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A hybrid ant colony optimization approach based local search scheme for multiobjective design optimizations

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ABSTRACT

This paper presents an optimal design of a linear motor considering two objective functions namely, maximum force and minimum saturation and design of air-cored solenoid with maximum inductance and minimum volume as the objective functions. The proposed approach differs from the traditional ones in its design of a multipheromone ant colony optimization (MACO) as well as the inclusion of steady state genetic algorithm (SSGA) and local search approach. Detailed numerical results on different multiobjective design applications are reported. The results obtained by our implementation substantiate the success of this new approach.

1. Introduction

The multiobjective or vector optimization is a very important research area in engineering studies because real world design problems require the optimization of a group of objectives. Thanks to the effort of scientists and engineers during the last two decades, particularly the last decade, a wealth of multiobjective optimizers have been developed, and some multiobjective optimization problems that could not be solved hitherto were successfully solved by using these optimizers [18]. In terms of robustness and efficiency of the available vector optimizers, these optimizers are still in need of improvements and hence there are many unresolved open problems [24].

It is also observed that most of the multiobjective optimization studies have been focused on the heuristic algorithms such as genetic (GA) or evolutionary algorithm (EA) [2,22], particle swarm optimization (PSO) method [3], simulated annealing algorithm (SA) [17] and Tabu search method [16], to name but a few, are proposed and used successfully to solve typical electromagnetic design problems.

Recently, to meet the ever increasing demands in the design problems, a new EA called ant colony optimization algorithm have all been used successfully to mimic the corresponding natural, or physical, or social phenomena. Ant colony optimization (ACO) is a metaheuristic inspired by the shortest path searching behavior of various ant species. Since the initial work of Dorigo, Maniezzo, and Colorni on the first ACO algorithm, the ant system [9], several researchers have designed ACO algorithms to deal with multiobjective problems such as vehicle routing, portfolio selection, Scheduling, among others [1,4,8,13,14,19,21,25].

Local search techniques have long been used to attack many optimization problems [15]. The basic idea is to start from an initial solution and to search for successive improvements by examining neighboring solutions. The local search used in this paper is based on a dynamic version of pattern search technique. Pattern search technique is a popular paradigm in Direct Search (DS) methods [20]. DS methods, as opposed to more standard optimization methods, are often called derivative-free as they do not require any information about the gradient or higher derivatives of the objective function to search for an optimal solution. Therefore direct search methods may very well be used to solve non-continuous, nondifferentiable and multimodal (i.e. multiple local optima) optimization problems.

The linear synchronous motor operates on the same working principle as that of a permanent magnet rotary D.C. motor [12]. As in a rotary motor there are two parts in a LSM, one is the set of per-

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manent magnets and the other is the armature that has conductors carrying current. The permanent magnets produce a magnetic flux perpendicular to the direction of motion. The flow of current is in the direction perpendicular to both the direction of the motion and the direction of the magnetic flux.

This paper intends to present an optimal design of a linear motor to replace a hydraulic actuator and design air-cored solenoid using hybrid ant colony optimization approach. This methodology consists of two phases. The first one employs the heuristic search by MACO based on SSGA to obtain near optimal solution, while the other employs efficient local search to improve the solution quality of multiobjective design optimizations. Our approach has several characteristic features. Firstly, the proposed approach implements MACO as a heuristic search technique. Secondly, SSGA is employed for enhancing the ant search. Finally, a dynamic version of pattern search technique was adopted to improve the solution quality of design problems.

The remainder of the paper is organized as follows. In Section 2 we describe some preliminaries on multiobjective optimization problem (MOP). In Section 3 we review the standard ACO metaheuristic. In Section 4 we present the proposed approach. Experimental results are given and discussed in Section 5. Section 6 indicates our conclusion and notes for future work.

2. Preliminaries

A general multiobjective optimization problem is expressed [18] by MOP:

$$\begin{array}{ll} \text{Min} & F(x) = (f_1(x), f_2(x), \ldots, f_Q(x)) \\ \text{s.t} & x \in S, \quad x = (x_1, x_2, \ldots, x_n)^T \end{array} \tag{1}$$

where $(f_1(x), f_2(x), \ldots, f_Q(x))$ are the Q objectives functions, $(x_1, x_2, \ldots, x_n)$ are the n optimization parameters, and $S \in R^n$ is the solution or parameter space. Obtainable objective vectors, $\{F(x) x \in S\}$ are denoted by Λ, so $\{F : S \to \Lambda\}$, S is mapped by F onto Λ. Because $F(x)$ is a vector, there is no unique solution to this problem, instead, the concept of noninferiority (also called Pareto-optimality) must be used to characterize the objectives.

Definition 1. (Dominance Criteria [18]). For a problem having more than one objective function (say, f_i, $i = 1, \ldots, Q$, $Q > 1$), any two solution x^1 and x^2 can have one of two possibilities, one dominates the other or none dominates the other. A solution x^1 is said to dominate the other solution x^2, if both the following condition are true

1. The solution x^1 is no worse (say the operator $\prec$ denotes worse and $\succ$ denotes better) than x^2 in all objectives, or $f_i(x^1) f_i(x^2)$ for all $i = 1, \ldots Q$ objectives.
2. The solution x^1 is strictly better than x^2 in at least one objective, or $f_i(x^1) \succ f_i(x^2)$ for at least one $i \in \{1, 2, \ldots, Q\}$.

If any of the above condition is violated, the solution x^1 dose not dominates the solution x^2.

Definition 2. (Pareto optimal solution). x^* is said to be a Pareto-optimal solution of MOP if there exists no other feasible x (i.e., $x \in S$) such that, $f_i(x) \le f_i(x^*)$ for all $i = 1, 2, \ldots, Q$ and $f_j(x) < f_j(x^*)$ for at least one objective function f_j.

3. The ACO metaheuristic

ACO makes use of agents, called ants, which mimic the behavior of real ants in how they manage to establish shortest- route paths from their colony to feeding sources and back [10]. Ants communicate information through pheromone trails, which influence which routes the ants follow, and eventually lead to a solution route.

ACO was initially designed to solve the Traveling Salesman Problem (TSP) as indicate in Fig. 1 and works as follows. In the TSP, a given set of n cities has to be visited exactly once and the tour ends in the initial city. We call d_{ij} ($i, j = 1, 2, \ldots, n$) the length of the path between cities i and j. In the case of Euclidean TSP, d_{ij} is the Euclidean distance between i and j (i.e., $d_{ij} = \| x_i - x_j \|_2$). The cities and routes between them can be represented as a connected graph (n,E), where n the set of towns and E is the set of edges between towns (a fully connected graph in the Euclidean TSP). The ants move from one city to another following the pheromone trails on the edges. Let $\tau_{ij}(t)$ be the trail intensity on edge (i,j) at iteration t. Then, each ant $k (k = 1, 2, \ldots, m)$ chooses the next city to visit depending on the intensity of the associated trail. When the ants have completed their city tours, the trail intensity is updated according to:

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}, \quad t = 1, 2, \ldots T \tag{2}$$

where ρ is a coefficient such that $(1 - \rho)$ represents the evaporation of trail between iteration t and $t+1$; T is the total is the number of iterations (generation cycles),

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau^k \tag{3}$$

where $\Delta\tau_{ij}^k$ is the quantity per unit of length of trail substance (pheromone in real ants) laid on edge (i,j) by the kth ant between iteration t and $t+1$, it is given by the following equation:

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{C}{W_k} & \text{if } k\text{th ant uses edge } (i, j) \text{ in its tour,} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

where C is a constant and W_k is the tour length of the kth ant.

An ant k at city i chooses the city j to go to with a probability $p_{ij}^k(t)$, which is a function of the town distance and of the amount of pheromone trail present on the connecting edge.

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}]^\beta}{\sum_{k \in U} [\tau_{ik}(t)]^\alpha \cdot [\eta_{ik}]^\beta}, & \forall j \in U_k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where U_k is a set of the cities can be chosen by the kth ant at city i for the next step, $\eta_{ij} = 1/d_{ij}$ is a heuristic function which is defined as the visibility of the path between cities i and j; parameters α and β determine the relative influence of the trail information and the visibility [11].

4. The proposed approach

In this section, we present a framework for the proposed approach that involves two phases. The first one employs the heuristic search by MACO to obtain approximate Pareto solution, while the other phase employs efficient local search to improve the obtained solution quality.

4.1. Multiobjective optimization via MACO

Dealing with several objectives in ant colonies that use the principles of MACO necessitates to answer three questions: (1) how to globally update pheromone according to the performance of each solution based on each objective, where each colony having its own pheromone structure (2) how does a given ant locally selects a path, according to the visibility and the desirability, at a given step of the approach (3) how to build the Pareto front. The main steps of the MACO are summarized as follows:

Step 1: Construct Q Colonies

In a multiobjective optimization problem, multiobjective functions $F = (f_1, f_2, \ldots, f_Q)$, need to be optimized simultaneously, there