

A Parallel Version of the Self-Adaptive Low-High Evaluation Evolutionary-Algorithm for Electromagnetic Device Optimization

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Abstract—The Self-Adaptive Low-High Evaluation Evolutionary-Algorithm (SALHE-EA) is used to solve multimodal optimization problems. SALHE-EA is able to find the multiple optima of a single objective function and to give an idea of the fitness landscape in the neighbourhood of these optima. This aspect is of crucial importance when the single objective function is obtained by means of the weighted sum of the objective functions each related to a different goal of the optimization problem. This paper presents an improved version of SALHE-EA. This new version has some different features, the most important is its suitability for parallelization.

Index Terms— Finite Element Methods, Optimization Methods, Evolutionary Computation, Parallel Algorithms.

I. INTRODUCTION

Optimization techniques are often applied in engineering applications. The solution of an optimization problem is more difficult when it requires to achieve many goals, i.e. in case of multi-objective optimization. A way to overcome this difficulty is to use a single objective function, obtained by means of the weighted sum of the objective functions related to each goal of the optimization problem. This weighted function (WF) is often multimodal, i.e. this function presents multiple optima in the feasible domain. In this case may be helpful to provide not only the global optimum but even the local ones. In fact these are useful if the global belongs to a small niche or if the designer a posteriori chooses to change the relevance of the goals.

In artificial intelligence, the Evolutionary Algorithms (EAs) [1] are optimization methods, inspired to natural evolution process, useful to solve different kind of multi-objective optimization problems (MOOPs), like electromagnetic problems.

The optimization of electromagnetic devices requires a method able to solve the optimization problem using only a few number of the objective function evaluations. This is due to the high computational cost of a single evaluation; in fact it usually requires solution by means of a numerical computational method (FEM, FDM, MOM, etc.). Many EAs such as Niching Genetic Algorithms (NGAs) [2] use niching techniques to maintain population diversity and to permit the investigation of many peaks at the same time, easily allowing the parallelization of the algorithm [3].

The SALHE-EA is able to find multiple optima of a multimodal function and to give information about fitness landscape in the neighborhood of these optima [4]. Moreover SALHE-EA works better than other optimization methods with

fewer evaluations of the objective function. This paper presents an improvement version of SALHE-EA. This new version has some different features respect to the original one, the most important is its suitability for parallelization.

II. SALHE-EA

In the following optimization will refer to maximization without loss of generality. SALHE-EA is a coupled stochastic-deterministic optimization algorithm. At the beginning of the stochastic section N individuals are random generated. After that, five fundamental steps are performed a fixed number of times ng (number of generations). These steps are: selection, mutation, elimination of useless individuals, identification of new hypothetical maxima (optima) and new hypothetical minima (they are "hypothetical" because they may differ from the true maxima or minima), evaluation of niche radii. At the end of the last generation the "doublets" are deleted. Doublets are the hypothetical maxima belonging to the same niche of another hypothetical maximum better of them. At the end of the stochastic section, a deterministic method, e.g. Pattern Search (PS), is applied to the remaining hypothetical maxima in order to improve their WF value. In the optimization of electromagnetic devices the computation effort due to the steps of the SALHE-EA is negligible compared to the time need to obtain a numerical solution. Moreover in each niche a PS is performed and, of course, can run in parallel. Furthermore since PS always starts from a point close to the optimum it converges with a little number of objective function evaluations. So, in order to estimate the overall optimization time only the number of objective function evaluations of the SALHE-EA stochastic section is relevant.

Each generation two individuals are selected for mutation by means of two different mechanisms. Each selected individual breeds two times. The fitness of the four generated individuals is computed. Note that in case of parallel computing this behavior makes ineffective the use of more than four CPU. Hence, for the stochastic section, the number of objective function evaluations nv is equal to:

$$nv = 4ng + N \quad (1)$$

where ng is generation number and N the initial population size. Therefore assuming that fitness evaluation needs an average time T_s for each individual, the overall optimization time T_{tot} is about:

$$T_{tot} = (4ng + N)T_s \quad (2)$$

Parallelizing SALHE-EA using a standard master/slave model [5] involves a lower limit on the overall optimization time equal to:

$$T_{tot} = (1+ng)T_s \approx \frac{nvT_s}{4} \quad (3)$$

In fact, a simple parallel version of SALHE-EA, requires (using a number of CPU $\geq N$) a time T_s for the initial population fitness evaluation plus a time ngT_s for the offspring fitness evaluation. The Parallel SALHE-EA (PSALHE-EA) presented here has some new features that permit to considerably reduce the overall optimization time respect to the limit (3).

III. PARALLEL VERSION OF SALHEA-EA

SALHE-EA and PSALHE-EA differ in several ways, e.g : the number of individuals selected for reproduction each generation, the number of offspring generated by each individual selected, the absence in PSALHE-EA of the mechanism of elimination of useless individuals and of the fitness comparison between parent and offspring, the introduction in PSALHE-EA of a replacement mechanism of the individuals that are identified as hypothetical maxima or minima and stored in an external archive and for this reason deleted from the population. The PSALHE-EA algorithm will be exhaustively explained in the extended version.

The most important feature of PSALHE-EA is the possibility to select more than two individuals for reproduction; this is not feasible using the comparison mechanism implemented in SALHE-EA.

If h and l individuals are selected for the reproduction by the two different selection mechanisms respectively and the number of generation is equal to ngp , the number of objective function evaluations nvp is equal to:

$$nvp = N + (h+l)ngp \quad (4)$$

with a overall optimization time:

$$Tp_{tot} = [N + (h+l)ngp]T_s \quad (5)$$

Making full use of parallelization this time can be reduced to:

$$Tp_{tot} = (1+ng)T_s \approx \frac{nvpT_s}{h+l} \quad (6)$$

Hence, using the same number of evaluations, $nvp=nv$, the PSALHE-EA computing time gain respect to SALHE-EA is:

$$Tp_{tot} = \frac{4}{h+l}T_{tot} \quad (7)$$

where the upper limit to the sum $(h+l)$ is due to the number of available CPUs.

IV. NUMERICAL RESULTS

The evaluation of performance was carried out applying PSALHE-EA to a set of mathematical functions, typically used for multimodal algorithm benchmarking [6], and to electromagnetic problems. Table I and Table II show the percentage of authentic maxima found on Shekel's Foxholes function (over 25 true maxima). Table I shows results obtained on a single CPU system, i.e. without parallelization. The new strategy adopted in PSALHE-EA gives comparable results using the same number of offspring of SALHE-EA ($h = l = 2$) and about the same overall optimization time.

Table II shows results for the case of $h=l=5$: when h and l increase, the performance slightly decreases (about 2%), but the use of parallel computing drastically reduces the optimization time. The results on mathematical functions are averaged over 100 trials.

The PSALHE-EA algorithm was also applied to various electromagnetic optimization problems. The validation was performed by means of the TEAM Workshop Problem 22 (SMES), for the discrete case with three parameters [7]. The device optimization required 1386 objective function evaluations and a computational time of about $200T_s$ ($100T_s$ for PSALHE-EA, $100T_s$ for PS). The method identified four niches: Table III shows values of each optimum.

More details and results will be given in the full paper.

TABLE I
COMPARISON BETWEEN SALHE-EA AND PSALHE-EA ON SHEKEL'S FOXHOLES FUNCTION

T_{tot}	ng	nv	PERCENTAGE OF SUCCESS	
			SALHE-EA	PSALHE-EA
$1000T_s$	249	1000	50.30%	48.07%
$2500T_s$	622	2500	87.00%	85.56%
$5000T_s$	1173	5000	97.76%	97.44%

TABLE II
PERFORMANCE OF PSALHE-EA USING PARALLELIZATION

T_{tot}	ngp	nvp	PERCENTAGE OF SUCCESS
$100T_s$	90	1000	40.31%
$250T_s$	228	2500	78.43%
$500T_s$	465	5000	93.15%

TABLE III
OPTIMA FOR THE SMES BENCHMARK WITH $h=l=5$

OPTIMUM	R_2	$h_2/2$	d_2	OBJECTIVE FUNCTION
O1	3.09494	0.25434	0.36584	0.089444
O2	3.17709	0.39029	0.22740	0.101432
O3	3.34220	0.78149	0.10246	0.145205
O4	3.11887	0.31150	0.29489	0.029608

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