Migration-corrected NSGA-II for improving multiobjective design optimization in electromagnetics

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The paper proposes a new strategy to improve the performance of a standard non-dominated sorting algorithm (NSGA) in approximating the Pareto-optimal solutions of a multi-objective problem by introducing new individuals in the population miming the effect of migrations. The design optimization of a power inductor, synthesizing a uniform magnetic field for magneto-fluid hyperthermia applications, is considered as a case study to assess the performance of the migration-modified NSGA algorithm.

***Index Terms*—Multiobjective optimization, genetic algorithm, Pareto optimality, magnetic field, finite-element analysis.**

I. Introduction

Evolutionary algorithms are successfully applied to optimize the design of electromagnetic devices [1]–[4]. In particular, NSGA-II is a popular and well-assessed genetic algorithm for general-purpose multiobjective optimization used in different fields to find Pareto front [1], [3], [5], [6]. This algorithm has proven to work very well when the population comprises a large number of individuals, so it is usually coupled with objectives described by analytical functions. In recent years, the NSGA-II has been also coupled to Finite Element Analysis (FEA) and objective function values are obtained from numerical solutions of field equations. Due to computational cost, the number of evaluated individuals has to be reduced and then, the optimization results sometimes are not completely satisfactory in terms of identification of the Pareto front. Some authors have proposed modifications in NSGA algorithm to improve algorithm convergence or quality of solutions [7].

In some cases, NSGA-II generation algorithm is not able to sufficiently perturb the population and its result can lead to finding local or incomplete Pareto Fronts. In this paper it is proposed to enhance the perturbation by means of a set of individuals that migrates in the current population. In the past, similar kinds of algorithms that include a migration strategy have been developed under the frame of parallel computing: accordingly, migration is referred to an exchange of individuals between islands that evolve autonomously [8]–[10]. In turn, "island" paradigms mimic the phenomenon of natural populations evolving without exchange with the external environment, such as those that might occur within ocean islands with limited migration [8]

In this paper, a straightforward correction to a standard NSGA-II [1], [3] in terms of a migrating population is proposed. The corrected algorithm improves the Pareto front estimation in problems for which the objective functions time computation does not allow the use of a large number of individuals for each generation. The design optimization of a power inductor, synthesizing a uniform magnetic field for magneto-fluid hyperthermia applications, is considered as the case study to assess the performance of Migration-NSGA [10].

II. Migration-corrected NSGA-II

NSGA-II mimics the evolution of a population with internal selection of better individuals. Here, the migration strategy is introduced as an external population enhancing the original one. Fig. 1 shows the flow chart of the proposed algorithm.

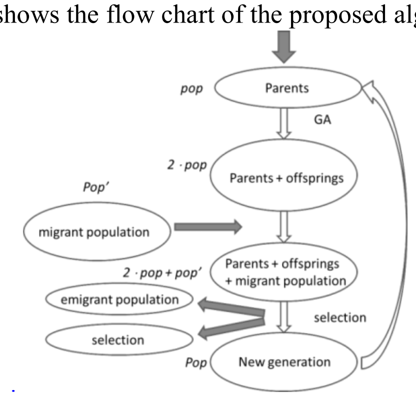

Fig. 1 Flow chart of MNSGA algorithm.

NSGA migration mimics a population that is suddenly increased by a group of individuals, immigrants that have different characteristics with respect to originating population. Immigrants can integrate with the original population carrying different genes. This way, genetic heritage of the population can mutate. In the proposed approach, the immigrated population arrives just after the generation of the new population and before the selection of better individuals. In this way, only the new individuals with better characteristics among the original and immigrating population are selected.

The migration of a population is ruled by two parameters:

a. T_m *i.e.* period of migration (e.g. T_m=1 is equivalent to introduce a migration at every iteration);
b. N_m *i.e.* number of individuals in the migrated population.

The number of individuals after selection is kept constant by means of selection and emigration events. The emigration step is managed in the selection algorithm. Among the eliminated individuals, a subgroup of individuals dies and a subgroup emigrates. In both cases some individuals drop out from the current population during the selection step of the NSGA-II algorithm.

III. Case Study: Power Inductor for Treating Magnetic Nanoparticles

The axial-symmetric geometry of a power inductor is sketched in Fig. 1: it incorporates a two-turn winding and four ferrite blocks. The field analysis problem is governed by **A**-V formulation and was solved by means of a FEA code [11], [12]. The design variables are the vertical positions of the ferrite ring on the top, the sizes of the ferrite block in the bottom and the vertical size and turn step of the inductor, respectively. The optimization objectives are the magnetic field inhomogeneity, to be minimized, and average magnetic field strength in the box P, to be maximized. In fact, this is a prerequisite for heating uniformly the solution of magnetic nanoparticles contained in P.

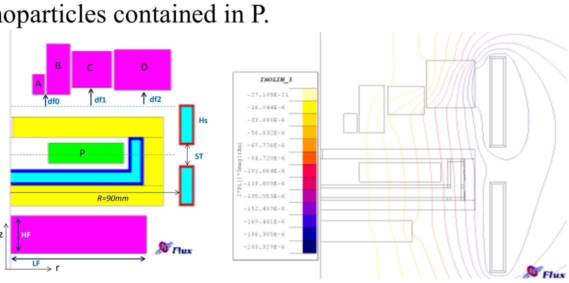

Fig. 2. Finite Element Analysis of the power inductor: geometry and magnetic field lines.

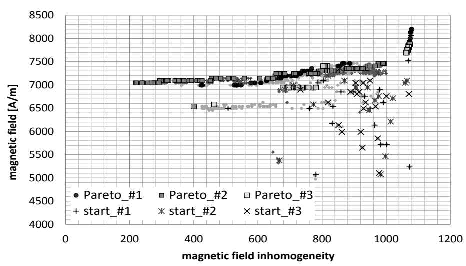

Fig. 3. Three different Pareto fronts and relevant starting individual sets for the same optimization problem.

Fig. 3 shows the obtained Pareto fronts obtained using a traditional implementation of NSGA-II [12], starting from three different initial populations of 20 individuals. The obtained fronts are different: therefore, NSGA fails in approximating the real Pareto front of the problem. In turn, migration NSGA has been applied to the same problem. Parameters T_m and N_m have been set equal to 2 and 20, respectively. The number of individuals at convergence is 494 (31 of which located on Pareto front) for MNSGA and 418 (45 of which located on Pareto front) for traditional NSGA algorithm. MNSGA converges after 17 generations, whereas NSGA converges after 21. As far as the convergence behavior is concerned, a stop criterion related to the distance of each individual from the utopia point of the objective space is defined. Fig. 4 (b) shows the value of stop criterion *vs* iteration for both NSGA and MNSGA: the convergence of both algorithms exhibits an oscillating behavior, but the one with migrating population, *i.e.* MNSGA, converges in fewer iterations for a given threshold.

Considering the same stating population, in Fig. 4 (a) the Pareto fronts obtained using MNSGA and standard NSGA-II algorithm are shown, respectively. Remarkably, the front obtained using MNSGA is broader than the other one.

(a)

(b)

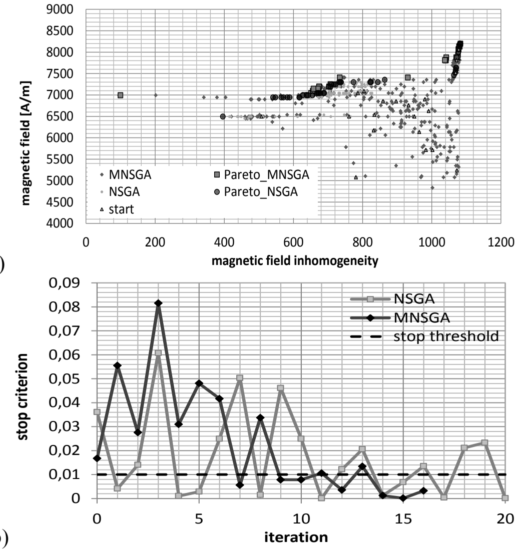

Fig. 4. (a) Pareto fronts find using MNSGA and traditional NSGA algortithm starting from the same population. (b) Convergence behavior.

IV. Conclusion

The proposed algorithm modifies a standard NSGA-II in terms of a migrating population. It improves the Pareto front approximation when the computational cost of the objective functions does not allow a large number of individuals per generation.

V. References

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