Ant Lion Approach Based on Tent Map for Multiobjective Transformer Design Optimization

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Metaheuristic is a generic computational approach aiming at efficiently solving optimization problems. Ant lion optimizer (ALO) is a nature inspired stochastic metaheuristic algorithm which mimics hunting behavior of ant lions in nature. In this paper, a Modified ALO (MOALO) approach is adapted to multiobjective optimization (MU-MOALO) using external archiving, ranking with crowding distance and control parameters tuning based on tent map with chaotic dynamical behavior to solve a Transformer Design Optimization (TDO) problem with two competing objectives. Simulations applied to a TDO problem demonstrate the effectiveness of the proposed multiobjective MU-MOALO algorithm.

***Index Terms* — Transformer design optimization, multiobjective optimization, optimization metaheuristics, ant lion optimizer.**

I. Introduction

TRANSFORMER is an essential equipment in many power systems and its optimal design is relevant in economic, operational and maintenance terms. However, several Transformers Design Optimization (TDO) problems [1],[2] are typically multiobjective, requiring a number of constraints to be satisfied. The algorithms needed to solve multiobjective TDO can be thus significantly different from single objective optimization.

In this context, optimization metaheuristics [3] can be useful. Optimization metaheuristics are stochastic approaches that set off with a randomly generated population also known as set of candidate solutions. The population is then updated by using a succession of different mathematical operations, which are primarily inspired by some activity of the natural law. Furthermore, these kind of metaheuristic algorithm has been invented and improved over the past few decades and applied with success in many application domains [3]-[5] to a variety of global optimization problems.

Nowadays there is a growing interest in applying meta-heuristics that can provide multiple alternative solutions simultaneously in a single run to multiobjective optimization problems (MOPs) to approximate the set of Pareto-optimal solutions.

A promising optimization metaheuristic algorithm recently proposed is the ant lion optimizer (ALO) [6]. It is a nature inspired stochastic metaheuristic algorithm which mimics hunting behavior of antlions in nature. One of the advantages of ALO is that it has few parameters to tune, making it a flexible algorithm for solving diverse problems.

The effectiveness of ALO approach was shown by the reported results and it has competitive results for single-objective problems related to exploration, local optima avoidance, and convergence criteria in solving global optimization problems [6].

On the other hand, in terms of metaheuristic algorithms for MOPs, it is essential to have a convenient balance between exploration of the whole search space (global search) and exploitation of certain promising area (local search).

In the literature, many methods [3] have been used to improve the performance of optimization metaheuristics. One of potentially attractive method used in these studies is the chaos theory. Chaotic dynamical systems, which are known to be highly sensitive to initial conditions and control parameters, generate randomlike, ergodic orbits possessing long period length and desired confusion and diffusion properties, among others. The tent map introduced by Ott [7] is an iterated function forming a discrete-time dynamical system for the generation of random-like real numbers uniformly distributed in [0,1] that demonstrates a chaotic dynamical behavior. It is considered among the most studied piecewise linear chaotic maps exhibiting chaotic behavior.

In this paper, a Modified ALO (MOALO) is proposed. Furthermore, a multiobjective MOALO (MU-MOALO) for MOPs applications is also proposed based on external archiving, ranking with crowding distance strategy and operator based on tent chaotic map function to find Pareto-optimal solutions for TDO problem.

For studying the performance of the MU-MOALO, it is tested in a multiobjective TDO problem which considers two minimization objectives for a given transformer power, the mass (f_1) and the losses (f_2), in order to achieve an appropriate trade-off between the objectives in the approximated Pareto front. Simulation results show promising results of the MU-MOALO and its applicability to TDO.

The remainder of the paper is organized as follows. Section II gives some fundamentals of the TDO. In Section III, the fundamentals of the ALO are mentioned. In Section IV, the results are presented and discussed. And the paper is concluded in Section V.

II. Fundamentals of the TDO

The transformer to be optimized 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%. It has the classical structure, which means the geometry of transformer with primary (N_1) and secondary (N_2) windings, as shown in Fig. 1, where the dimensions *c*, *bw* and *hw* represent, respectively, the yoke, the window width and the window height.

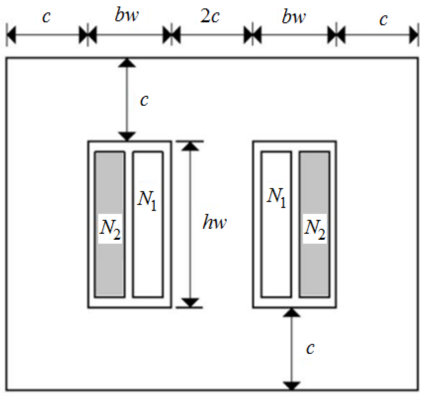

Fig. 1. Transversal transformer cutaway: dimensions of core, primary (N_1) and secondary (N_2) windings.

The multiobjective optimization problem aims to minimize both mass (f_1), in kg, and the losses (f_2), as a percentage of the input power, while ensuring the operational requirements and constraints. The design variables are the core dimensions, turns of windings, and currents densities. Hence, the two objective functions are given by:

$$f_1 = \min(\rho_c V_c + \rho_{cu} W_{cu} MLT) \quad \text{and} \tag{1}$$

$$f_2 = \min(1-\eta)\,. \tag{2}$$

where ρ_c is the core density, V_c is the core volume, ρ_{cu} is the cupper density, MLT is the mean length per turn, W_{cu} is the area occupied by the copper, and η is the transformer efficiency.

III. ALO and MU-MOALO Approaches

The ALO algorithm [6] mimics the interaction between ant lions and ants in the trap. To model such interactions, ants are required to move over the search space and antlions expected to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, its movement has been modeled using random walk.

To model the hunting process of ant lions, ant lions and ants need to interact with each other for which ants are required to move over the search space. Since ants move stochastically in nature while searching for food, a random walk is chosen for modelling ants' movement in the original ALO algorithm. Unlike the original ALO, which is briefly described in the pseudo code shown in Fig. 2, the proposed MOALO employs a mechanism with a chaotic dynamical behavior based on tent map to enhance the exploration during the ants' movement.

On the other hand, the trade-off between obtaining a well-converged and well-direbuted set of Pareto-optimal solutions is an importante issue in multi-objetive optimization. The MU-MOALO is a multiobjective version that uses the crowding distance and the domination concept for selecting the elite (best antlion) and a tournament mechanism to select the antlions to perform the random walk.

```
Definition of objective function and population size (NP)
Generate population of antlions and ants
Evaluate the fitness of the antlions
Initialize the generation's counter, t = 1
While t < maximum of iterations
   For each ant from 1 to NP do
      Perform random walk around a random antlion
      Perform random walk around the elite (best antlion)
      Update the position and check the search boundaries
      Evaluate the fitness of the ant
   End for
   Update antlion positions based on the ants
   Update the elite and keep it in the population
   Update the generation's counter, t = t + 1
End while
Returns the fittest antlion (the elite)
```

Fig. 2. Pseudo code of the ALO for single-objective problems

IV. Optimization Results

The Pareto optimal set of solutions consists of all solutions, which are impossible to improve in any objective without a worsening another objective. The results in Fig. 2 show that the proposed MU-MOALO presents a well-distributed Pareto front to the TDO problem. Finding the best compromise solution is a tedious task when multiple objectives are involved. In this context, the best normalized aritmetic mean value is adopted.

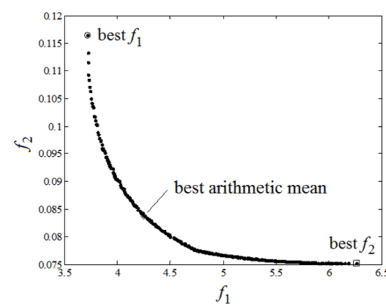

Fig. 2. Pareto front (filtered after 30 runs) of MU-MOALO.

V. Conclusion

One of the aims of the multiobjective optimization algorithms is to find nondominated solutions as diverse as possible in the Pareto set obtained. Applying the proposed MU-MOALO to MOPs is a promising research topic and has been successfully applied to a TDO problem.

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