# Multi-objective PSO tool for electromagnetic problems with grid computing

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**Abstract — This paper presents a modular optimization tool for handling numerical multi-objective problems. The optimization method chosen for this is Particle Swarm Optimization (PSO), a stochastic, evolutionary algorithm. Modifications are introduced to the original algorithm, in order to improve its capacity to deal with complex multi-objective problems. The optimization tool is used in a bench test of a Finite Element Model of TEAM 22 and of a Permeance Network model of a switched reluctance motor. In order to reduce the computational burden, the model evaluations are done on a cluster of 3 machines, with 24 cores.**

## I. Introduction

The electromagnetic phenomena linked to the dynamic operation of electromagnetic systems are difficult to model. There are a number of numerical and analytical methods that can be used in this process. The Finite Element Analysis (FEA), although it provides a very high accuracy, it requires significant computing power especially in the case of dynamic simulations. Permeance Network Analysis (PNA) is another method used for complex systems that present important coupling between the magnetic and electric circuits and that has the advantage of a very low computation time and resources.

Electromagnetic problems are usually multi-objective, with compromises that need to be reached in order to obtain an optimal solution. The presence of constraints raises new difficulties due to the limitations imposed on the search space. Moreover, the optimization variables are usually discrete, which means that only non-gradient methods can be successfully employed (e.g. stochastic). The Particle Swarm Optimization (PSO) algorithm has proven to be very well adapted for this kind of problems. This is why we chose to implement it in a modular tool that optimizes electromagnetic systems.

The multi-objective approach is improved with a new guide selection strategy and a constraint-handling method. The aim of these improvements is to simplify the overall optimization algorithm and to provide a quick and precise solution for the discussed problems. The algorithm being very well suited for distributed calculus, the model evaluations are done in parallel on a small grid of 24 cores, thus leading to an important computational time gain.

## II. Multi-objective particle swarm Optimization

### A. General algorithm

Particle Swarm Optimization is a population based stochastic algorithm, inspired from the social behavior of groups of animals. The technique involves the experience of a number of individuals (also named particles) which make up the population. Every particle keeps a record of information about its previous experience and the experience of the rest of the swarm during their exploration of the search space.

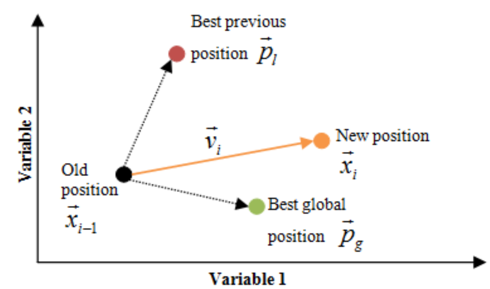


Figure 1.Position update for one individual in a two dimensions variable space

Each particle is defined at one particular step $i$ by its position $\vec{x}_i$ and its speed $\vec{v}_i$ as follows:

$$\begin{cases} \vec{v}_i \leftarrow \omega\vec{v}_{i-1} + \vec{U}(0,\phi_1)\otimes c_1(\vec{p}_l - \vec{x}_{i-1}) + \vec{U}(0,\phi_2)\otimes c_2(\vec{p}_g - \vec{x}_{i-1}) \\ \vec{x}_i \leftarrow \vec{x}_{i-1} + \vec{v}_i \end{cases} \quad (1)$$

The movement of a particle is determined by the previous position $\vec{x}_{i-1}$ its best found position $\vec{p}_l$ and the collective best position of the entire swarm $\vec{p}_g$ (Figure 1). The balance between the particle's experience and the swarm's collective experience is achieved through the $c_1$ and $c_2$ "trust" parameters. The speed is also influenced by a weight inertia coefficient $\omega$ which acts as a limiter on the particle's speed in order to keep it inside the search space. The two vectors $\vec{U}$ are randomly chosen from the interval $[0,\phi_i]$ and $\otimes$ represents component-wise multiplication.

### B. Multi-objective implementation

Although PSO was originally designed as a mono-objective optimization method, a considerable number of multi-objective techniques have been developed based on it [1] [2].

The multi-objective approaches using PSO have proven to have a better convergence for this kind of problem than other stochastic methods (such as GA or simulated annealing) [3] [4] and have been successfully applied in electromagnetic design [2] [5] [6].

A multi-objective approach based on the crowding-distance MOPSO [7] is implemented and two different swarm distributions techniques are used in order to improve the algorithm's convergence. The handling of constraints is also considered as well as front quality evaluation techniques.

After the evaluation of the individuals from the swarm and the external repository and their classification using crowding distance, a sub-swarm approach is used to guide the swarm's individuals towards the Pareto front. In the first iterations, three individuals are chosen as guides: the two extremes of the front and the individual closest to the ideal point (Figure 2) and the sub-swarms dominated by these individuals are guided towards them. This ensures that the front is well extended and at the same time that extremes solutions are not lost. After a number of iterations, when the Pareto front is reasonably defined, the three most isolated individuals from the front are chosen as guides for the three sub-swarms. A spacing metric is used to measure the quality of the front distribution.

### C. Constrained Optimization

Constraints have an important role in the analysis of real-world problems. They can introduce discontinuities and restrict the solution domain. The method presented by Li et al. in [8] is chosen as a basis for dealing with constraints. Thus, besides the classic domination of individuals presented above, a "constraint-domination" is also added that introduces information about constraint violations for each individual and influences the front selection technique. The speed of the individuals violating the variable domain is set to zero so that at the next iteration the influence of their previous best position and the global position will draw them back inside the allowed region.

### D. Distributed computing

The PSO algorithm is very well adapted to distributed computing, the individual's evaluation in one generation being completely independent. The distribution technique can also be employed for updating the speed and position of the individuals in the three sub-swarms simultaneously.

## III. Multiobjective Shape Design Problems

The wide applicability of the constrained multiobjective optimization PSO formulation is proven on two shape design problems. Both require high computation times and resources and are representative sample of Multiobjective Shape Design in Electricity and Magnetism.

The first model used to test the optimization tool is the Superconducting Magnetic Energy Storage (SMES) system –TEAM 22 problem (Figure 3.a), with 8 parameters, two objective functions and two constraint functions [9].

A second model used to evaluate the optimization tool is a dynamic PNA model of a switched reluctance motor (Figure 3.b). Two variables are linked to the geometry of the motor and one to the switching strategy, so that both design and control are optimized at the same time. The optimization functions are average torque and torque ripple while the constraints are linked to the geometrical feasibility of the motor.

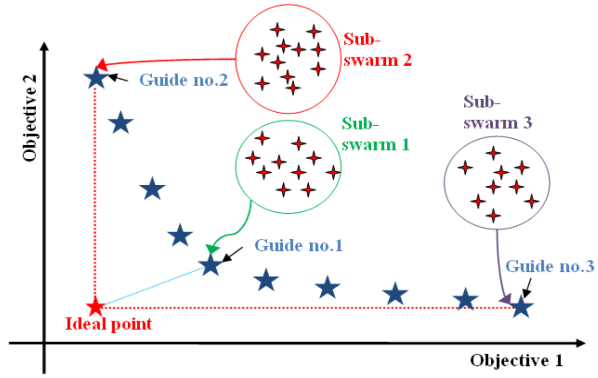


Figure 2.Choice of swarm guides from the Pareto front

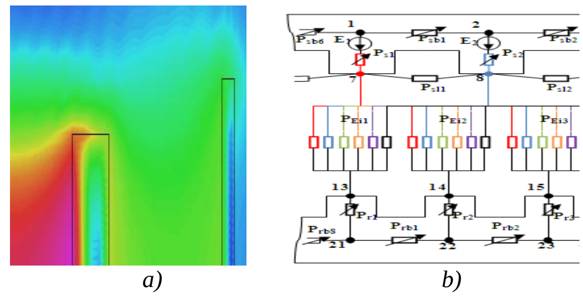

Figure 3.Optimization problems: a) SMES b) Permeance Network Model for a 6/8 SRM (detail)

The model evaluations performed by the swarm individuals are distributed to the 24 cores and the gains in optimization time for the two models are compared.

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