Multiobjective Optimization of Transformer Design Using a Chaotic Evolutionary Approach

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***Abstract*— Multiobjective optimization problems (MOPs) consist of several competing and incommensurable objective functions. Recently, as a search and optimization technique inspired by nature, evolutionary algorithms (EAs) have been broadly applied to solve MOPs. Various EAs have been proposed for this purpose, and their usefulness has been demonstrated in several application domains of science and engineering. In this paper, we propose the unrestricted population-size evolutionary multiobjective optimization algorithm (UPS-EMOA) approach combined with chaotic sequences (CMOA). Our approach integrates the merits of both UPS-EMOA and chaotic sequences to improve the efficiency of optimization procedure. Numerical results of transformer design optimization demonstrate the effectiveness of the proposed CMOA when compared with the UPS-EMOA approach to preserve the diversity of the solutions and find nondominated solutions.**

***Index Terms*— Transformer design optimization, evolutionary algorithms, multiobjective optimization, chaotic sequences.**

I. Introduction

The design of a transformer must meet minimum requirements of efficiency and regulation, maximizing the power to be transferred per unit of mass or volume, and supports well defined a maximum elevation of temperature. The transformers design optimization (TDO) problems [1] are typically multiobjective optimization problems (MOPs) under complex constraints.

Since mid-1980s, a considerable amount of multiobjective evolutionary algorithms have been presented to solve the MOPs [2]. Aittokoski and Miettinen [3] proposed the unrestricted population-size evolutionary multiobjective optimization algorithm (UPS-EMOA). The basic feature of UPS-EMOA is the use of a population that has no artificial size limit.

On the other hand, many chaotic maps in the literature possess certainty, ergodicity and the stochastic property. Recently, chaotic sequences have been adopted instead of random sequences and interesting and somewhat good results have been shown in many applications. Examples of chaotic sequences applications are presented in [4],[5].

In this paper, we propose a chaotic approach integrated with the UPS-EMOA with the adopted acronym CMOA. Simulation results of TDO demonstrate the effectiveness of the proposed CMOA when compared with the UPS-EMOA.

II. Fundamentals of the TDO

The transformer considered in this work is a shell core, dry-type, single-phase transformer with the following ratings: S = 400 VA, voltages V_1 = 110 V and V_2 = 220 V, frequency equal to 50 Hz, and minimum efficiency of 80%. Fig. 1 shows the geometry of the transformer with the dimensions of core, primary (N_1) and secondary (N_2) windings.

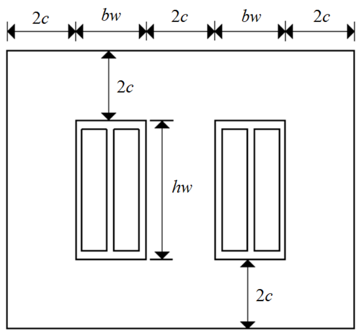

Fig. 1. Transversal transformer cutaway: dimensions of core, primary (N_1) and secondary (N_2) windings. Furthermore, the transformer has a profundity t.

The multiobjective optimization problem is to minimize mass (f_1) and the losses (f_2) while ensuring the operational requirements. The design variables are the core dimensions, turns of windings, and currents densities.

III. Description of the UPS-EMOA and CMOA

In this section, the UPS-EMOA is first described, followed by the CMOA and its features are mentioned.

A. The basic UPS-EMOA

The UPS-EMOA presents the following features: i) growing population contains all non-dominated solutions found during the optimization; ii) continuous convergence to the non-dominated set because the population cannot oscillate; iii) improved efficiency in the beginning of the process (small population converges faster); and iv) better capability to capture the characteristics of the Pareto optimal set (higher number of points in the end). The steps of the UPS-EMOA can be summarized as follows [3]:

Step 1: Initialize the population using *minsize* random points within the given search space.

Step 2: Evaluate the objective function values of the new points.

Step 3: Combine the current population with the new points. Identify non-dominated solutions and move all these to the next population. If the minimum size of population is not reached, take non-dominated solutions from the remaining points and continue until the minimum size is reached.

Step 4: Select randomly the *burstsize* points from the current population to be used as parents. Generate one new child point for every parent point using the point generation mechanism of differential evolution (DE) [6]. In the creation of the new point, all points in the current population may participate. Points which are not inside the given search space are truncated to the border, similarly as in NSGA-II (Non-Dominated Sorting Genetic Algorithm – version II) [7].

Step 5: Evaluate the objective function values of the child population, and if the budget for objective function evaluations (adopted stopping criterion) is not exhausted, go back to *Step 3*.

B. *The proposed CMOA approach*

DE has proven to be a promising candidate for optimization of real-valued, multi-modal objective functions. Recent report [8] has highlighted excellent performance of DE approaches on benchmark functions.

The UPS-EMOA uses a classical DE approach. However, choosing suitable control parameter values is, frequently, a problem dependent task and requires previous experience of the user. The control parameters of crossover rate (*CR*) and mutation factor (*MF*) of DE are generally the key factors affecting the DE's convergence.

An essential feature of chaotic systems is that small changes in the parameters or the starting values for the data lead to vastly different future behaviors, such as stable fixed points, periodic oscillations, bifurcations, and ergodicity.

In the proposed CMOA, chaotic sequences generated by logistic map are employed to tune of *CR* and *MF* factors of DE in range [0,1]. The utilization of chaotic sequences in tuning of DE's control parameters can be useful to escape more easily from local minima than with the traditional DE approach with constants values for *CR* and *MF*.

IV. Optimization Results

Simulation results in Table I showed the performance of the UPS-EMOA and the proposed CMOA in terms of spacing and Euclidian distance indices. By the result shown in Fig. 2, the proposed CMOA slightly outperformed the UPS-EMOA approach to a TDO design. Nevertheless, when the diversity of the Pareto set is compared, CMOA's diversity is better than the UPS-EMOA one. The results of UPS and CMOA with arithmetic mean minor of the normalized f_1 and f_2 values are presented in Table II.

TABLE I
SPACING AND EUCLIDIAN DISTANCES INDICES
(MEAN OF 30 RUNS WITH NORMALIZED OBJECTIVE FUNCTIONS VALUES)

Indices	UPS-EMOA	CMOA
Spacing (f_1,f_2)	0.000875	0.001146
Euclidean distance (f_1,f_2)	0.8434	0.7808

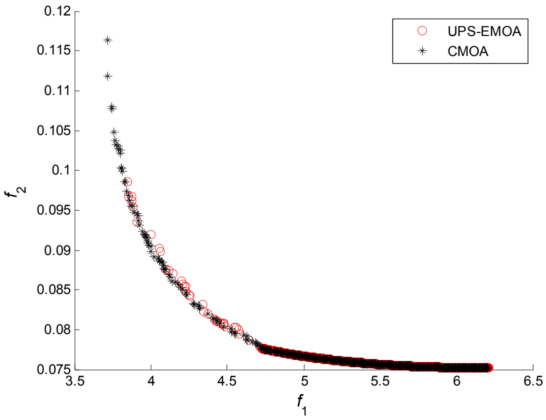

Fig. 2. Pareto front (filtered in 30 runs) of UPS-EMOA and CMOA.

TABLE II
COMPARING OPTIMIZED AND ANALYTICAL RESULTS

Parameter	Analytical	UPS-EMOA	CMOA
c [cm] *	2.5	2.6	1.6
t [cm] *	4.0	4.0	4.0
h_w [cm] *	15	10	10
b_w [cm] *	2.5	1.5	1.8
N_1	231	210	327
N_2	507	423	659
Mass [Kg], f_1	8.1	6.11	4.20
Losses, f_2	0.08	0.07	0.08

* optimized variables

V. Conclusion

This paper proposed a CMOA to TDO. In terms of solution quality and convergence of the Pareto front, the results show that the CMOA presented promising solutions. As future direction of research, we will use statistical tests to improve the evaluation process of the performance of the UPS-EMOA and CMOA.

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