Multiobjective Optimization of Air-core Reactor Using Nondominated Sorting Genetic Algorithm With a Local Search Strategy

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Abstract —Elitist Nondominated Sorting Genetic Algorithm II (NSGA-II) is adopted and improved for the multiobjective optimum of air-core reactor. The multiobjective optimization model of air-core reactor is formulated. The first objective is the minimization of aluminum wire weight and the second objective is the minimization of power loss. To improve the efficiency of NSGA-II and the quality of the Pareto-optimal solutions, two modifications are proposed. One is incorporation of the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) as a local search strategy, and the other is introduction of an external archive in NSGA-II. The simulation results show that the improved NSGA-II is more effective than NSGA-II and it converged to a better Pareto front.

I. INTRODUCTION

Most literatures about air-core reactors are focused on the fast and accurate computation of the inductance and magnetic field [1], [2], and very few about design and optimization of air-core reactors. A traditional design method is given in [3], the authors approach this task by iteratively evaluating candidate designs and improving them according to their experience. However, the existence of powerful stochastic optimization techniques makes it possible to automate the design procedure. The optimal design using adaptive genetic algorithm is introduced in [4], the proposed method improves the quality of global convergence. A new optimum design model is built based on the balance of three additional constraints, and a hybrid genetic algorithm combined with simplex method is proposed to optimize the round-wire air-core reactor [5], which enhances the local searching ability and improves the optimization efficiency. However, the above optimization methods take the aluminum wire weight (or material cost) as optimization objective, the power loss is either treated as a constraint condition or is not taken into account at all.

In this paper, the multiobjective optimization design model of litzen-wire air-core reactor is built. The design problem is treated as a two-objective optimization problem: the minimization of aluminum wire weight and the minimization of power loss.

The NSGA-II [6] is adopted for the two-objective optimization design of air-core reactor. Although NSGA-II is a powerful algorithm that captures a global search space and obtains well distributed Pareto front, it is time-consuming to solve the complex design problem above, meanwhile, its elite-preserving mechanism may result in the loss of optimal solutions. Therefore, a local search strategy based on the CMA-ES [7] method is used to speed up the convergence. Furthermore, in order to improve the quality of the Pareto front, an external archive is introduced into NSGA-II.

II. PROBLEM FORMULATION

The optimal design of air-core reactor is equivalent to finding a set of best decision vectors that minimizes the two competing objective functions, the aluminum wire weight and the power loss, subject to several equality and inequality constraints. Its mathematical model can be described as follows.

The objective function of aluminum wire weight minimization can be represented by

$$\min W_{AL} = \pi\rho \sum_{i=1}^{N_c} A_i B_i D_i w_i \tag{1}$$

where W_{AL} is the aluminum wire weight, A_i and B_i are the radial-side length and the axial-side length of the ith layer litzen wire, D_i is the middle diameter of the ith layer litzen wire, w_i is the turns of the ith layer litzen wire, N_c is the number of winding layer, ρ is the mass density of aluminum.

The objective function of power loss minimization can be defined as follows:

$$\min P_{Loss} = \frac{\pi K_{Loss}}{\gamma} \sum_{i=1}^{N_c} \frac{D_i w_i I_i^2}{A_i B_i} \tag{2}$$

where P_{Loss} is the power loss, I_i is the current through the ith layer litzen wire, K_{Loss} is the loss coefficient, γ is the conductivity of aluminum.

The constraints include voltage balance constraints, height balance constraints, temperature rise balance constraints and current density constraints.

III. DESCRIPTION OF THE PROPOSED ALGORITHM

NSGA-II algorithm, which is described in detail in [6], has been demonstrated as one of the most efficient and famous algorithms for multi-objective optimization. However, the capabilities of the convergence of standard NSGA-II are limited when solving the engineering optimization problem with complex fitness landscapes and difficult search spaces. To improve the effectiveness of NSGA-II, a local search strategy based on the CMA-ES is used to solve the air-core reactor optimization problem.

The CMA-ES is probably one of the most powerful self adaptation mechanisms. It uses a covariance matrix to construct the mutation distribution and adapts this covariance matrix from cumulation paths of successful mutations.

Although the best individuals of the parent and offspring populations are kept using the elite strategy for each generation, they are probably lost during performing the recombination and mutation operators in the next generation. Therefore, an external archive is introduced into NSGA-II to preserve the elite individuals, and only individuals in the first non-dominated front are stored in the archive.

IV. TEST RESULTS

To verify the effectiveness of the proposed algorithm, the NSGA-II and the improved NSGA-II are used to the optimization design of a 50 KVA (i.e., 317.5 V, 157.5 A) air-core reactor, and comparisons are made between their results.

A. *Parameter settings*

The main parameters of the proposed algorithm and the 50 KVA air-core reactor are given in Table I.

TABLE I
PARAMETERS FOR THE PROPOSED ALGORITHM AND THE 50KVA AIR-CORE REACTOR

Parameters	Values
Population size	100
Archive size	100
Maximum function evaluation	10000
Crossover probability	0.9
Mutation probability	0.01
Minimum number of winding package	2
Maximum number of winding package	7
Minimum value of inner diameter [mm]	400
Maximum value of inner diameter [mm]	1000
Minimum value of average side length [mm]	2
Maximum value of average side length [mm]	4
Minimum value of current density [A/mm^2]	0.9
Maximum value of current density [A/mm^2]	1.5
Expectant degree of users [℃]	75

B. *Results and discussion*

In order to evaluate the performance of the proposed algorithm, the convergence metric and the two set coverage measure are used as indicators.

To compare the proposed algorithm with the standard NSGA-II, the two algorithms run for 10 times, respectively, with 10 initial populations of random solutions (one for each run). For the optimization problem discussed in this paper, there is no known true Pareto front, so a reference set is used to calculate the performance metric. The reference set is obtained by adopting all the Pareto-optimal solutions from all of the 20 runs.

Fig. 1 describes the changes in the mean values of the convergence metric of the standard and improved NSGA-II versus the number of function evaluation. It is obvious that the improved NSGA-II has the faster convergence than the standard NSGA-II, and the smaller convergence metric values than the standard NSGA-II.

Fig. 2 presents the mean values of the two set coverage metric $CS(P', P'')$ and $CS(P'', P')$ against the number of function evaluation, here P' and P'' are the Pareto-optimal sets of NSGA-II and the improved NSGA-II, respectively. The comparison between the two algorithms in the coverage of two sets shows that most solutions obtained by NSGA-II are weakly dominated by the solutions obtained by the improved NSGA-II.

Fig. 3 shows the nondominated solutions obtained from the two algorithms at the 10000th function evaluation. The Pareto fronts obtained from the improved NSGA-II is obviously much more converged to the reference set than the standard NSGA-II, especially in the early generations.

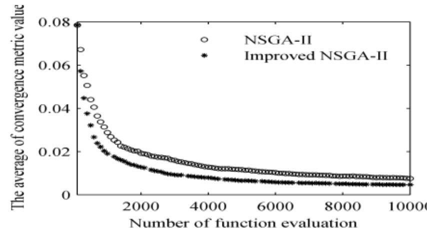

Fig. 1. The average of convergence metric value

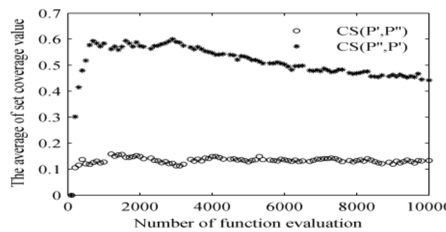

Fig. 2. The average of set coverage value

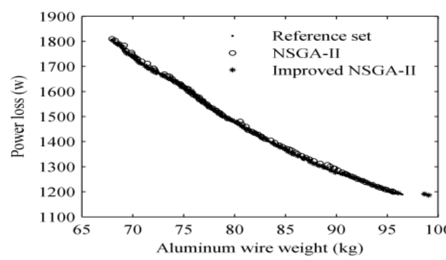

Fig. 3. Pareto fronts of NSGA-II and the improved NSGA-II

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