Multiobjective Exponential Particle Swarm Optimization Approach Applied to Hysteresis Parameters Estimation

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Abstract —Particle swarm optimization (PSO) is a kind of swarm intelligence that is based on social-psychological principles and provides insights into social behavior, as well as contributing to electromagnetic optimization applications. In this paper, a multiobjective PSO approach based on Exponential distribution probability operator (MOPSO-E) is proposed. Numerical comparisons with results using a multiobjective PSO with external archiving and the proposed MOPSO-E demonstrated that the performance of the MOPSO-E is promising in Jiles-Atherton vector hysteresis model parameter identification. The proposed MOPSO-E to find nondominated solutions that represent the good trade-offs among the objectives in the evaluated case study.

I. INTRODUCTION

Multiobjective optimization has become an important research topic for scientists and researchers because real world problems are multiobjective in nature. Researchers have developed many multiobjective optimization algorithms to deal with them.

In multiobjective optimization problems (MOPs), there is no unique optimal solution, but rather a set of alternative solutions and these solutions are optimal in the wider sense that no other solutions in decision space are superior to them when all objectives are considered. They are known as Pareto optimal solutions, also termed nondominated, noninferior, admissible, or efficient solutions.

Recently, the use of multiobjective procedures based on evolutionary algorithms and swarm intelligence has become popular to solve MOPs due to their ability to find multiple solutions in a single run, work without derivatives, and converge speedily to Pareto-optimal solutions with a high degree of accuracy. Particle swarm optimization (PSO) is one of metaheuristics of swarm intelligence field and has been successfully applied in MOPs [1]. Its basic idea is based on the simulation of simplified animal social behaviors, such as fish schooling and bird flocking. PSO works by maintaining a swarm of particles that move around in the search-space influenced by the improvements discovered by the other particles.

In order to obtain a good performance in MOPs in terms of the distribution of non-dominated solutions in Pareto front, this paper proposes a multiobjective PSO based on Exponential distribution probability operator (MOPSO-E).

In this paper, the proposed MOPSO-E is evaluated in terms of quality of solutions and robustness in Jiles-Atherton vector hysteresis model parameter identification described in [2]. Furthermore, the performance of MOPSO-E is compared with the MOPSO proposed in [3] (called here RNMOPSO). In the RNMOPSO, a nearest neighbor density estimation method is applied to obtain the density value of each particle for selecting the global best (*gbest*) particle. Besides, the MOPSO uses the constraint-handling technique from the NSGA-II (Nondominated Sorting Genetic Algorithm version II), an external archive of nondominated solutions and a mutation operator maintains the diversity in the external archive.

II. FUNDAMENTALS OF MOPSO-E

The computational flow of the MOPSO-E is given by the following steps:

Step 1 (Initialization of particles in swarm): Generate randomly *NP* particles in a swarm with positions and velocities using a generator of random solutions based on uniform distribution over the parameter search space. Set the counter of iterations (generations), $t = 0$;

Step 2 (Evaluation of particles in swarm and external archive updating): Evaluate the particles and store nondominated ones in an external archive A with size A_s;

Step 3 (Crowding distance computation): Compute the crowding distance of each member of A and sort it in descending crowding distance order;

Step 4 (Selection of *gbest*): A random selection is used, i.e., by using a uniform distribution the *gbest* for the swarm form a specified top portion (e.g. top 20%) for the sorted *A,* and store its position in *gbest*;

Step 5 (Updating of velocities and positions): Update velocities and positions of particles according to:

$$v_{i,j}(t+1) = w \cdot v_{i,j}(t) + c_1 \cdot ed \cdot [p_{i,j}(t) - x_i(t)] + c_2 \cdot Ed \cdot [p_{g,j}(t) - x_{i,j}(t)] \quad (1)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + \Delta t \cdot v_{i,j}(t+1) \quad (2)$$

where i=1,2,…,N indicates the particles of swarm; t=1,2,…t_{max} indicates the iterations (generations), w is defined as inertia weight factor; $v_{i,j}(t+1)$ stands for the velocity of the i-th particle with respect to the j-th dimension in iteration t; and $p_{i,j}(t+1)$ represents the best previous position of the i-th particle to the j-th dimension. The variable $p_{g,j}(t)$ is the best previous position among all the particles along the j-th dimension in iteration t. Positive constants c_1 and c_2 are the cognitive and social factors, respectively, which are the acceleration constants responsible for varying the particle velocity towards *pbest* (personal best) and *gbest*, respectively. Index *g* represents the index of the best particle among all the particles in the swarm. Variables *ed* and *Ed* are two random numbers using Exponential distribution truncated in range [0,1].

Step 6 (Mutation): Apply the mutation operator;

Step 7 (Evaluating of current positions of particles): Evaluate the particles in swarm;

Step 8 (Updating of external archive): Insert all new nondominated solution into *A* if they are not dominated by any of the stored solutions;

Step 9 (Increasing the counter): Update the iteration counter, $t = t + 1$;

Step 10 (Verify the stopping criterion): Return to *Step 3* until a criterion is met. In this work, a maximum number of iterations, t_{max}, is adopted.

III. OPTIMIZATION RESULTS

The vector J-A model is considered in its two-dimensional version (x,y) so it is necessary ten parameters for the modelling of an anisotropic material: magnetization (M_S), a, α, tensor (c) and second rank symmetric tensor (k) for the transverse and rolling directions [2]. Experimental data, obtained from a Rotational Single Sheet Tester (RSST) are used in the curve fitting [4]. The Mean Squared Error (MSE) and loss error (LE) between calculated and measured curves must be minimized. In other words, the MSE (MSEx + MSEy) and LE (LEx + LEy) are the two objective functions f_1 and f_2, respectively, to be minimized using MOPSO-E and RNMOPSO approaches.

We adopted the following control parameters for tested RNMOPSO and MOPSO-E approaches: number of independent runs is 30, the population size (*NP*) is 20 particles, the size of external archive (*A*) is 200, and stopping criterion (t_{max}) of 500 evaluations of objective functions. In RNMOPSO, it is adopted factors c_1=c_2=1.0.

Simulation results were summarized in Table I and showed that the MOPSO-E (see the Pareto set in Fig. 1) obtained a better distribution that the RNMOPSO of non-dominated solutions in Pareto front. In this case, the Euclidian distance and spacing indices uses a new Pareto front generated using all data stored in external archive during the 30 runs.

TABLE I
SPACING AND EUCLIDIAN DISTANCES INDICES (MEAN OF 30 RUNS)

Indices	RNMOPSO	MOPSO-E
Spacing (f_1,f_2)	1241.08	450.54
Euclidian distance (f_1,f_2)	1073.12	905.35
Pareto solutions	600	1290

The result of MOPSO-E (see Fig. 1) with arithmetic mean minor was $f_1 = 3.6202\times10^4$ and $f_2 = 0.3594$. The parameter set obtained is given by Table II. In this context, the arithmetic mean was calculated using normalized f_1 and f_2 values. Fig. 2 shows measured and calculated curves with the parameters set obtained by MOPSO-E.

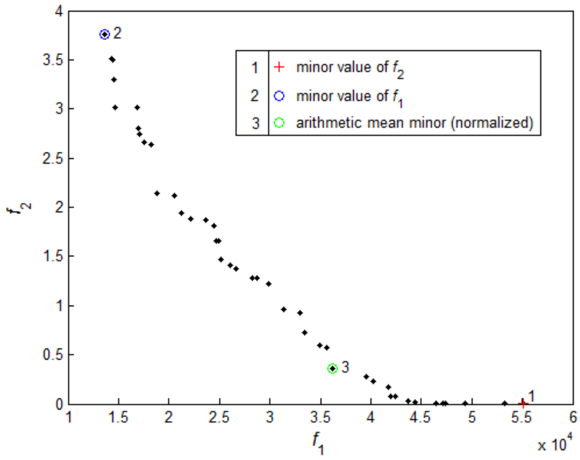

Fig. 1. Pareto set points obtained in 30 runs using MOPSO-E.

TABLE II
PARAMETERS SET OBTAINED BY MOPSO-E

Variable	Rolling direction	Transverse direction
M_S	1.897 $\times 10^6$ [A/m]	2.345 $\times 10^6$ [A/m]
k	3.622 $\times 10^1$ [A/m]	5.995 $\times 10^1$ [A/m]
c	2.256 $\times 10^{-1}$	2.031 $\times 10^{-1}$
a	8.917 $\times 10^1$ [A/m]	1.288 $\times 10^2$ [A/m]
α	1.509 $\times 10^{-4}$	2.097 $\times 10^{-4}$

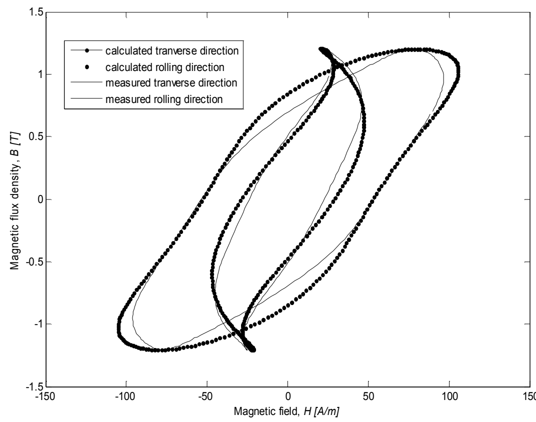

Fig. 2. Calculated and measured *B-H* curves for the material under rotational excitation.

In this paper, the utilization of MOPSO-E was effective and efficient for finding approximations of the Pareto front in the parameters identification of the Jiles-Atherton vector hysteresis model in the RSST.

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