also be advantageously used in the design of electromagnetic structures in cooperation with suitable analysis tools e.g. a full wave solver, antenna design tool, etc.

This thesis implements a relatively new stochastic Self-Organizing Migrating Algorithm (SOMA) [1] for multi-objective optimization of electromagnetic components. A novel Multi-Objective Self Organizing Migrating Algorithm (MOSOMA) is derived.

Multi-objective optimization is relatively young part of evolutionary optimization. The importance and topicality can be proven by furious growth of number of books, journal and conference papers published per year during last two decades. Data from years 1990 to 2010 taken from [2] are depicted in Fig. 1.2. It seems that the growth reached its peak in year 2009.

The first attempts to use stochastic optimization algorithms in electromagnetics are dated into last decade of the 20th century [3], [4]. These methods are usually based on evolution (e.g. Genetic Algorithms [5]) or swarm cooperation (e.g. Particle Swarm Optimization [6]). They are very attractive, because their use is relatively simple. They can be implemented with basic knowledge of programming and mathematics. In fact, the only problematic task for a designer is to define the objective functions properly.

Our novel MOSOMA is extension of original algorithm SOMA that was introduced in 2000 by Ivan Zelinka in [1] and shows very good performance on many various single-objective problems. Although the author states in [8] that his algorithm is able to solve multi-objective optimization problem (MOOP) it is not fully true. The only implementations of SOMA [8] that solved multi-objective problems used the conventional methods that transform multi-objective problem into single-objective one (SOOP).

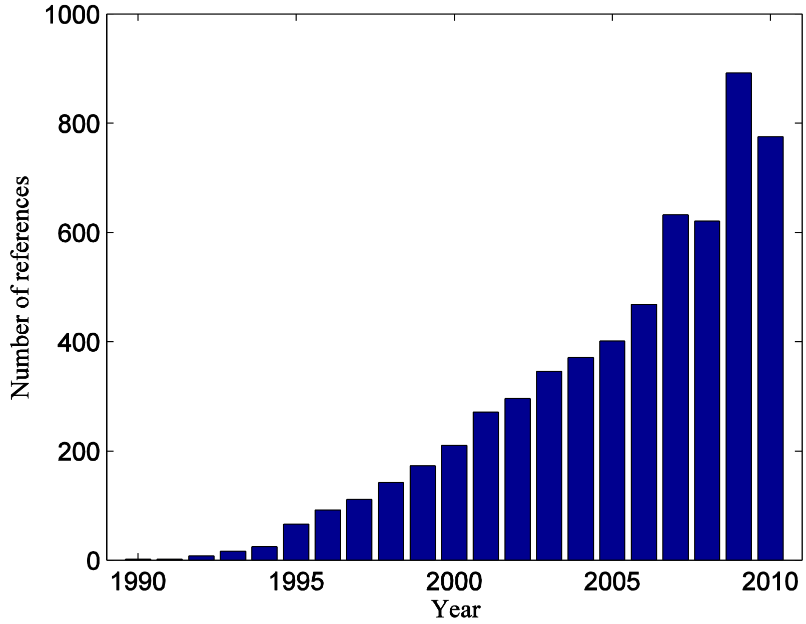

Fig. 1.2: Number of multi-objective optimization references per year from 1990 to 2010.

Since stochastic multi-objective optimization is relatively new discipline, principles necessary for proper understanding of a development and understanding of our novel algorithm are briefly introduced in this chapter. Also, the principles of SOMA and its applications are briefly described. Most of the properties discussed in the following subchapters are summarized in [PK 5]. Finally, the main objectives of this doctoral thesis are formulated at the end of the first chapter.

Generally, multi-objective optimization problem (MOOP) deals with a finite number of objective functions that should be either minimized or maximized. The transformation from a decision space of the input variables into an objective space of the two-variable two-objective problem is depicted in Fig. 1.3.

Almost every stochastic multi-objective optimizer that searches for the Pareto optimal set involves a principle of dominance. It compares two solutions and tries to decide, if one dominates the other or both are non-dominated. It is defined [9]:

Solution $\mathbf{x}_1$ *is said to dominate the other solution* $\mathbf{x}_2$*, if both conditions 1 and 2 are true:*

1. Solution $\mathbf{x}_1$ *is no worse than* $\mathbf{x}_2$ *in all objectives.*

2. Solution $\mathbf{x}_1$ *is strictly better than* $\mathbf{x}_2$ *in at least one objective.*

The set of non-dominated solutions *P* from the set of all researched solutions *Q* can be found using the principle of dominance. The non-dominated set can be defined [9]:

The non-dominated set P consists of solutions from Q, which are not dominated by any member of set Q.

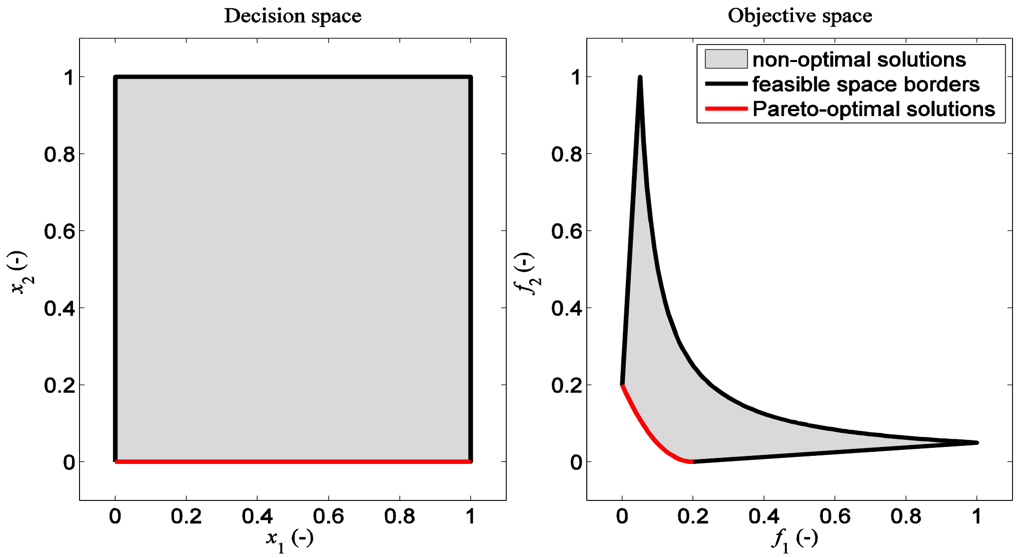

Fig. 1.3: The transformation from the decision space (left), to the objective space (right) of the optimization problem.

1.2 Self-Organizing Migrating Algorithm

The Self-Organizing Migrating Algorithm (SOMA) is a relatively new stochastic optimization tool introduced by I. Zelinka and J. Lampinen in 2000 [1]. The comprehensive description and analysis of the algorithm performance was published in [8]. The algorithm is based on the self-organizing behavior of group of individuals called agents. Agents migrate in the *N*-dimensional hyperspace of optimized parameters to find the vector of input variables with best value of fitness function. The knowledge about the researched space is shared within the entire group of individuals. The run of SOMA can be generally described in following steps:

Step 1: Defining controlling parameters of the algorithm.

Step 2: Generating the initial population and evaluating the fitness function.

Step 3: Migrating individuals, evaluating their new fitness values.

Step 4: Testing for stopping condition. If no stopping condition is accomplished, go back to Step 3.

Step 5: Assigning the solution.

The detailed description of SOMA can be found in [8] and in chapter 1.2.6 of the thesis.

The algorithm was successfully used on many real live problems. Some of them observed more than one objective. In every case, the multiple objectives were transformed into one single-objective function and optimized using basic single-objective version of SOMA. In [1], SOMA was tested on plenty of test functions and compared with conventional evolutionary algorithms (DE, GA). It achieved at least comparable results with conventional algorithms. The article [12] deals with a convergence issues of the algorithm. The distributed version of SOMA is described in [13].

The proposed algorithm was in [14] successfully applied for finding of an optimal trace for a robot. The results obtained by SOMA were better than from method based on simulated annealing. Authors in [15] employ SOMA for the optimization of the two-dimensional Henon map deterministic chaos model control. In [16], SOMA is used for trimming an aircraft to the steady state flight upon the various flight conditions. SOMA was applied also for finding of optimal parameters of the vibrating power generator as described in [17]. The article [18] deals with a design of a Loney´s solenoid using the modified SOMA approach with the advance of so called normative knowledge that assigns regions in decision space with better values of fitness function. The paper [19] introduces a modified SOMA approach based on a Gaussian operator to solve the reliability-redundancy optimization problems. According to our knowledge, SOMA has been never used for solution of pure multi-objective optimization problems by other authors.

1.3 Dissertation Objectives

The most important objectives of this dissertation thesis can be summarized into the following list:

- Creation of a new multi-objective technique based on self-organizing migration.
- Study of convergence properties of the newly proposed algorithm.
- Implementation of the proposed algorithm for solving of real-life design problems in electromagnetics.

The most important objective of this dissertation thesis is to derive a new stochastic algorithm for solving multi-objective optimization problems based on the principles of the self-organizing migrating algorithm. The novel algorithm should be able to solve problems with an arbitrary number of input variables and objective functions. The algorithm should reveal the desired number of Pareto front members. These solutions should be as close as possible to the true Pareto front but also the claim on the diversity of solutions should be satisfied.

The properties of the newly developed method have to be studied. The influence of the controlling parameters of the algorithm should be revealed. Also convergence properties of the algorithm should be studied. It has no sense to exploit a tool that does not ensure the convergence to the correct answer. As described in [20] the behavior of convergence properties of the stochastic optimization algorithms can be described using so called finite Markov chains.

After the convergence of the algorithm is proved satisfactorily, it can be applied to solve electromagnetic design problems. Two types of problems should be considered: previously solved by other multi-objective techniques (so that results of MOSOMA can be compared) and newly defined unsolved problems.

2 MOSOMA

This chapter introduces an original Multi-Objective Self-Organizing Migrating Algorithm (MOSOMA). As described in subchapter 3.1.1 of the thesis, transforming the MOOP into the SOOP and use of single-objective algorithm (e.g. SOMA [7]) is not efficient for solution of multi-objective optimization problems. The optimizer should be able to solve constrained or unconstrained MOOPs having any number of decision space variables *N* and objectives *M*. The algorithm should handle with multi-objective problems having convex, non-convex or discontinuous Pareto front. It should be able to work with continuous and discrete decision space also.

Our novel stochastic Multi-Objective Self Organizing Migrating Algorithm (MOSOMA) was introduced in [PK 2], the extension of MOSOMA for solution of MOOPs having more than two objectives was then published in [PK 3]. MOSOMA combines two basic principles: exploring the *N*-dimensional decision space defined in the original SOMA, and choosing the non-dominated set of individuals from the current population in *M*-dimensional objective space.

The run of the algorithm can be described by following steps:

Step 1: Defining controlling parameters of the algorithm.

Step 2: Generating the initial population, evaluating objective functions.

Step 3: Choosing external archive from the current population.

Step 4: Migrating agents to members of external archive. Evaluating objective functions for new positions. Updating the external archive. Selecting migrating agents for next migration loop.

Step 5: Testing for stopping condition. If no stopping condition is accomplished, go back to Step 4.

Step 6: Choosing final non-dominated set from the current external archive.

The migration principle remains the same as in case of single-objective algorithm as described in subchapter 1.2.4 of the thesis. As the number of executed migration loops increases, agents explore the *N*-dimensional decision space more deeply.

Migration of agents is steered by information about objective values of the agents. All agents share the external archive where the so far found non-dominated solutions are stored. It ensures that all members of the population have idea about the changes in objectives within different parts of the decision space.

Basic principle of MOSOMA is to let the agents migrate towards members of external archive as depicted in Fig. 2.1. This procedure enforces the agents to scan regions with best values of objective functions from viewpoint of all objectives more carefully.

The general pseudo-code of the whole MOSOMA is depicted in Fig. 2.2. The whole procedure starts with random generation of group of agents $P(1)$. External archive members are selected according to non-dominated sorting of the whole group of agents. In every migration loop, selected agents then migrate towards members of $EXT(i-1)$ and their temporary locations **tmp** are determined by equation:

$$\mathbf{tmp}_{p,s}(i) = \mathbf{x}_p(i-1) + \left(\mathbf{x}_q(i-1) - \mathbf{x}_p(i-1)\right) \cdot \frac{s}{ST} \cdot PL \cdot \mathbf{PRTV}_{p,s} \tag{2.1}$$

where $\mathbf{tmp}_{p,s}$ is the vector specifying the new position of the p-th individual resulting from the s-th step of the movement to the q-th individual. ST defines the number of steps for one migration ($s = 1, 2, \dots, ST$). The parameter PL defines the length of the trajectory. If PL is equal to one, then the migration ends in the position of the q-th individual exactly. So called perturbation vector **PRTV** has the same size as the vector defining the position of an individual **x** and consists of zeros and ones. **PRTV** is defined for each migration by N randomly generated numbers:

$$\mathbf{PRTV}(n) = \begin{cases} 1 & if\ rnd(n) > PR \\ 0 & if\ rnd(n) \le PR \end{cases} \tag{2.2}$$

where PR denotes the probability of perturbation defined by user. The perturbation has the same effect for SOMA as the mutation for GA. Then, new $\underline{EXT}(i)$ is built from first non-dominated front solutions of non-dominated sorting of union of $EXT(i-1)$ with **tmp.**

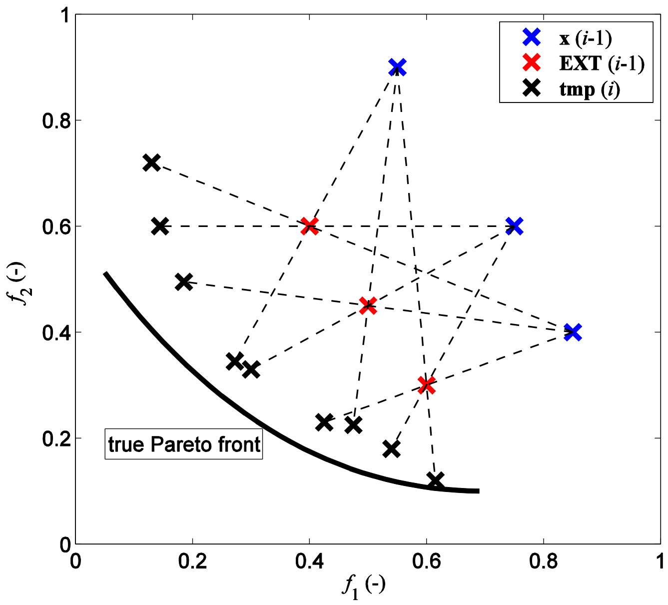

Fig. 2.1: Main principle of the Multi-Objective Self-Organizing Migrating Algorithm [PK 2].

After a new external archive is determined, set of migrating agents T is determined. There are several options, how to select these agent: e.g. they can remain in same positions as defined at the start of the algorithm, their positions can be chosen randomly, also some members of EXT can be chosen to T. According to our experience, it is suitable to fill T partly with randomly generated agents (the premature convergence to local optimum - advancing front - can be suppressed) and with members of external archive (the region of the best solutions is researched carefully which can speed up the whole procedure). The migration proceeds until a stepping condition is met. Since number of solutions in final set EXT is usually much higher than number of wanted solutions on the Pareto front N_{exf}, final set P is chosen from EXT so that the found Pareto front is covered uniformly.

```
Start
    Define initial population Q(1)
    Compute objective functions in tmp
    Find external archive EXT
    While i < I | FFC < N_f,max | |EXT(i)| < N_ex,max
        For q = 1 : |Q(i - 1)|
            x_q  migrates to all members of EXT(i - 1)
            Compute objective functions in tmp
        End
        Find EXT(i) from tmp ∪ EXT(i - 1)
        While |EXT(i)| < N_ex,min
            Find advancing front and crowding distance
            Fill EXT_i with best agents from advancing front
        End
        Choose T agents to Q(i)
        i++
    End
    Chose final set P from EXT(i)
End
```

Fig. 2.2: Pseudo-code of MOSOMA [PK 3].

The main parameters and complex procedures of the algorithm are described in the original version of the thesis precisely. Since the size of external archive grows usually very quickly the new approach for selecting final non-dominated set P from current external archive was proposed in [PK 2] and [PK 3]. This procedure enhances the spread of final Pareto-optimal set. This procedure is applied only if the size of external archive is larger than desired number of non-dominated solutions $|P|$, after any of the stopping conditions are met. First, M extreme solutions (having minimal value of particular f_m) are saved into P. The rest of P is filled with members of EXT so that members of P cover the Pareto front uniformly.

2.1 Conclusions

The extension of the single-objective self-organizing migrating algorithm has been derived in this chapter. The proposed algorithm is applicable on problems having any number of decision space variables and objective functions. MOSOMA is also able to deal with constrained optimization problems.

A novel procedure for choice of the final non-dominated set has been proposed. This approach significantly enhances the uniform spread of final non-dominated set found by the optimizer. The most important contributions of this chapter were presented in journal Radioengineering [PK 2] and in proceedings of conference Radioelektronika 2012 [PK 3].

3 Convergence of MOSOMA

The study of convergence properties is very important for every novel optimizer. Generally speaking, the convergence should be ensured for every numerical method. Nevertheless, theoretical proofs of stochastic algorithms that are strongly influenced by random processes are very rare. Therefore, the convergence properties of stochastic optimizers are usually shown on benchmark methods, first.

In this chapter, results of two comparative studies are derived here to show efficiency of MOSOMA in context of commonly used optimizers. Also the sensitivity analysis of the controlling parameters was performed to provide recommended values to help other users with a proper setting of MOSOMA. Finally, the proof for theoretical convergence of MOSOMA is derived.

3.1 Comparison with Benchmark Methods

Applying a new multi-objective optimizer on large suite of test problems is the first logic step to ensure, that the proposed method is able to solve multi-objective problems efficiently. The quality of achievements can be expressed by means of metrics applied for benchmark problems with known Pareto fronts.

Several performance metrics can be used for comparison of results obtained by two different multi-objective optimizers. Following performance metrics were used for our comparative studies: generational distance ([10]), spread ([7]), hit rate ([11]) and hypervolume error ([10]). It should be noted, that in [PK 3] we have proposed an original approach to compute spread metric also for problems with more than two objectives based on finding of the minimum spanning tree [22] (for further details please refer to subchapter 3.2.1.2 of the thesis).

We have made two comparative studies of MOSOMA with other multi-objective optimizers that exhibit very good performance on various problems (NSGA-II, SPEA2). Brief description of these algorithms can be found in Appendix 2 of the thesis. The results of these two studies have been published in [PK 2] and [PK 3]. First one considers various types of two-objective problems. The second paper is focused on MOSOMA efficiency when it is solving problems with more than two objectives (three-objective problems have been used so that obtained results can be displayed easily). Definitions of the used benchmark problems with their properties can be found in Appendix 3.

3.1.1 Two-objective Problems

Results of MOSOMA were compared with results obtained by NSGA-II and SPEA2 on SC1, SCH1, FON, POL, ZDT1 and ZDT2 problems in [PK 2]. Both the algorithms were set to provide 50 Pareto optimal solutions and to compute the objective functions 25000-times. Therefore, parameter *FFC* of MOSOMA was set to the same value to satisfy fairness of the comparison.

Detailed description of MOSOMA settings and obtained results can be found in subchapter 3.2.2.1 of the thesis. MOSOMA achieves comparable results of *GD* metric as optimizers SPEA2 and NSGA-II (see Tab. 3.3 in the thesis). It should be noted here, that usually, MOSOMA executed less number than the other algorithms as indicated in Tab. 3.5 of the thesis. On the other hand, MOSOMA excels in spread metric values. It achieved significantly better values of Δ for all test problems (see Tab 3.4 in the thesis). Values of all metrics are worse for the ZDT1 and ZDT2 problems having large number of decision space variables. More robust settings of the optimizer (higher $P(1)$, FFC…) should be used for solving these problems. Pareto-optimal solutions found by MOSOMA are depicted in Fig. 3.6 of the thesis for all used test problems. Randomly chosen results were taken. MOSOMA reached the true Pareto front with very good spread in all cases except ZDT1 problem.

3.1.2 Three objective Problems

Five three-objective problems have been used in [PK 3] to prove that MOSOMA is able to solve problems with more than two-objectives efficiently. The definitions of TP1, GSA2, DLTZ1, DLTZ2 and UF8 can be found in Appendix 3 of the thesis. Detailed description of MOSOMA settings and obtained results can be found in subchapter 3.2.2.2 of the thesis.

MOSOMA was the best in all used problems for the generational distance metric as can be seen in Tab 3.6 of the thesis. The difference between MOSOMA and other two optimizers is not so significant. MOSOMA excels in coverage of the Pareto front expressed by spread metric (see Tab 3.7 in the thesis). It is significantly better also in more complex problems (DLTZ family and UF8). MOSOMA outperforms other two optimizers in hypervolume error metric (Tab 3.8 of the thesis), also.

3.2 Sensitivity of Controlling Parameters

Since multi-objective optimization problems are highly non-linear, accuracy and efficiency of their solution strongly depends on settings of a used algorithm [9]. From the viewpoint of a user, a proper setting of the parameters controlling the optimizer is a rather difficult task. On one hand, the settings have to be very robust so that the optimizer can achieve the global optimum with high probability. On the other hand, the parameters should be chosen to ensure high efficiency of the optimization process. Therefore, many researchers put their efforts to reveal rules for controlling parameters of multi-objective algorithms and to formulate recommendations for proper setting of optimizers.

The benchmark suite should be large enough to cover different types of problems. Therefore, we have chosen 9 different unconstrained problems having a different number of decision space variables, different number of objective functions and different shapes of Pareto fronts. All fitness functions are formulated as minimization objectives. The well-known problems DTLZ1, DTLZ2, FON, GSA2, SCH1, UF8, TP1, ZDT1 and ZDT2 are used here.

The sensitivity analysis of MOSOMA convergence was performed for seven control parameters:

- The total number of computations of the fitness function FFC.
- The minimal size of the external archive $N_{ex,\min}$.
- The size of the initial population $P(1)$.
- The path length PL.
- The probability of perturbation PR.
- The number of steps ST.
- The number of migrating agents T.

Since each benchmark problem from the test suite has a different number of decision space variables, some control parameters are normalized to the number of the decision space variables N (FFC, $P(1)$ and T) or the initial population size $P(1)$ ($N_{ex,\min}$). During the sensitivity evaluation of a selected parameter, other parameters remain constant. Constant values of parameters are summarized in Tab. 3.1. These settings were chosen according to the results of previously performed tests [PK 2] and [PK 3].

FFC/N (-)	$N_{ex,\min}/P(1)$ (-)	$P(1)/N$ (-)	PL (-)	PR (-)	ST (-)	T/N (-)
12000	2/3	10	1.5	0.15	4	8

Tab. 3.1: MOSOMA settings for the sensitivity analysis of the controlling parameter.

For the settings of each parameter, MOSOMA has been run 50 times to search for 50 Pareto optimal solutions. Some statistics were computed for the generational distance, the spread and the hyper-volume error metric.

Totally, MOSOMA was run approximately 50000-times (50 repetitions × 7 parameters × 16 values per parameter × 9 test problems). Detailed results for every metric and test problem can be found in subchapter 3.3 and Appendix 4 of the thesis. Here, only the recommended intervals for all watched control parameter are presented in Tab. 3.2. It should be noted here, that the recommendations were made according to all results which are available in Appendix 4 of the thesis.

Par.	FFC/N (-)	$N_{ex,\min}/P(1)$ (-)	$P(1)/N$ (-)	PL (-)	PR (-)	ST (-)	T/N (-)
Min	8000	0.3	5;	1.2	0.1	2	5
Max	15000	0.6	12	1.7	0.3	5	10

Tab. 3.2: Recommended intervals for MOSOMA control parameters [PK 8].

3.3 On Theoretical Convergence of MOSOMA

It is very difficult to tell something about theoretical convergence of stochastic optimization algorithms because run of these optimizers is influenced by a large number of random processes. Although theoretical proofs are very rare even for single-objective algorithms, some works dedicated to theoretical convergence of multi-objective optimizers can be found in [20], [23] and [24]. All these works presume that multi-objective optimizer is a *Markov process*. Future state of the Markov process can be predicted solely on its present state.

Thanks to the concept of perturbation described in section 1.2.6 of the thesis (the migration can proceed in $2^N - 1$ directions where N is the number of decision space variables) and partly random positions of migrating agents described in section 2.1 of the thesis (the migration can start in any position of the decision space and therefore any position in the decision space can be visited) MOSOMA can be viewed as a homogeneous finite Markov chain with regular and therefore irreducible transition matrix. Therefore, considering the definition about convergence of homogenous finite Markov chains [25] we can make following **proposition** as in [20]:

In case of MOSOMA, the sequence $B(t)$ is a homogenous finite Markov chain with irreducible transition matrix. Therefore, distance between members of minimal set defined by

MOSOMA and corresponding members of true minimal set $d(f(A(t)), F^*) \rightarrow 0$ with probability one at $t \rightarrow \infty$.

Here, $B(t)$ is the sequence of positions visited by agents, $A(t)$ denotes set of minimal elements (external archive) and $d(f(A(t)), F^*)$ is the distance measured in the objective space, between some member of set of minimal elements and set of true Pareto-optimal solutions F^*.

Proof: It is guaranteed, that the set $f(A(t))$ contains all incomparable elements so far found. If an element of the true minimal set F^* enters $f(A(t))$, it will stay there forever. Next, we can show that all elements of F^* will be found after some random time. Since $A(t + 1)$ is determined from union of previous $A(t)$ and new $B(t + 1)$, non-optimal elements can be discarded from $A(t)$ in future time step. Since $(F, \preccurlyeq)$ is a complete poset, it is guaranteed that there exists some element $x \in X$ such that $f(x) \prec f(a) : f(\mathrm{a}) \notin F^*$. Since the transition matrix of the chain is irreducible, it is ensured that every position from set X^* will be visited infinitely often. Therefore, non-optimal elements will be eliminated after finite number of iterations with probability one.

Summing up: all optimal elements will enter to A in finite time with probability one. If all optimal elements are in A, then all non-optimal elements had to be eliminated from A. The size of A grows with the run of the algorithm to the size of the true minimal set. This slows down the procedure for finding incomparable (non-dominated) elements for real-life use of the algorithm.

Obviously, this theoretical proof cannot be considered in real life, since it presumes infinite time devoted for the optimization. On the other hand, it shows that MOSOMA should not suffer from freezing in local optimum, because there is always a nonzero probability, that the optimal point in the decision space can be visited during any migration.

3.4 Conclusions

This chapter concentrated on convergent properties of our novel algorithm MOSOMA. Only optimizers that prove very good convergence on various types of problems can be considered for further use. Therefore, we have shown at first, that using the original single-objective SOMA together with conventional methods aggregating multiple objectives into one fitness function is not sufficient. These methods suffer from problems with revealing concave Pareto front parts and with very difficult setting of weights for individual objectives a priori. We have shown that MOSOMA is able to overcome these problems efficiently. Work related to this problem was published at the conference Radioelektronika 2011 [PK 1].

Next, the novel algorithm has to be compared with other methods to show its efficiency. We have published two comparative studies: the first one (considering two-objective benchmark problems only) in Radioengineering journal paper [PK 2] and the second one (considering three-objective problems) in the Radioelektronika 2012 conference paper [PK 3].

Performance metrics defined for sets of Pareto-optimal solutions are necessary for comparative studies. The well-known Δ metric was defined to evaluate the spread of Pareto-optimal solutions found. Unfortunately, this metric was defined only for two-objective problems. Therefore, we have proposed a new approach for evaluating the spread metric in the Radioelektronika 2012 conference paper [PK 3]. The method is based on finding the so-called minimum spanning tree, which can be found for fronts having any number of objectives, including two.

The results of an ideal optimizer should be totally independent of its own settings. Obviously, such behavior cannot be achieved. Therefore, sensitivity analysis of parameters controlling the run of optimization is necessary. The work related to the sensitivity of parameters controlling MOSOMA was submitted to the Radioengineering journal [PK 8]. Results of this analysis enable to define recommended intervals for MOSOMA parameters that should make it easier for other users to setup the proper settings.

Finally, we have adopted a theoretical convergence proof derived in [20] for our algorithms. We have shown that MOSOMA finds every Pareto-optimal solution with a probability one, when run for an infinite long time.

4 EM Applications

MOSOMA can be applied to solve optimization problems in any field of engineering activities e.g. mechanical engineering, economics, chemistry etc., because it has been derived as a general tool able to solve any type of multi-objective optimization problems. We focus on applications from electromagnetics.

MOSOMA was applied to solve EM problems such as adaptive beam forming in time domain for an array of slot antennas (see chapter 4.1 in the thesis), design of digital filter for reflection-less truncation of waveguides when applying FDTD method (chapter 4.2), design of various types of dielectric layered filters (chapter 4.3) or Yagi-Uda antennas (chapter 4.4). Some of these problems (dielectric filter and Yagi-Uda design) were previously solved by other authors, so that results obtained by MOSOMA can be compared with references. Other problems have not been yet solved by any other author according to our knowledge. In this short version of the thesis, we present only application of MOSOMA for design of layered dielectric filters.

4.1 Dielectric Filter Design

Results described in this subchapter can be found in [PK 7]. Dielectric filter design for microwave bands involves optimization of a relative permittivity and width of individual layers of the filter. Venkatarayalu *et al.* formulated the optimization of widths and relative permittivities of individual layers of a filter as constrained two-objective problem in [26]. They proposed new evolutionary algorithm (MOEA) for its solution. Goudos *et al.* has used multi-objective algorithm based on swarm intelligence (MOPSO) for solution of band-pass, low-pass and band-stop filter design [27].

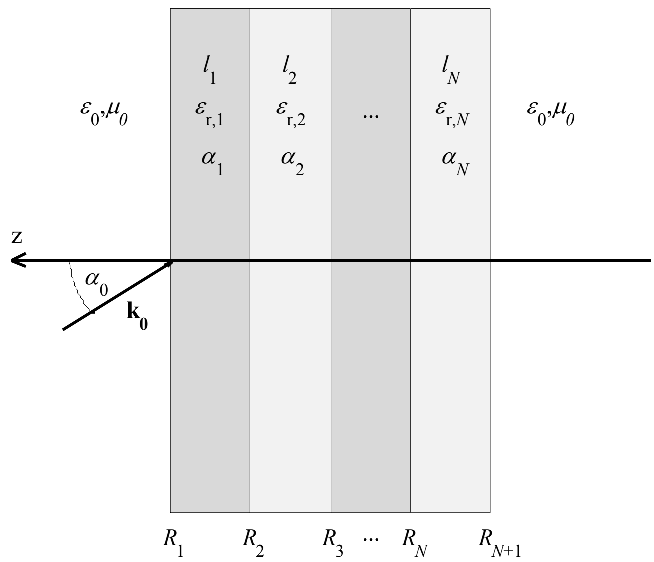

Fig. 4.1: Description of the layered medium [PK 7].

Considering the filter having N layers, $2N$ parameters are changed during the optimization process. The layered medium is depicted in Fig. 4.1. Here, $\mathbf{k_0}$ stands for the wave vector of the impinging wave, l_n denotes width of n-th layer, $\varepsilon_{r,n}$ denotes relative permittivity of n-th layer, α_n is the incident angle for n-th interface and R_n is the reflection coefficient of n-th interface. Interface between the first and second dielectric layer is denoted by R_2.

Considering homogeneous lossless nonmagnetic materials ($\sigma = 0$, $\mu_r = 1$), generalized recursive reflection coefficient R_n for n-th interface can be derived from [28]:

$$R_n = \frac{r_n + R_{n+1}\exp\left(2j\,\mathbf{k}_n l_n\right)}{1 + r_n R_{n+1}\exp\left(2j\mathbf{k}_n l_n\right)} \tag{4.1}$$

where the wave vector $\mathbf{k}_n$ in n-th layer can be computed using equation:

$$\mathbf{k}_n = \frac{2\pi f}{c}\sqrt{\varepsilon_{\mathrm{r,n}}} \tag{4.2}$$

Assuming the reflection coefficient for TE mode:

$$r_{n,\mathrm{TE}} = \frac{\sqrt{\varepsilon_{\mathrm{r,n-1}}\left(1-\sin^2\alpha_{n-1}\right)} - \sqrt{\varepsilon_{\mathrm{r,n}}\left(1-\sin^2\alpha_n\right)}}{\sqrt{\varepsilon_{\mathrm{r,n-1}}\left(1-\sin^2\alpha_{n-1}\right)} + \sqrt{\varepsilon_{\mathrm{r,n}}\left(1-\sin^2\alpha_n\right)}} \tag{4.3}$$

and for TM mode:

$$r_{n,\mathrm{TM}} = \frac{\varepsilon_{\mathrm{r,n}}\sqrt{\varepsilon_{\mathrm{r,n-1}}\left(1-\sin^2\alpha_{n-1}\right)} - \varepsilon_{\mathrm{r,n-1}}\sqrt{\varepsilon_{\mathrm{r,n}}\left(1-\sin^2\alpha_n\right)}}{\varepsilon_{\mathrm{r,n}}\sqrt{\varepsilon_{\mathrm{r,n-1}}\left(1-\sin^2\alpha_{n-1}\right)} + \varepsilon_{\mathrm{r,n-1}}\sqrt{\varepsilon_{\mathrm{r,n}}\left(1-\sin^2\alpha_n\right)}} \tag{4.4}$$

where the angle of incidence for n-th layer is defined:

$$\alpha_n = \sin^{-1}\left(\frac{\sqrt{\varepsilon_{r,n-1}}}{\sqrt{\varepsilon_{r,n}}}\sin\alpha_{n-1}\right) \tag{4.5}$$

Such a defined, total reflection coefficient of the layered medium is then the coefficient between the free space and the first medium denoted R_1.

In [26] the two objective functions for design of filter with seven layers have been defined:

$$\begin{aligned} F_1 &= \sum_{p=1}^{P}\left[\left|R_{1,\mathrm{TE}}\left(f_p\right)\right|^2 + \left|R_{1,\mathrm{TM}}\left(f_p\right)\right|^2\right] \\ F_2 &= \sum_{s=1}^{S}\left[2 - \left|R_{1,\mathrm{TE}}\left(f_s\right)\right|^2 - \left|R_{1,\mathrm{TM}}\left(f_s\right)\right|^2\right] \end{aligned} \tag{4.6}$$

where f_p and f_s denotes the passing and stopping frequencies of the filter respectively. The capital letter F (objective function) is used here just to distinguish between objective function and frequency. Objective function F_1 minimizes the reflection of the layered media in the passing band while the other function F_2 maximizes reflection in the stopping band. Under this definition, Pareto fronts obtained by different authors cannot be compared because values of objective functions are influenced by the discretization of the frequency axis. Therefore, we propose a slight modification of the objective functions:

$$F_1 = \frac{1}{P}\sum_{p=1}^{P}\left[\left|R_{1,\mathrm{TE}}\left(f_p\right)\right|^2 + \left|R_{1,\mathrm{TM}}\left(f_p\right)\right|^2\right]$$
$$F_2 = \frac{1}{S}\sum_{s=1}^{S}\left[2 - \left|R_{1,\mathrm{TE}}\left(f_s\right)\right|^2 - \left|R_{1,\mathrm{TM}}\left(f_s\right)\right|^2\right] \tag{4.7}$$

Now, P and S stands for size of the used frequency vectors and both the functions are normalized to number of examined frequency points and fully comparable.

The definition of the optimization problem is fully completed by formulation of the constraint functions for passing and stopping band respectively [26]:

$$\begin{aligned} 20\log\left|R_{1,\mathrm{TE}}\left(f_{pc}\right)\right| &< -10\,\mathrm{dB} \\ 20\log\left|R_{1,\mathrm{TM}}\left(f_{pc}\right)\right| &< -10\,\mathrm{dB} \\ 20\log\left|R_{1,\mathrm{TE}}\left(f_{sc}\right)\right| &< -5\,\mathrm{dB} \\ 20\log\left|R_{1,\mathrm{TM}}\left(f_{sc}\right)\right| &< -5\,\mathrm{dB} \end{aligned} \tag{4.8}$$

where f_{pc} and f_{sc} denote the passing and stopping frequencies considered for constraints, respectively.

So called penalty function approach [21] can be used for handling with constraints. This approach was briefly described in section 2. Since values of both the objective functions should vary in interval $\langle 0; 2\rangle$ the penalty operator was set for both objective functions to $R = 5$. This procedure disqualifies the solutions violating any constraint from further search of the algorithm.

The design of seven-layer filter evolves optimization of 14 parameters. The incidence angle was fixed to $\alpha_0 = 45°$. Width of every layer $x_{1\text{-}7}$ can vary in the interval $\langle 1\ \mathrm{mm}; 10\ \mathrm{mm}\rangle$. The relative permittivity of all layers can be chosen from commercially available dielectric materials {1.01, 2.20, 2.33, 2.50, 2.94, 3.00, 3.02, 3.27, 3.38, 4.48, 4.50, 6.00, 6.15, 9.20, 10.20} [26].

The controlling parameters of MOSOMA were set so that its results can be compared with results published in [26] and [27]. The settings are summarized in Tab. 4.1.

Par.	*FFC*	*PR*	*PL*	*ST*	*P*(1)	*T*	$N_{ex,\min}$
	15000	0.1	1.3	5	30	20	15

Tab. 4.1: Settings of MOSOMA parameters for the dielectric filter design.

4.1.1 Band-pass Filter

In [PK 7], design of band-pass, band-stop and low-pass filter can be found. The only experiment considered in this short version of doctoral thesis is the design of the band-pass filter. The frequency bands for the filter and for the constraint functions are summarized in Tab. 4.2.

Band	Lower bound (GHz)	Upper bound (GHz)
f_p	28	32
f_s	24; 32	28; 36
f_{pc}	29	31
f_{sc}	24; 34	26; 36

Tab. 4.2: Frequency bands for the band-pass filter optimization.

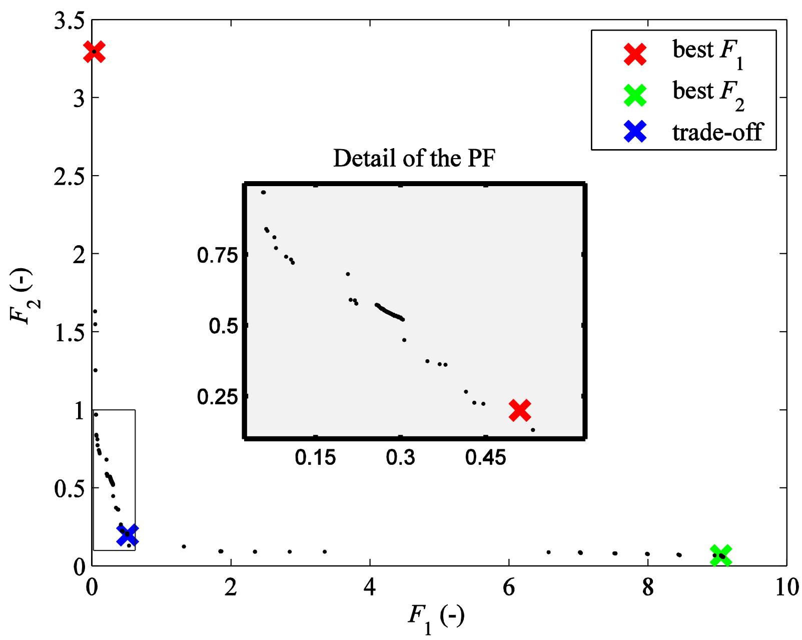

Fig. 4.2: Pareto front of the band-pass filter multi-objective optimization using MOSOMA. The detailed plot depicts the trade-off solutions non-violating the constraints [PK 7].

The Pareto front of the optimized problem is depicted in Fig. 4.2. It is obvious, that some of the Pareto-optimal solutions are violating the constraint functions, because their value of objective function is higher than 2. Three solutions are highlighted here: the best solution according to the first (red marker) and second (green) objective and the trade-off solution (blue). Fig. 4.3 depicts the frequency behavior of the reflection coefficients for these solutions. Here, colors correspond to markers in Fig. 4.2. The red solution ideally satisfies the first objective, but the last two constraints are violated. On the contrary, green solution suits the second objective but violates first two constraint functions. Finally, blue solution respects both the objectives and does not violate any constraint function.

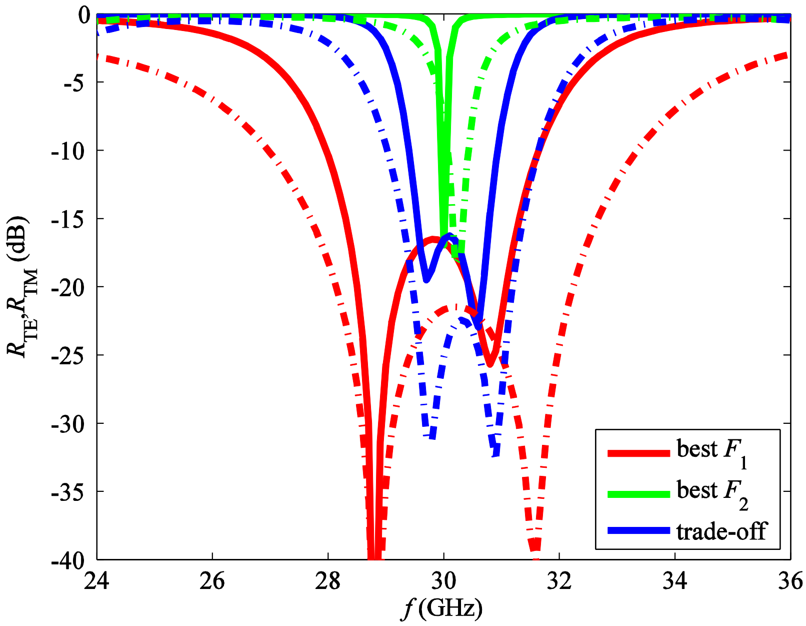

Fig. 4.3: Reflection coefficient TE (solid line) and TM (dashed) for three band-pass filters designed by MOSOMA: red line (the best solution according to F_1), green (the best F_2) and blue (trade-off) [PK 7].

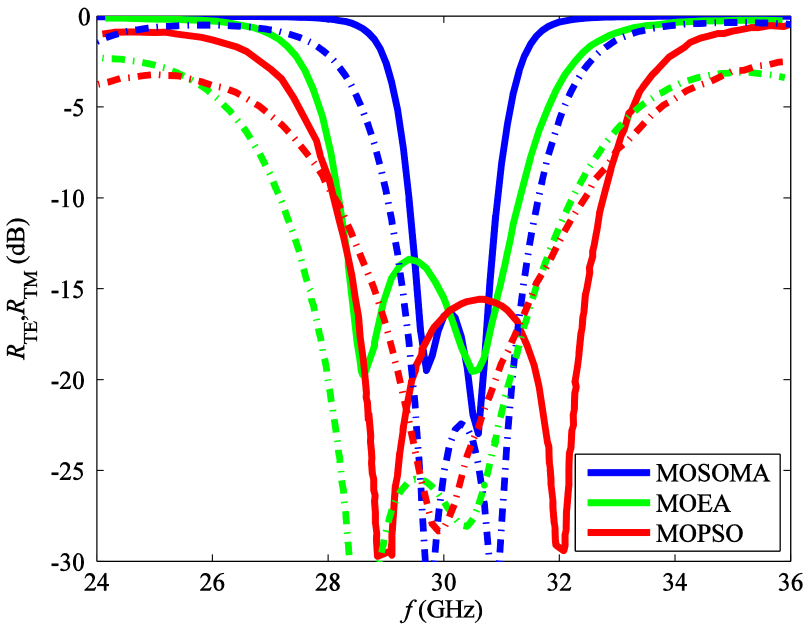

Fig. 4.4: Comparison of the TE (solid line) and TM (dashed) reflection coefficient for band-pass filter design obtained by MOSOMA (blue) [PK 7], MOEA [26] (green) and MOPSO [27] (red).

The trade-off solution composed of layers having width {4.686, 1.995, 4.739, 1.001, 1.003, 1.002, 8.663} mm and relative permittivities {10.20, 1.01, 10.20, 1.01, 1.01, 2.94, 2.35} was chosen as the final trade-off solution. Fig. 4.4 compares its reflection coefficients with solutions published in [26] and [27]. Total width of our design is 23.08 mm compared to 33.44 mm [26] and 21.35 mm [27]. Reflection coefficient for our solution remains below - 16 dB for the TE mode and -22 dB for the TM mode in the whole operational band. Coefficients R_{TE} and R_{TM} of our proposal decrease steeper at the boundaries of the desired frequency band than for solutions from [26] and [27].

4.2 Conclusions

Thanks to the growing speed of computational resources, efficient stochastic optimization methods became an essential part of the design process. After showing MOSOMA´s ability to solve theoretical benchmark problems efficiently, this chapter considered applying MOSOMA on various EM design problems.

Firstly, MOSOMA was used to control radiation of an array of slot antennas, so that the radiated energy is focused to specific places in the irradiated domain and vanishes in other defined places. This two-objective problem was defined and successfully solved using MOSOMA in the ICEAA 2011 conference paper [PK 4].

Then, MOSOMA was employed to find the optimal parameters of a digital filter that terminates a waveguide with a reflection-less absorbing boundary condition. The two-objective unconstrained problem was defined and different solutions from the Pareto front found by MOSOMA were discussed. Work about designing digital filter was published at the conference Radioelektronika 2012 [PK 6].

MOSOMA was also applied for solving previously studied problems: design of layered dielectric filters and Yagi-Uda antennas. The design of dielectric filters considers two objectives and four constraints. MOSOMA was able to handle continuous and discrete decision space variables at the same time. MOSOMA was successfully connected with external 4NEC2 software devoted for analyzing wire antennas to automatically design Yagi-Uda antennas with maximized gain, minimized side lobe level and proper impedance matching. The work related to those designs was submitted for publication in the IEEE Antennas and Propagation Magazine [PK 7]. MOSOMA achieved comparable or better results than optimizers used in previous studies. The Yagi-Uda antenna design exhibiting filtering properties of gain in a specified direction was submitted for publication in the Radioengineering journal [PK 9].

5 Conclusions

Multi-objective optimization brings users extra information about solved problems. The Pareto front expresses a trade-off between particular objectives. Furthermore, the user can assign the importance of individual objectives according to the shape of the determined Pareto front. On one hand, the trade-off solutions can be found, on the other hand, limits of the optimized problems can be determined within a single run of the optimizer.

An analytic solution of multi-objective optimization problems is possible only for a few particular cases. Therefore, the use of stochastic optimizers is necessary. The use of these optimizers is relatively simple, because they can be implemented with only basic knowledge about programming. Further, the user has to define just the objective functions which can be positive and negative. On one hand, there is no need for deeper understanding of the solved problem. On the other hand, it can lead to unnecessary presumptions of these powerful but time-consuming tools.

This dissertation thesis tried to solve three general objectives formulated in subchapter 1.3:

- To derive a novel efficient multi-objective algorithm based on the concept of self-organized migration.
- To study convergent properties of the newly proposed algorithm.
- To apply the newly proposed algorithm for solving real-life problems in electromagnetics.

Our novel Multi-Objective Self-Organizing Algorithm adopts the basic concept of migration of a group of agents from the Self Organizing Migrating Algorithm. SOMA has shown very good efficiency on plenty of benchmark and real-life problems [8]. The description of MOSOMA was published in [PK 2] and [PK 3]. During every migration loop of MOSOMA, every agent reveals several positions in the decision space where the objective functions are evaluated. The basic idea is to let the agents migrate towards the best solutions found so far which should lead the whole group of agents towards the region of the true Pareto-optimal solutions.

Our proposed algorithm is able to solve various types of problems:

- constrained or unconstrained,
- with convex or concave Pareto front,
- with continuous or discontinuous Pareto front,
- with continuous or discontinuous decision space,
- with any number of objectives.

The ability of MOSOMA to solve multi-objective problems efficiently was proved by two comparative studies [PK 2] and [PK 3]. MOSOMA competed with two commonly-used benchmark tools NSGA-II and SPEA2. The comparisons were made on a large suite of test problems having two or three objectives. MOSOMA achieved at least comparable or better results in generational distance and hypervolume error metrics. MOSOMA outperformed both the algorithms in spread metric significantly.

The sensitivity analysis of the parameters controlling the run of MOSOMA was then performed [PK 8]. This analysis was made for a large suite of different benchmark problems. The analysis proved that the results of MOSOMA remain constant when the controlling parameters are chosen from certain intervals. These recommended intervals should help other users to set the algorithm so that it works efficiently with very high probability of getting the correct results.

Next, the theoretical convergence of the algorithm was studied. We have proved that MOSOMA is a homogeneous Markov chain with an irreducible transition matrix which means that the algorithm cannot freeze in a local optimum and always has the chance for finding a global optimum.

After showing MOSOMA´s ability to work efficiently on benchmark problems, it was applied on a couple of design problems in electromagnetics. MOSOMA was employed to find the trade-off solutions of problems such as adaptive beam forming in time domain [PK 4], digital filter design for the FDTD ABC parameters definition [PK 6], dielectric layered filter design [PK 7] and Yagi-Uda antenna design [PK 7] and [PK 9].

While working on this doctoral thesis, we encountered some problems that could not be solved before finalizing the thesis. First, proving the theoretical convergence was done just for the generalized form of the algorithm. The theoretical convergence analysis should be performed for a detailed variant of MOSOMA. Next, MOSOMA could be applied for a variety of other real-life problems like solving some inverse problems for microwave imaging, planar antennas design, etc. Further, MOSOMA could be used to find solutions of some design processes with enhanced stability of parameters. Another objective function expressing the stability of those parameters could be defined in this case. Then, the Pareto front should express trade-off between the quality of the proposed solution and its stability. Furthermore, MOSOMA could be combined with a powerful full-wave solver (e.g. CST-Microwave studio or HFSS) to achieve a strong automatic design tool.

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The references are divided into two parts for easier orientation in the text. The first part contains references to papers of other authors; the second part denoted by PK contains citations of our papers.

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Computer skills

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Sports (floorball), books, music, movies

Abstrakt

Práce se zabývá popisem nového stochastického vícekriteriálního optimalizačního algoritmu MOSOMA (Multiobjective Self-Organizing Migrating Algorithm). Je zde ukázáno, že algoritmus je schopen řešit nejrůznější typy optimalizačních úloh (s jakýmkoli počtem kritérií, s i bez omezujících podmínek, se spojitým i diskrétním stavovým prostorem). Výsledky algoritmu jsou srovnány s dalšími běžně používanými metodami pro vícekriteriální optimalizaci na velké sadě testovacích úloh. Dále byla uvedena nová technika pro výpočet metriky rozprostření (spread) založené na hledání minimální kostry grafu (Minimum Spanning Tree) pro problémy mající více než dvě kritéria. Doporučené hodnoty pro parametry řídící běh algoritmu byly určeny na základě výsledků jejich citlivostní analýzy. Algoritmus MOSOMA je dále úspěšně použit pro řešení různých návrhových úloh z oblasti elektromagnetismu - návrh Yagi-Uda antény a dielektrických filtrů, adaptivní řízení vyzařovaného svazku v časové oblasti…

Abstract

This thesis describes a novel stochastic multi-objective optimization algorithm called MOSOMA (Multi-Objective Self-Organizing Migrating Algorithm). It is shown that MOSOMA is able to solve various types of multi-objective optimization problems (with any number of objectives, unconstrained or constrained problems, with continuous or discrete decision space). The efficiency of MOSOMA is compared with other commonly used optimization techniques on a large suite of test problems. The new procedure based on finding of minimum spanning tree for computing the spread metric for problems with more than two objectives is proposed. Recommended values of parameters controlling the run of MOSOMA are derived according to their sensitivity analysis. The ability of MOSOMA to solve real-life problems from electromagnetics is shown in a few examples (Yagi-Uda and dielectric filters design, adaptive beam forming in time domain…).