



Title:

Multi-objective Topology Optimization with Ant Colony Optimization and Genetic Algorithms

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Introduction:

Topology Optimization (TO) [1-4] is a design process used to explore new designs by optimally distributing material in the design region. The best designs are achieved in accordance with the objectives and constraints defined for a specific application. Since the pioneering works by Bendsoe and Kikuchi [2], TO methods have been applied to various physical systems, including electromagnetic devices and machines [1,3].

In this study, we present a multi-objective approach for TO that uses multi-objective evolutionary algorithms [6]. The first stage consists of applying a multi-objective Ant Colony Optimization (ACO) to find tradeoff topologies with different material distributions. In the second stage, we parameterize the boundaries of the topologies found by using NURBS. Multi-objective genetic algorithms are applied as a heuristic optimization engine to optimize the control points of the curves in order to smooth and refine the boundaries of the topology. The main advantage of this multi-objective approach is that the designer can identify, explore and refine a number of tradeoff topologies. The proposed methodology is illustrated in the design of an Interior Permanent Magnet (IPM) machine [5]. The design region of a TO problem is represented by a finite and bounded d -dimensional subset $\Omega \subset \mathbb{R}^d$, with $d = 2$ or 3 , in which $c \in \Omega$ denotes a cell within this geometric space. Each cell c is associated with one of n possible states. After the state of a given cell is considered to be the material properties at that point, the general multi-objective TO problem can then be defined as the problem of finding the optimal distribution of material in the cells of the design region that minimizes the objective functions while satisfying the problem constraints, which are mathematical representations of the system requirements and limitations.

Main idea:

In the proposed approach we extend the ACO method first described in [1] to solve multi-objective topology problems. Although a number of studies have examined the use of genetic algorithms for topology optimization, the definition of a suitable representation for the genome and genetic operators is very cumbersome. With ACO, we can represent the design region as a grid and the allocation of material as a graph in this grid, thus reducing topology optimization to the problem of finding an optimal route in this graph. The resulting topologies represent tradeoff topology designs that are approximations of the Pareto-optimal solutions of the multi-objective TO problem. These topologies are coarse initial designs that should be smoothed and refined; nonetheless, the designer can obtain an initial overview of the design possibilities.

Next, after the designer chooses one topology from the tradeoff set, we use a boundary detection algorithm to identify the boundaries of the regions with different materials. The points along each boundary are used to fit and define a NURBS curve for that boundary. The control points of the curves

are then optimized by means of multi-objective GA, using the same objective and constraint functions as in the original problem. In this way, another set of tradeoff solutions is generated around the topology chosen by the designer. This new Pareto front represents possible refinements of the initial coarse topology identified in the previous stage. The final design can be selected from among the tradeoff solutions by using any decision-making methodology. The designer can go back to the solutions identified in the first stage, select another topology from this set and apply NURBS parameterization and GA optimization to this topology in order to analyze other design alternatives.

The research described in [5] addresses the optimization of an Interior Permanent Magnet (IPM) machine design based on field solutions calculated by means of the Finite Element Method (FEM) using a single objective optimization. The goal of the design is to find an optimal material distribution that maximizes the output torque of the machine, while minimizing the volume of the permanent magnet. The cost of the permanent magnet material is related to the volume of PM in the machine, and it accounts for a significant part of the cost of the IPM machine due to the high price of this rare earth material. On the other hand, the permanent magnet increases the output torque. This leads to an obvious tradeoff between maximizing the torque in the machine and minimizing the volume of the permanent magnet material used in the design, leading to a multi-objective TO problem.

The design starts with an empty rotor that is divided into many small cells. Each cell can be filled with one of three different materials: air, iron (M19 stainless steel) and permanent magnet (DfES). In this case, the design domain is a 5×18 grid, as shown in Fig. 1(a). Based upon symmetry, the considered region is half of this in size, i.e., a 5×9 grid. This discretization of the IPM design domain facilitates presenting an approximated structure of a physical device. The tradeoff topologies found by the proposed multi-objective ACO are shown in Fig. 1(b), where the axes are the negative torque in the machine and the volume of the permanent magnet material. Fig. 1(c) illustrates two alternative designs from the Pareto-optimal front.

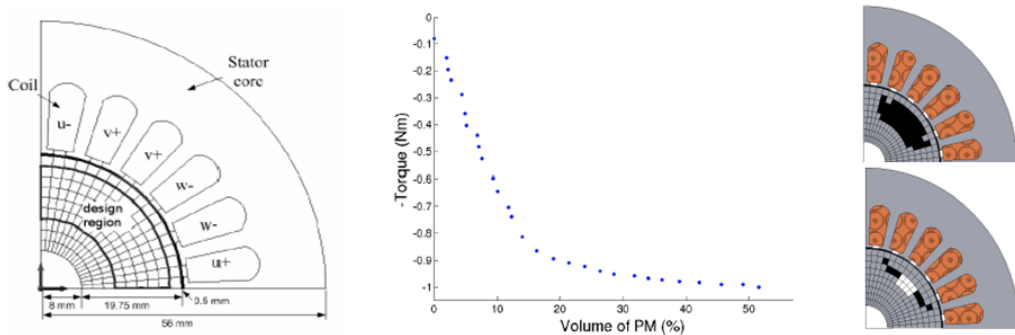


Fig. 1: (a) Discretization of the domain region for the IPM machine design example. (b) Estimated Pareto-optimal front for the IPM machine design example. (c) Two alternative topology designs from the Pareto-optimal front.

Conclusions:

This study has described an approach that integrates topology and shape optimization. This approach is capable of handling problems that involve the distribution of several materials in a design domain. The representations used are simple and the results are given in parametric models based on NURBS curves. With a suitable choice of parameters, the NSGA-II was able to improve the results obtained by the MOACO algorithm, thus demonstrating the adequacy and usefulness of the proposed approach to multi-objective electromagnetic topology optimization.

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