Adaptive Parameter Controlling Non-dominated Ranking Differential Evolution for Multi-objective Optimization of Electromagnetic Problems

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***Abstract*—This paper proposes an adaptive parameter controlling non-dominated ranking differential evolution (AP-NRDE) for multi-objective optimal design of electromagnetic problems. The variable parameters such as mutation and crossover rates are generated based on the information of successful parameters and the number of Pareto-front in current iteration. The proposed algorithm, in mutation step, incorporates with multi-guiders to guide the population toward Pareto-front, and combines, via selection operator, the advantages of DE with the mechanisms of non-dominated ranking and crowding distance sorting, respectively. The proposed AP-NRDE is applied to a multi-objective version of TEAM 22.**

***Index Terms*— Adaptive control, Differential evolution algorithm, Multi-objective optimization, TEAM 22**

I. INTRODUCTION

Many real world problems can be formulated as optimization problems with multiple objectives. Since the first attempt to solve multi-objective optimization problems by using evolutionary algorithms [1], multi-objective evolutionary algorithms (MOEAs) have been much researched and are widely used to solve numerous applications [2] in recent years. Differential Evolution (DE) [3] is one of the most commonly used EAs. In order to apply the DE algorithm for solving MOGO problems, the original scheme has to be modified since the multi-objective problems do not consist of single solution. There are two issues when designing a multi-objective evolutionary algorithm: population diversity and survivor selection. The first issue is directly related to the question of how to guide the search towards the Pareto-optimal front [4] and how to control the parameters. The second one addresses the question of which individual will be kept during the evolution process. Parameter settings can be separated into two parts [5] as showing in Fig. 1. *Papameter tunning*: the parameters defined by user before the run. *Parameter control*: parameters can changed during the run based on spacific rule with and witout feedback information. If the parameters changed bused on feedback information, we call it adavtive parameter control otherwise determanistic. In this paper we suggest the adaptive parameter control mechenism based on the number of non-dominated solution in the current population and the parameter information of succesful individuals. The proposed AP-NRDE algorithm for multi-objective electromagnetic problems is presented in following section.

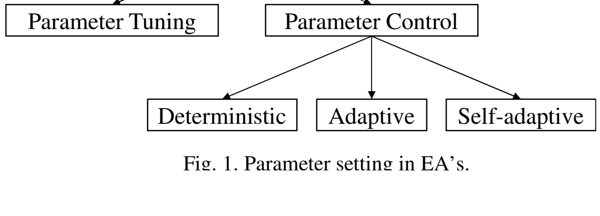

Fig. 1. Parameter setting in EA's.

II. PROPOSED ALGORITHM

In DE, generation of new individuals is mainly dependent on mutation operator where the mutation rate, *F*, and crossover, *Cr*, play an important role. The mutation rate has influence on the speed of converge and the diversity of the solutions by deciding the search range [6]. Usually, optimization algorithms favor global search at early stages for exploring all feasible domain, and then local search at the latter stages for accelerating converge. The crossover rate has influence on the information of the parent population.

For each target vector, $\mathbf{x}_{i,G}$, we initialize F_i and Cr_i randomly. If the trial vector, $\mathbf{u}_{i,G}$, successfully enters the next generation, the F_i and Cr_i will be saved into successful parameter pool for the *i*-th individual for next generation. Based on above strategy, $F_{i,G+1}$ and $Cr_{i,G+1}$ will be generated as follows

$$F_{i,G+1} = MAX\left(Fg\left(F_{suc,aver},0.1\right), 1-\frac{P}{Np}, F_{min} \right) \tag{1}$$

$$Cr_{i,G+1} = MAX\left(Fg\left(C_{suc,aver},0.1\right), 1-\frac{P}{Np}, Cr_{min} \right) \tag{2}$$

where Fg is the Gaussian random number with mean $F_{suc,aver}$ and standard deviation of 0.1; $F_{suc,aver}$ is the average value of the successful parameter pool; P is the number of non-dominated solution in the current population; Np is the number of current population; F_{min} and Cr_{min} are the user defined minimum values for mutant and crossover parameters respectively. The suggested algorithm also incorporates non-dominated ranking and multi-guiders methods. The algorithm keeps two populations: the main population which is the target population and external population *A* (to archive non-dominated solutions and provide guiders). Additionally, in mutation step, we considered feasibility of solution when we select the guiders; this action will be taking into account in case of performance constraint problems. The proposed AP-NRDE is summarized in Algorithm 1.

Algorithm 1: ***P-NRDE Algorithm***

1. ***Initialize***
   - Randomly generate *Np* target population, and set $G = 0$.
   - Randomly generate mutation parameter F_i and Cr_i .
   - Evaluate objective and constraint function values for all population, and then apply non-dominated sorting and calculate crowding distance for each front.
   - Store non-dominated solutions into external archive *A*.
2. ***Generate mutant populations*** $\mathbf{v}_{i,G}$
   - Randomly select the first guider $\mathbf{g}_1$.
   - Select second guider $\mathbf{g}_2$ if the fist one is not extreme solution as follows [5]:

$$\mathbf{v}_{i,G} = \mathbf{g}_1 + F_i \cdot X \cdot (\mathbf{g}_2 - \mathbf{x}_{r1,G}) + F_i \cdot (\mathbf{x}_{r2,G} - \mathbf{x}_{r3,G}) \quad (3)$$
$$i \in (1, 2, ..., Np)$$

   where, $\mathbf{v}_i$ is the *i*-th mutant vector; $\mathbf{x}_{r1}$, $\mathbf{x}_{r2}$ and $\mathbf{x}_{r3}$ are randomly selected difference vector; *Np* is number of population; $X = 0$ when the g_1 is an extreme solution.
3. ***Crossover operation***
   - Generate trial vector $\mathbf{u}_{i,G}$ using binominal crossover as follows:

$$\mathbf{u}_{i,G} = u_{j,i,G} = \begin{cases} v_{j,i,G} & \text{if } rand_j(0,1) \le Cr \\ & \text{or } j = j_{rand} \\ x_{j,i,G} & \text{othervise.} \end{cases} \quad (4)$$

   where Cr_i is crossover rate, j_{rand} randomly selected index.
4. ***Selection***
   - Combine target population $\mathbf{x}_{i,G}$ and trial population $\mathbf{u}_{i,G}$ (i =1, 2,…*Np*) into 2*Np* population, and select *Np* solutions for $\mathbf{x}_{i,G+1}$ as following rule:

   - Update the number of feasible solutions *n*.

   1) ***if(n>Np)*:** apply non-dominated ranking method for all feasible solutions to select *Np* individuals.

   2) ***if(n<Np)***: *n* feasible solutions and (*Np-n*) solution with lowest sum of constraint violation solutions will be selected for the next iteration.
5. ***Update non-dominated solutions.***
   - Update external archive *A:* If non-dominated solutions in *A* exceeds its maximum, remove the non-dominated solutions which have small crowding distance
6. ***Update parameters***
   - Update the mutant factor $F_{i,G+1}$ and crossover rate $Cr_{i,G+1}$ according to (1) and (2) respectively.
7. ***Termination check.***
   - If termination condition (maximum number of iteration) is not satisfied, go to Step 2 otherwise terminate.

III. Results and Conclusions

The multi-objective version of TEAM problem 22 proposed [4], is continuous, constrained, and two conflicting objectives: the stray field along two given lines and the achievement of a required stored energy, and two constraint functions are defined in (5)-(6).

$$\text{Minimize } \mathbf{f}(f_1, f_2) = \left(\frac{B^2_{stray}}{B^2_{normal}}, \frac{|Energy - E_{ref}|}{E_{ref}} \right) \quad (5)$$

$$\text{subject to} \quad \begin{aligned} |J_1| \le (-6.4|B_1| + 54.0) \quad (A/mm^2) \\ |J_2| \le (-6.4|B_2| + 54.0) \quad (A/mm^2) \end{aligned} \quad (6)$$

where, the reference stored energy and stray field are Eref=180 MJ and Bnormal = 200μT, respectively. J1, B1 and J2, B2 are current density and magnetic flux density in inner and outer coil, respectively. The definition of B2stray and more information about this problem can be found in [4]. Fig. 2 and Fig. 3 are showing Pareto front obtained by MGC-MOPSO [4] and proposed AP-NRDE respectively. As a result the suggested AP-NRDE provides more uniformly solutions than MGC-MOPSO without losing extreme solutions.

In the full paper we will present the numerical comparison results and the optimization results of the three objective analytic functions.

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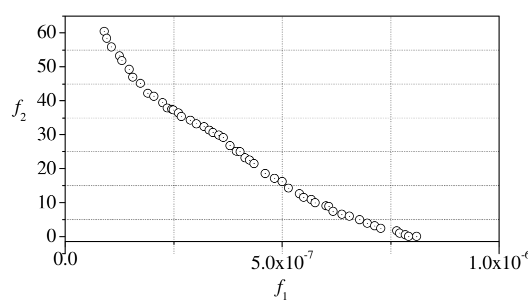

Fig. 2. Pareto-front obtained by MGC-MOPSO

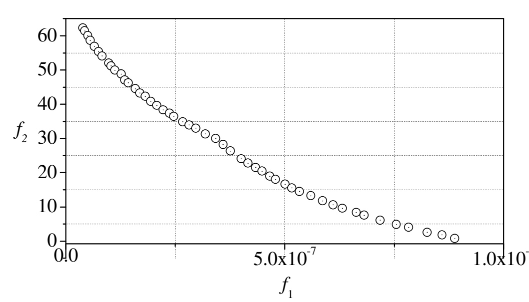

Fig. 3. Pareto-front obtained by P-NRDE