An Analysis of the Effect of Multiple Layers in the Multi-Objective Design of Conducting Polymer Composites

Laetitia Jourdan[1], Oliver Schütze[2], Thomas Legrand[1], El-Ghazali Talbi[1], and Jean Luc Wojkiewicz[3]

[1] INRIA Lille Nord Europe, LIFL, CNRS
Parc scientifique de la Haute-Borne Bâtiment A, Park Plaza
40, Avenue Halley
59650 Villeneuve dAscq Cedex
France
{laetitia.jourdan,thomas.legrand,el-ghazali.talbi}@lifl.fr,
[2] CINVESTAV-IPN
Computer Science Department
México City 07360
México
schuetze@cs.cinvestav.mx
[3] Ecole des Mines de Douai, 941, rue Charles Bourseul,
BP 10838 - 59508 Douai Cedex,
France
wojkiewicz@ensm-douai.fr

Abstract. In the design of materials for the shielding of electric devices there is a recent trend to use multi-layer compounds due to some restrictions in the making process of the materials but also since they are supposed to have a higher potential to offer 'better' characteristics than the related mono-layered materials. In this work, we investigate the possible impact of the number of layers in a compound critically. It will turn out that—at least for the general objectives we study here and for conducting polymer composites—multi-layered materials are suitable to only a limited extent. To be more precise, when 'just' aiming for a high shielding efficiency the task can be accomplished with merely one layer. If in addition the cost of the material comes into play, however, a second layer may be helpful, but further layers do not seem to have a significant impact on the performance of a material. Here we extend an existing multi-objective design problem for the design of shielding materials for our purpose, and attack the resulting multi-objective optimization problem with evolutionary strategies, and finally analyze the results in the viewpoint of the *required* number of layers within a shielding material.

1 Introduction

Electromagnetic shielding materials are used to protect electronic circuits in an enclosure under electromagnetic wave aggression. The shielding is achieved using

conducting materials as a barrier to limit the coupling between an electromagnetic field and a circuit. Many types of materials are commercially available including metals, loaded polymers with carbon black, metals fibres or flakes [4]. The resulting composites become conductive but their mechanical properties are deteriorated with the rate of loading (i.e., the mass fraction of the conducting polymer in the insulating matrix). Since the conductivity of the composite depends on this parameter new conductive materials have received considerable attention. Among these materials, intrinsically conducting polymers have some advantages: low specific mass, easiness of synthesis, the possibility to modulate easily the electronic properties from insulating to conducting materials through chemical process. From these materials polyaniline (PANI) is one of the best candidates for electromagnetic interference (EMI) applications. It can have very high conductivity, a very good environmental stability [15] and PANI can not only reflect but also absorb electromagnetic waves [20]. In our previous work [11, 19] we have shown that nanocomposites of polyaniline-polyurethane (PANI/PU) can have conductivity from 10-12 to 104 S/m. Polyaniline was doped with camphor sulfonic acid and a blend with polyurethane can be obtained by co-dissolution in a solvent. The films were realized by spray coating on a polyimide film. Mono layers and multi-layered materials were studied as shielding materials in the microwave band. We have shown that these materials can respect standards of 40dB for civil applications and 80 dB for military applications. For aeronautic applications, we used a genetic algorithm to optimize the structure for a desired value of shielding effectiveness and to reduce the thickness and the weight of the materials [11]. It was found that for a total thickness inferior to one millimeter and for a mass inferior to $200g/m^2$, the objectives are reached.

Shielding films such as PANI/PU films are preferably produced by spray coating methods which limits the thickness of the layer. For instance, it is difficult to produce 'thick' materials with high conductivities since they offer very poor mechanical properties. A common way out to produce thicker materials is to use multi-layer materials (e.g., [17]), i.e., a compound of several layers of PANI/PU films. This leads on one hand to a higher potential to obtain 'better' materials with respect to the goals for modern shielding materials (e.g., shielding efficiency, weight and cost of the material) due to the increased design possibilities, but on the other hand exactly this larger variety of possibilities can represent a challenge on the designer of such materials. This is given by: (i) the design of the characteristics of each layer (e.g., thickness and conductivity), and (ii) the number of layers as well as their disposition within the compound. Next to the continuous optimization problem in (i) (see, e.g., [19]) there is in addition a combinatorial problem induced by (ii). Hence, some guidelines how to design and arrange the layers would be desired.
In this work we investigate the impact of the structure of a multi-layered material with respect to their performance. Concerning this matter, the total number of the layers within a compound and the composition of them are of particular interest. To achieve this goal, we will take and adapt an existing model which

contains the relevant objectives for modern shielding materials. Further, we will attack this *multi-objective optimization problem* (MOP) with specialized evolutionary algorithms (EAs) which can compute the solution sets—the so-called Pareto sets—of such MOPs efficiently, and will finally analyze the structure of the optimal solutions. It will turn out that there are basically two different structures which are optimal according to our goals: mono-layered materials—respectively a compound of several layers where each layer has the same characteristic—for highest shielding efficiencies and certain two layer materials by which the cost of the material can be decreased due to a lower mass percentage of the overall compound.

The remainder of this paper is organized as follows: in Section 2 we briefly state the background required for the understanding of the present work which includes the multi-objective design problem which we will modify for our purpose in Section 3. In Section 4, we present some numerical results on this model coming from multi-objective evolutionary strategies which we discuss in Section 5. Finally, we draw our conclusions in Section 6.

2 Background

Here we state the required background for the understanding of the sequel: we introduce multi-objective optimization problems and one class of algorithms, multi-objective evolutionary algorithms, for their numerical treatment, and define the design problem which is the basis for our considerations.

2.1 Multi-Objective Optimization

In the following we consider continuous multi-objective optimization problems

$$\min_{x \in Q} \{F(x)\}, \tag{MOP}$$

where F is defined as the vector of the objective functions $F : Q \to \mathbb{R}^k, \quad F(x) = (f_1(x), \ldots, f_k(x))$, with $f_i : Q \to \mathbb{R}$ being the i-th objective of the MOP. $Q \subset \mathbb{R}^n$ is the feasible set or domain of F. In many cases including the problem which is under investigation here Q can be expressed by an n-dimensional box

$$Q = B_{l,u} := \{x \in \mathbb{R}^n \ : \ l_i \leq x_i \leq u_i, \ i = 1, \ldots, n\}, \tag{1}$$

where $l, u \in \mathbb{R}^n$ with $l_i \leq u_i, i = 1, \ldots, n$ are the vector of lower and upper bounds for each parameter value. In the next definition we state the classical concept of optimality for MOPs.

Definition 1. *Let $v, w \in Q$. Then the vector v is* less than *w ($v <_p w$), if $v_i < w_i$ for all $i \in \{1, \ldots, k\}$. The relation $\leq_p$ is defined analogously. $y \in Q$ is* dominated *by a point $x \in Q$ ($x \prec y$) with respect to (MOP) if $F(x) \leq_p F(y)$ and $F(x) \neq F(y)$. $x \in Q$ is called a* Pareto optimal point *or* Pareto point *if there is no $y \in Q$ which dominates x.*

The set of all Pareto optimal solutions is called the *Pareto set* (denoted by P_Q). The image $F(P_Q)$ of the Pareto set is called the *Pareto front*.

2.2 Multi-Objective Evolutionary Algorithms

The most prominent class of algorithms for the approximation of the solution sets of MOPs is probably given by multi-objective evolutionary algorithms (MOEAs). For a thorough discussion we refer to [6, 5], here we just briefly describe the two MOEAs used in this paper.

Indicator-Based Evolutionary Algorithm (IBEA) IBEA, introduced by Zitzler and Künzli [21], is an indicator-based metaheuristic. The fitness assignment scheme of this EA is based on pairwise comparison of solutions contained in a population by using a binary quality indicator. In IBEA no diversity preservation technique is required. The selection scheme for reproduction is a binary tournament between randomly chosen individuals. The replacement strategy is an environmental replacement that consists in deleting one-by-one the worst individuals, and in updating the fitness values of the remaining solutions each time there is a deletion; this is done until the fine population size is reached. Moreover, an archive stores solutions that correspond to potentially non-dominated vectors in order to prevent their loss during the stochastic optimization process. But, contrary to the IBEA defined in [21], in our implementation, this archive is updated at each generation since the beginning of the EA, so that the output size is not necessarily less than or equal to the population size. The indicator used within IBEA is the ϵ-indicator which has been proposed in [23, 21] and which is particularly well-adapted to indicator-based optimization and seems to be efficient on different kinds of problems (see, e.g., [21, 1]). It allows to obtain both a well-converged and a well-diversified Pareto set approximation. This indicator computes the minimum value by which a solution $x_1 \in Q$ has to or can be translated in the objective space to weakly dominate another solution $x_2 \in Q$. For a minimization problem, it is defined as follows:

$$I_{\epsilon+}(x_1, x_2) = \max_{i \in \{1,\ldots,n\}} (f_i(x_1) - f_i(x_2)) \tag{2}$$

Furthermore, to evaluate the quality of a solution according to a whole population P and a binary quality indicator I, different approaches exist [1]. As proposed in [21], we will here consider an additive approach that amplifies the influence of dominating points over dominated ones.

Non-dominated Sorting Genetic Alorithm II (NSGA-II) At each generation of NSGA-II ([7]), the solutions contained in the population are ranked into several fronts. Individuals from the first front all belong to the best non-dominated set; individuals from the second front all belong to the second best non-dominated set; and so on. Two values are computed for every solution of the population. The first one corresponds to the *rank* the corresponding solution belongs to, and represents the quality of the solution in term of convergence. The second one, the

crowding distance, consists in estimating the density of solutions surrounding a particular point in objective space, and represents the quality of the solution in terms of diversity. A solution is said to be better than another one if it has the best rank, or in case of tie, if it has the best crowding distance. The selection strategy is a deterministic tournament between two randomly chosen solutions. And, at the replacement step, only the N best individuals survive (where N stands for the population size). Likewise, an external population is added to the steady-state NSGA-II in order to store all the efficient solutions found during the search.

2.3 The Design Problem

Here we briefly describe the multi-objective design problem which was introduced in [19] and which will be the basis for our further studies.
When an electromagnetic wave (EM) arrives at the surface of a material, three phenomena can occur : (multiple) reflection, absorption and transmission of the incidental wave (see Figure 1).

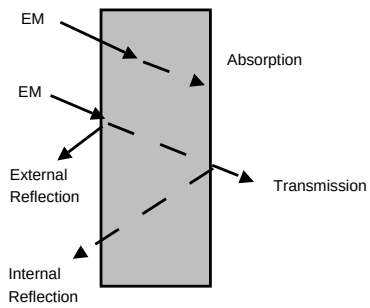


Fig. 1. The three kinds of physical wave interaction: reflection, absorption and transmission.

For the design of shielding materials it is sufficient to consider reflection and transmission. Naishadham [17] proposed a theoretical model for these two wave interactions which we describe in the following. For this, we consider a compound consisting of N layers and assume each layer to be homogeneous and isotropic. The design parameters of the i-th layer, $i = 1, \ldots, N$, are the conductivity σ_i, the permittivity[4] ϵ_i, and the thickness d_i of the material of each layer.
The *characteristic matrix* $M_i \in \mathbb{C}^{2\times 2}$ of the i-th layer is given by:

$$M_i = \begin{bmatrix} cos(A_i) & -jZ_i sin(A_i) \\ -\frac{j}{Z_i} sin(A_i) & cos(A_i) \end{bmatrix}, \tag{3}$$

[4] This parameter is in fact only important for materials consisting of one layer. In the multi-layer case, each layer with conducting polymers is highly conductive and hence the permittivity can be neglected, see [11].

where

$$A_i = \omega d_i \sqrt{\mu_0 \epsilon_0 \left[\epsilon_i - j\frac{\sigma_i}{\omega\epsilon_0}\right]}, \qquad Z_i = \sqrt{\frac{\mu_0}{\epsilon_0\left[\epsilon_i - j\frac{\sigma_i}{\omega\epsilon_0}\right]}}, \tag{4}$$

with $\omega = 2\pi f$, where f is the frequency of the electromagnetic wave, and j denotes the imaginary unit. Z_i is the impedance of the i-th layer. Due to their contact to air media, the impedances of the outer layers are set to $Z_1 = Z_N = 377(\Omega)$.
The characteristic matrix of the entire compound is given by the product of the characteristic matrices for each layer, i.e.

$$M = M_1 \cdot M_2 \cdot \ldots \cdot M_N = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}. \tag{5}$$

The coefficients for the reflection R and the transmission T are given by:

$$R = \frac{(M_{11}Z_0 - M_{12}) - Z_0(M_{22} - M_{21}Z_0)}{(M_{11}Z_0 - M_{12}) + Z_0(M_{22} - M_{21}Z_0)}, \tag{6}$$

and

$$T = \frac{2[M_{22}(M_{11}Z_0 - M_{12}) + M_{12}(M_{22} - M_{21}Z_0)]}{(M_{11}Z_0 - M_{12}) + Z_0(M_{22} - M_{21}Z_0)}. \tag{7}$$

Now we are in the position to state the objectives which are relevant for the design of modern shielding materials. Without loss of generality we state all objectives as minimization problems. Certainly the most important goal for the design of materials for electromagenetic shielding is the shielding efficiency itself which reads as

$$f_s(x) = 20\log(|T|). \tag{8}$$

Another potentially interesting objective is the reflection

$$f_r = -|R|, \tag{9}$$

which is for instance of particular interest when the material should be radar absorbing [3, 9, 18, 12] (in many other applications, however, f_s and f_r are correlated and have thus not to be considered concurrently).
Next to these physical objectives there are some economic goals which have to be taken into account (note that shields are mass products: in an airplane, for instance, 300 to 500 kilometers of cable have to be shielded). The cost of the PANI/PU shield is higly determined by the mass percentage of the polyaniline inside the polymer compound[1]. The objective related to the mass percentage is as follows:

$$f_p = \sum_i^N \frac{d_i}{d_1 + \ldots + d_N} \log p_i, \qquad p_i = \left(\frac{\sigma_i}{\sigma_0}\right)^{\frac{1}{t}} + pc, \; i = 1, \ldots, N, \tag{10}$$

[1] Here we take a modification of the mass percentage presented in [19] which includes the thickness of the material.

where σ_0 is a reference conductivity, pc the percolation threshold, and t a critical exponent. p_i is the mass percentage of the i-th layer.
Finally, the tickness of the compound could be interesting since this value directly influences the weight of the product:

$$f_t = \sum_i^N d_i. \tag{11}$$

3 The Optimization Problem

In this section we extend the MOP which is presented in the previous section according to our need. As discussed above, it is desired to have a model for the design of shielding materials where the number of layers in the compound is variable, and this is not realized adequately in the above model since a fixed number N of layers has to be assumed. The following observation on the model presented above is the key for our modification: if the thickness of layer i is set to $d_i = 0$ then also $A_i = 0$ (see (4)) and thus it holds for the characteristic matrix M_i for the i-th layer:

$$M_i\big|_{d_i=0} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} =: I_2, \tag{12}$$

which implies that

$$M\big|_{d_i=0} = M_1 \cdot M_2 \cdot \ldots M_{i-1} \cdot M_{i+1} \cdot \cdots \cdot M_N, \tag{13}$$

for the characteristic matrix of the entire compound. That is, if—but only if—d_i is set to 0 the function values of f_s, f_r and f_p of the N layer model are equal to the values of the corresponding $N-1$ layer model, but for thicknesses $d_i > 0$ the objective values differ. The latter can hinder the optimization algorithm (in particular stochastic search algorithms) to identify compounds which do not contain of the maximal number of layers: it can be observed that when comparing 'similar' compounds with different number of layers, the compounds with the larger amount of layers tend to have better values, but the improvements are negligible in most cases (see for instance Figure 4 and the related discussion). Since further too small values of d_i cause problems for the making process we suggest to replace the parameter d_i by $\tilde{d}_i$ which is equal to d_i if this value is larger than a given threshold $d_{min} \in \mathbb{R}_+$, else $\tilde{d}_i$ is set to 0. Hence, the characteristic matrix M_i of the i-th layer is replaced by

$$\tilde{M}_i := \begin{cases} I_2 & \text{if } d_i \leq d_{min} \\ M_i & \text{else} \end{cases}, \tag{14}$$

which allows for the desired effect (13) for an entire *range* of values $d_i \in [0, d_{min}]$ which implies that there is a positive probability to detect such solutions for stochastic search methods. Using this modification, the model described above can be used for our purpose since the number of layers is not fixed any more but

variable from 0 to N, which represents now the maximal number of layers.
In the following we will consider the following modified MOP:

$$\begin{aligned} F :&\mathbb{R}^{3N} \to \mathbb{R}^3 \\ F(x) &= (f_s, f_r, f_p), \end{aligned} \tag{15}$$

where $x = (\sigma_1, \ldots, \sigma_N, \epsilon_1, \ldots, \epsilon_N, d_1, \ldots, d_N) \in \mathbb{R}^{3N}$, which aims for a high shielding efficiency (f_s), a high reflection coefficient (f_r), and a low cost of the material (f_p).

4 Results

Here we present and compare some results for the given multi-objective design problem using two different MOEAs. Since we are in particular interested in the impact of the number of layers within a compound, we consider MOP (15) for different values N which determine the maximal number of layers in a compound. To be more precise, we consider mono-layer materials which we compare to materials which contain at most three and five layers, respectively. That is, we consider three variants of MOP (15) with $N_1 = 1$, $N_2 = 3$, and $N_3 = 5$. As we will see later, larger values for N are not required. In order to obtain a fair comparison, we fix the maximal thickness of the entire compound in all cases by the same value, i.e., we postulate

$$\sum_{i=1}^{N_i} d_i \leq d_{max}, \tag{16}$$

where $d_{max} \in \mathbb{R}_+$ is a given threshold. Table 1 shows the parameter values and ranges used for the three models. Note that the maximal thickness for each layer is equal to $d_{max} = 800\mu m$, that is, for each instance $N_i, i = 1, 2, 3$, a material consisting of one single layer can be detected. This thickness, however, is hard to obtain by spray coating methods, but as we will see later on, one 'thick' layer l_1 can be replaced by two (or more) thinner layers l_2 and l_3 if (i) l_2 and l_3 have the same conductivity as l_1 and (ii) the thickness of l_1 is equal to the sum of the thicknesses of l_2 and l_3. As discussed in [11] the permittivities of the outer layers can be neglected (i.e., $\epsilon_1 = \epsilon_N = 0$). Since the intermediate layers act only as a support of the two outer layers, they are hence insulating with permittivities around 3 (thus, we have set $\epsilon_2, \ldots, \epsilon_{N-1} = 3$).

For the approximation of the Pareto sets we have decided to use MOEAs since such methods have shown their effectiveness in various applications. MOEAs are of global nature and can cope with the discontinuities induced by (14).
For each instance N_i and each metaheuristic, a set of 10 runs, each one with a different initial population, has been performed. In order to evaluate the quality of the non-dominated front approximations obtained for a specific test instance, we follow the protocol given in [14]. First, we compute a reference set $Z_N^\star$ of non-dominated points extracted from the union of all these fronts. Second, we

Table 1. Parameters and constraints for MOP 15 with maximal number of layers N.

Parameter	Value/Range	Description
d_i	from 0 to 800 μm	thickness of layer i
σ_i	from 30 to 1e4 Sm^{-1}	conductivity of layer i
ϵ_1, ϵ_N	0	permittivity of outer layers
$\epsilon_2, \ldots, \epsilon_{N-1}$	3	permittivity of inner layers
d_{min}	10 μm	minimal thickness of a layer
d_{max}	800 μm	maximal thickness of the compound
f	$5.0 \times 10^7 s^{-1}$	frequency of incoming wave
σ_0	3.67 Sm^{-1}	reference conductivity
pc	0.19	percolation threshold for f_p
t	2.3	critical exponent for f_p

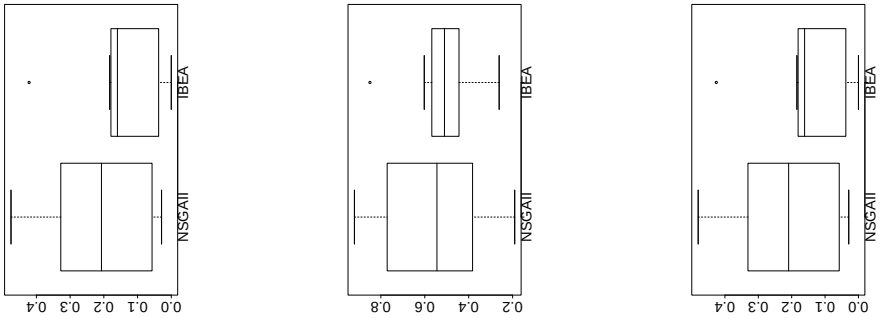
define $z^{max} = (z_1^{max}, z_2^{max})$, where z_1^{max} (respectively z_2^{max}) denotes the upper bound of the first (respectively second) objective in the whole non-dominated front approximations. Then, to measure the quality of an output set A in comparison to $Z_N^\star$, we compute the difference between these two sets by using the unary hypervolume metric [22], $(1.05 \times z_1^{max}, 1.05 \times z_2^{max})$ being the reference point. The hypervolume difference indicator (I_H^-) computes the portion of the objective space that is weakly dominated by $Z_N^\star$ and not by A. Furthermore, we also consider the R2 indicator proposed in [10] with a Chebycheff utility function defined by $z^\star = (1, 1)$, $\rho = 0.01$ and a set Λ of 500 uniformly distributed normalized weighted vectors. As a consequence, for each test instance, we obtain 10 hypervolume differences and 10 R2 measures, corresponding to the 10 runs, per algorithm. Finally, we consider the additive ϵ-indicator proposed in [22]. This indicator is used to compare non-dominated set approximations, and not solutions. The unary additive ϵ-indicator ($I_{\epsilon+}^1$) gives the minimum factor by which an approximation A has to be translated in the criterion space to weakly dominate the reference set Z_N^*.
$I_{\epsilon+}^1$ can be defined as $I_{\epsilon+}^1(\mathrm{A}) = I_{\epsilon+}^1(A, Z_N^*)$, where

$$I_{\epsilon+}^1(A, B) = min_\epsilon\{\forall z \in B, \exists z' \in A : z_i' - \epsilon \leq z_i, \forall 1 \leq i \leq n\}. \tag{17}$$

As suggested by Knowles et al. [14], once all these values are computed, we perform a statistical analysis on pairs of optimization methods for a comparison on a specific test instance. To this end, we use the Mann-Whitney statistical test as described in [14], with a p-value lower than 10%. Note that all the performance assessment procedures have been achieved using the performance assessment tool suite provided in PISA[2] [2].
For all the metaheuristics, the optimization process stops when a running time is reached. A population size of 100 has also been experimented for IBEA and NSGA-II, as suggested in the initial papers (respectively in [21] and [7]). Based on this analysis, we can conclude that IBEA statistically outperforms NSGA II

[2] The package is available at http://www.tik.ee.ethz.ch/pisa/assessment.html.

for the mono-layer model. On the other models the difference is not so evident: the p-value was often equal to 0.11 for the other model—i.e., slightly more than 10 percent—that means that we can not claim a statistical difference. Figure 2 shows boxplots for each algorithm and each metric for N_3 which indicates the performance of IBEA over NSGA II as the metrics have to be minimized.
The metaheuristics have both been implemented using the ParadisEO-MOEO[3] library3 [16]. ParadisEO-MOEO is a C++ whitebox object-oriented framework dedicated to the reusable design of metaheuristics for multi-objective optimization. All the algorithms share the same base components for a fair comparison between them.
In general it can be said that both MOEAs—and certainly also other related state of the art evolutionary algorithms—are well-suited for the computation of the solution set of the given (moderate dimensional) multi-objective design problem. With both algorithms satisfying approxiations of the Pareto set/front could be obtained within several minutes which is more than reasonable for such problems.



(a) ϵ-indicator (b) Hypervolume indicator (c) R_R^2 indicator

Fig. 2. Boxplots of the different metrics for the 5 layer model.

Figure 2 shows one obtained Pareto front for the 5 layer model. For the visualization we have used a box collection which covers the set of nondominated solutions found by NSGA-II (see also [19]). By this, on one hand the information gets more coarse compared to the data points, but on the other hand by the boxes a 3D effect is introduced which helps the viewer or decision maker to identify the location of the Pareto front in objective space. Since the Pareto fronts of the three instances are close together, a comparison and interpretation of the different fronts can not be done graphically (in particular not when using

[3] ParadisEO is available at http://paradiseo.gforge.inria.fr.

Table 2. Comparison of results obtained by NGSA-II and IBEA using the ϵ-indicator (Eps), the hypervolume indicator (Hyp), and the R2 indicator (R2). Here, $A \prec B$ indicates that algorithm A outperforms algorithm B (analogously $A \succ B$). If no such statement holds, A is said to be equal to B (i.e., $A \equiv B$).

		Eps		Hyp		R2	
		NSGA-II	IBEA	NSGA-II	IBEA	NSGA-II	IBEA
5 layers	NSGA-II	-	$\equiv$	-	$\equiv$	-	$\equiv$
	IBEA	$\equiv$	-	$\equiv$	-	$\equiv$	-
1 layers	NSGA-II	-	$\equiv$	-	$\prec$	-	$\prec$
	IBEA	$\equiv$	-	$\succ$	-	$\succ$	-
3 layers	NSGA-II	-	$\prec$	-	$\equiv$	-	$\equiv$
	IBEA	$\succ$	-	$\equiv$	-	$\equiv$	-

box collections). Since in our examples the shielding efficiency and the reflection coefficient are correlated (the total thickness d_{max} is still so thin that the absorption can not play an important role, and thus, an incoming wave can basically either be reflected by a material or be transmitted (see Figure 1)), a comparison can be done by looking at the values for the shielding efficiency and the mass percentage, which we will do in the following section.

The aim of the extended model was that the 'optimal' number of layers in the compound can be adjusted automatically by the optimization procedure. In our test runs, we have obtained the following distribution of the number of layers in the final solution sets (averaged):

$$\begin{aligned} N_2: &\quad \text{1 layer}: 2\%, \quad \text{2 layers}: 95\%, \quad \text{3 layers}: 3\% \\ N_3: &\quad \text{1 layer}: 3\%, \quad \text{2 layers}: 25\%, \quad \text{3 layers}: 34\%, \quad \text{4 layers}: 31\%, \\ &\quad \text{5 layers}: 7\% \end{aligned} \tag{18}$$

Regarding this, it can be said that the goal was achieved.

5 Discussion

In order to discuss the results and in particular the impact of the number of layers in our multi-objective design problem it seems to be best to analyze the obtained results for the restricted bi-objective MOP given by $\tilde{F} = (f_s, f_p)$ which we do in the following. It will be sown that multiple layers are in principle not needed when aiming for the maximal shielding efficiency, but a second layer can be advantageous if the cost of the material plays an important role. Further layers do not increase the performance significantly.

Figure 4 shows one result for each instance for the bi-objective problem, where we have taken the nondominated solutions according to $\tilde{F}$ of the results obtained in Section 4. The figure shows the part of the results with $f_s \leq -40$

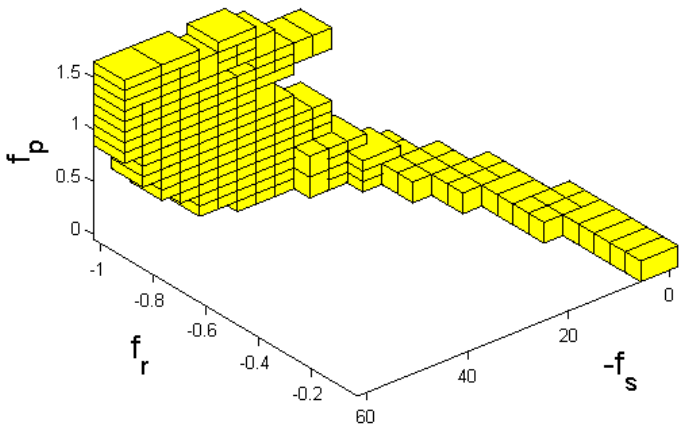


Fig. 3. Nondominated front of the objectives related to the shielding efficiency (f_s), the mass percentage (f_p), and to the reflection (f_r) for MOP (15) for 5 layers.

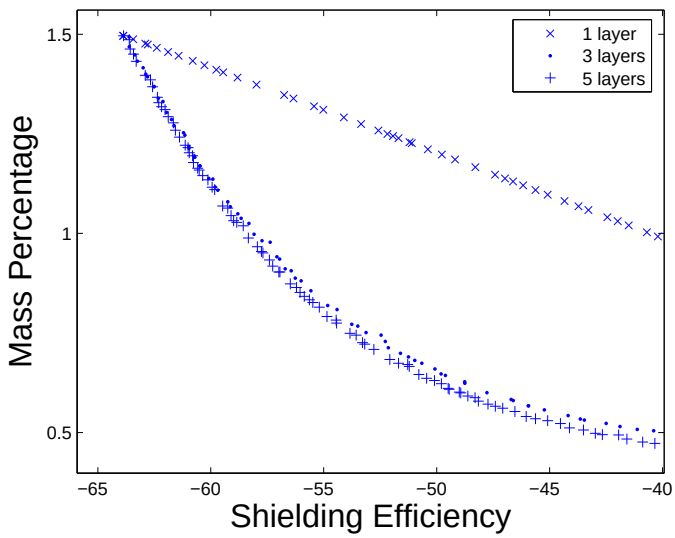


Fig. 4. Solution for the restricted model $\tilde{F} = (f_s, f_p)$ of MOP (15) for $N_i, i = 1, 2, 3.$.

(i.e., solutions with a shielding efficiency of at least 40 dB), and thus, the part where international standards for the shielding efficiency are satisfied ([13, 8]). It can be observed that there is a difference between the front for N_1 and the fronts for N_2 and N_3, and that the latter two fronts are close together. Though the front for N_3 is obviously 'better' than the front for the 3 layer model, however, these differences are apparently not significant.

To understand the results and in particular the structure of the compounds we have a look at the extreme points of the three curves (see Table 3). To obtain the maximal shielding efficiency, for all three instances the same solution has been found (x_1, x_3, and x_5): a material with one layer of thickness $d_1 = 800\,\mu m$ and conductivity $\sigma_1 = 10,000\,S/m$. Since these are the upper bounds on the parameter values it means that maximal shielding efficiency can be reached with a material with both maximal thickness and maximal conductivity. Since in our case all layers have the same structure, the result is one layer for each instance. The conductivity $\sigma_1 = 10,000 S/m$ corresponds to a mass percentage of $p_1 \approx 31.5\%$ (see (10)). The situation changes when looking at the solutions which reach a shielding efficiency of $40dB$ (y_1, y_3, and y_5 in Table 3). For the mono-layer material (y_1) we obtain the thickness $d_1 = 800\,\mu m$ (i.e., maximal) and a conductivity of $\sigma_1 = 672\,S/m$. y_3 and y_5 on the other side consist both of one thin layer with maximal conductivity (layer 1 for y_3 and layer 3 for y_5) and a thicker layer with minimal conductivity (y_5 contains of three layers, but since layers four and five have both the same conductivity, they are equal to one layer of thickness $383\,\mu m + 382\,\mu m = 765\,\mu m$ and conductivity $30S/m$). Though all solutions y_i are nearly equal according to f_s this does not hold for f_p: the compounds consisting of two layers offer both better values than y_1. (a conductivity of $\sigma = 30S/m$ corresponds to a mass percentage of $p_1 \approx 2.68\%$ which is much lower than for the maximal value of σ.) A similar trend can be observed for the solutions which lie in between these two extreme solutions x_i and y_i: a point on the Pareto set can be obtained by one layer L_1 with high conductivity (and high cost) and another layer L_2 with low conductivity (and low cost). The thickness of L_1 increases for higher shielding efficiencies while the thickness of L_2 decreases. In addition to this trend there are also other solutions which involve more layers. Such solutions can be viewed as variants of the above structures which e.g. devide L_1 and L_2. Such solutions offer some advantages due to the multiple reflection caused by such materials, but such advantages are almost negligible (see for instance the difference of the solutions for N_2 and N_3 in Figure 4, further computations with $N > 5$ have confirmed this observation). That is, if the maximal shielding efficiency is sought, multi-layer materials do not offer an advantage except for a simplification in the making process since both maximal thickness and maximal conductivity, which are needed to obtain the highest shielding efficiency, result in a material with one layer. This changes, however, if lower values for f_s can be accepted. In that case, two-layered materials can be designed which offer better values for f_p and are thus less expensive than mono-layer materials. More than two layers can improve the performance, but

not in a significant amount, and hence, they do not seem to be required for engineering applications.

Table 3. Selected solutions of MOP (15) for the 1 layer material (x_1, y_1), the 3 layer material (x_3, y_3), and the 5 layer material (x_5, y_5). Values $d_i < d_{min}$ have been repaced by $\tilde{d}_i = 0$, and in this case the conductivity has been set to $\sigma_i = 30$, i.e., to the minimal value (σ_i has no influence on the objective values for $d_i = 0$).

Point	f_s (dB)	f_p	d_1 (μm)	d_2 (μm)	d_3 (μm)	d_4 (μm)	d_5 (μm)	σ_1 (S/m)	σ_2 (S/m)	σ_3 (S/m)	σ_4 (S/m)	σ_5 (S/m)
x_1	-63.9	1.5	800	–	–	–	–	1e4	–	–	–	–
x_3	-63.9	1.5	800	0	0	–	–	1e4	30	30	–	–
x_5	-63.9	1.5	800	0	0	0	0	1e4	30	30	30	30
y_1	-40.2	1.0	800	–	–	–	–	672	–	–	–	–
y_3	-40.3	0.50	53	702	0	–	–	1e4	30	30	–	–
y_5	-40.3	0.47	0	0	33	383	382	30	30	1e4	30	30

6 Conclusions

In this work we have focussed on the impact of multiple layers in the multi-objective design of materials for electromagnetic shielding. For this, we have adapted an existing multi-objective optimization problem in order to obtain a model which is flexible with respect to the number of layers involved in the compound, and have attacked such problems with multi-objective evolutionary search strategies. It turned out that if merely the shielding efficiency is of interest, mono-layered structures can accomplish this task (in case the desired thickness cannot be produced effectively, the layer can be decomposed into several thinner layers of the same material). In order to reduce the mass percentage which influences the cost of the material, a two layer structure seems to be optimal consisting of a thin layer with high conductivity and a ticker layer with low conductivity. Further layers, however, can influence the performance, but not in a significant amount, and do thus not seem to be usefull for engineering applications.

References

1. M. Basseur and E. K. Burke. Indicator-based multi-objective local search. In *Congress on Evolutionary Computation (CEC' 2007)*, 2007.
2. S. Bleuler, M. Laumanns, L. Thiele, and E. Zitzler. PISA — a platform and programming language independent interface for search algorithms. In C. M. Fonseca, P. J. Fleming, E. Zitzler, K. Deb, and L. Thiele, editors, *Evolutionary Multi-Criterion Optimization, Second International Conference (EMO'03)*, volume 2632 of *Lecture Notes in Computer Science*, pages 494–508, Faro, Portugal, 2003. Springer-Verlag.

3. P. Chandrasekar and K. Naishadham. Broadband absorption and shielding properties of a polyaniline. *Synthetic Metals*, 105:115–120, 1999.
4. D. D. L. Chung. Electromagnetic interference shielding effectiveness of carbon materials. *Carbon*, 39:279–285, 2001.
5. C. A. Coello Coello, D. A. Van Veldhuizen, and G. B. Lamont. *Evolutionary Algorithms for Solving Multi-Objective Problems*. Kluwer Academic Publishers, 2002.
6. K. Deb. *Multi-Objective Optimization using Evolutionary Algorithms*. Wiley, 2001.
7. K. Deb, S. Agrawal, A. Pratab, and T. Meyarivan. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In *Proceedings of the 6th International Conference on Parallel Problem Solving from Nature (PPSN VI)*, pages 849–858, Paris, France, 2000.
8. W. G. Duff. *A handbook series of electromagnetic interference and compatibility, Fundamentals of electromagnetic compatibility. Volume 1 Interference Control Technologies*. Gainesville, (VA), 1998.
9. R. Faez, M. Soto-Oviedo, M. A. de Paoli, M. C. Rezende, and A. D. Reis. Microwave absorbing coatings based on a blend of nitrile rubber, epdm rubber and polyaniline. *Polymer Bulletin*, 55(4):299–307, 2005.
10. M. P. Hansen and A. Jaszkiewicz. Evaluating the quality of approximations of the non-dominated set. Technical Report IMM-REP-1998-7, Institute of Mathematical Modeling, Technical University of Denmark, 1998.
11. N. H. Hoang, J.-L. Wojkiewicz, J.-L. Miane, and R. S. Biscarro. Lightweight electromagnetic shields using optimised polyaniline composites in the microvawe band. *Polymers for Advanced Technologies*, 17:257–262, 2007.
12. S.V. Jadhav and V. Puri. Microwave absorption and permittivity of polyaniline film using overlay technique. To appear in Microelectronics Journal, doi 10.1016/J.mejo.2008.04.005, 2008.
13. B. Kaiser. *Principles of Electromagnetic Compatibility*. Artech House, Norwood, MA, 1987.
14. J. Knowles, L. Thiele, and E. Zitzler. A tutorial on the performance assessment of stochastic multiobjective optimizers. Technical report, Computer Engineering and Networks Laboratory (TIK), ETH Zurich, Switzerland, 2006. (revised version).
15. K. K. Satheesh Kumar, S. Geetha, and D. C. Trivedi. Freestanding conducting polyaniline film for the control of electromagnetic radiations. *Current Applied Physics*, 5:603–608, 2005.
16. A. Liefooghe, M. Basseur, L. Jourdan, and E.-G. Talbi. Paradiseo-MOEO: A framework for evolutionary multi-objective optimization. In S. Obayashi et al., editor, *Evolutionary Multi-criterion Optimization (EMO 2007)*, volume 4403 of *Lecture Notes in Computer Science*, pages 386–400, Matsushima, Japan, 2007. Springer-Verlag.
17. K. Naishadham. Shielding effectiveness of conductive polymers. *IEEE Transaction on Electromagnetic Compatibility*, 34(1):47–50, February 1992.
18. P. Saville, T. Huber, and D. Makeiff. Fabrication of organic radar absorbing materials. a report on the tief project. Technical report, DRDC atlantic, TR2005-124 May 2005. Defense R&D Canada Atlantic, 2005.
19. O. Schütze, L. Jourdan, T. Legrand, E.-G. Talbi, and J.-L. Wojkiewicz. New analysis of the optimization of electromagnetic shielding properties using conducting polymers and a multi-objective approach. *Polymers for Advanced Technologies*, 19:762–769, 2008.

20. K.H. Wu, T.H. Ting, G.P. Wang, C.C. Yang, and C.W. Tsai. Synthesis and microwave electromagnetic characteristics of bamboo charcoal/polyaniline composites in 240ghz. To appear in Synthetic Metals, 2008.
21. E. Zitzler and S. Künzli. Indicator-based selection in multiobjective search. In *Proceedings of the 8th International Conference on Parallel Problem Solving from Nature (PPSN VIII)*, volume 3242, pages 832–842, Birmingham, UK, 2004. Springer-Verlag.
22. E. Zitzler and L. Thiele. Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach. *IEEE Transactions on Evolutionary Computation*, 3(4):257–271, 1999.
23. E. Zitzler, L. Thiele, M. Laumanns, C. M. Foneseca, and V. Grunert da Fonseca. Performance assessment of multiobjective optimizers: An analysis and review. *IEEE Transactions on Evolutionary Computation*, 7(2):117–132, 2003.