Meta-PSO for Multi-Objective EM Problems

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Recently, the Particle Swarm Optimization (PSO) method has been successfully applied to many different electromagnetic optimization problems. Due to the complex equations, usually calling for a numerical solution, the associated cost function is in general very computationally expensive. A fast convergence of the optimization algorithm is hence of paramount importance to attain results in an acceptable time.

In this chapter few variations over the standard PSO algorithm, referred to as Meta-PSO, aimed to enhance the global search capability, and, therefore, to improve the algorithm convergence, are analyzed.

The Meta-PSO class of methods can be furthermore subdivided into the Undifferentiated and a Differentiated subclasses, whether the law updating particle velocity is the same for all particles or not, respectively.

In recently published open literature the results of the application of the Meta-PSO to the optimization of single-objective problems have been shown. Here we will prove their enhanced properties with respect to standard PSO also for the optimization of multi-objective problems, through their test in multi-objective benchmarks and multi-objective optimization of an antenna array.

6.1 Introduction

Dealing with real life optimization problems, as practical applied engineering problems and more specifically electromagnetic ones, it is rather common to have to handle problems that intrinsically present more than one objective function.

In such problems, the objectives to be optimized are typically in conflict one with respect to each other, and this means that trying to define what
is the single optimal solution for this class of problems is pointless. On the contrary, the challenge is to find good “trade-off” solutions that represent the best possible compromises among all the objectives, extending the concept of best solution to multi-objective problems.

In view of this, multi-objective optimization may be defined as a strategy to address multiple design constrains in practical engineering problems. Several approaches have been proposed to address this kind of optimization problems [1, 2]. Among them, one of the most commonly adopted is the so called weighted sum method (WSM); it consists in rephrasing the multi-objective optimization problem in a suitably defined equivalent single-objective one, whose fitness function is the linear combination of several separate fitness functions $f_k(x)$, each of which takes into account only one of the design constrains. This approach is equivalent to projecting the hyper-search-space on a suitable plane, and the resulting overall fitness function has the form

$$f(x) = \sum_{k=1}^{K} w_k f_k(x) \quad (6.1)$$

where $w_k$ is the weight that the $k^{th}$ constrains has with respect to the others. Usually the weighting coefficients are chosen in order to satisfy the normalization relationship

$$\sum_{k=1}^{K} w_k = 1 \quad (6.2)$$

and by changing their values it is possible to control the relative importance of each design constrain, obtaining consequently different overall fitness functions and sets of solutions.

The key issue of the WSM approach is therefore to find out the best trade-off between all the weighting coefficients and this requires a good knowledge of the relative importance of each of them with respect to the others. For this reason WSM often requires an extensive tuning of the weighting coefficients $w_k$, particularly for problems where objectives are unrelated. Another issue related to this approach is the inability to find the Pareto-optimal solutions in non-convex regions (as will be explained in the following), although a solution of this approach is always Pareto-optimal.

Another approach traditionally adopted to handle multi-objective problems is the so called $\varepsilon$-constrained method ($\varepsilon$CM) [2], according to which all the objectives are constrained but one, so that, among the several $f_k(x)$ to be optimized, the task is reduced to the minimization of $f_\mu(x)$, subject to $f_k(x) \leq \epsilon_k$, when $k \neq \mu$. An example of this approach has already been considered by the authors in the cost function definition of [3]. The difficulties with $\varepsilon$CM are the need to know relevant $\varepsilon$ vectors and the non-uniformity in Pareto-optimal solutions, although any Pareto-optimal solution can be found with this approach.