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Optimization Algorithms Inspired by Electromagnetism and Stigmergy in Electro-technical Engineering

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Abstract: - This paper presents a comparative study of two stochastic optimization methods: the electromagnetism-like algorithm (EMA) and the multilevel ant stigmergy algorithm (MASA) in computer-assisted design of universal electric motor rotor/stator geometry. The design goal was to minimize the power losses. The output of this study can be summarized in several important findings. Above all, both compared optimization methods were able to significantly improve the original engineering design. Comparing the tested methods, the MASA generated the minimum power loss designs. Its additional advantage shown on this problem was the capability of successfully performing the optimization from random starting points, which was not the case with the EMA.

Key-Words: - electromagnetism, multilevel, stigmergy, optimization, design

1 Introduction

The paper provides a comparative study of two stochastic optimization methods in designing optimal universal AC or DC motor rotor/stator geometries where the primary objective is to minimize the motor power losses to compare the performance of both methods on a high-dimensional nonlinear engineering optimization problem, and to check whether the engineering design already used in regular production can be improved through automated optimization.

A conventional universal motor design procedure is as follows: First, an experienced engineer made the initial estimation of the rotor/stator geometry. Then the suitability of this geometry is usually analyzed by means of a numerical simulation of the electromagnetic field and the manual procedure is repeated until the satisfactory evaluation results are obtained. The important role of this approach is that with their experience the engineers can significantly influence the progress of the design process and react intelligently to any noticeable electromagnetic response with proper geometry redesign.

However, this design approach has its own weaknesses, which reflects in non-optimal design and extremely large time consumption. Therefore, a conventional design approach can be upgraded with stochastic optimization techniques, which—in connection with reliable numerical simulators—allow for highly automated design process where the need for an experienced engineer to navigate the process is significantly reduced.

The paper is organized as follows. In Section 2, the design of universal motors is outlined. Section 3 presents the applied optimization methods. Numerical experiments and the obtained results are presented in Section 4, where the applied methods are evaluated with respect to their performance. The paper concludes with the summary of the findings of this study and directions of future work.

2 Universal Motor Design

2.1 Power Losses and Motor Efficiency

The efficiency η of a universal motor is defined as the ratio of the output power P_{out} to the input power P_{inp} and depends on various power losses. They include copper losses P_{Cu}, iron losses P_{Fe}, and additional losses P_{add} (such as brush, ventilation and friction losses) [8].

When considering all the mentioned losses and the output power P_{out}, the overall efficiency η of an electric motor can be defined as follows:

$$\eta = \frac{P_{out}}{P_{inp}} = \frac{P_{out}}{P_{out} + P_{Cu} + P_{Fe} + P_{add}}. \quad (1)$$

2.2 Rotor/Stator Geometry

In our case, ten mutually independent variable parameters defining the rotor and stator geometry are subject to optimization, which needs to find the geometry parameter values that would generate the rotor and stator geometry with minimum power losses.

2.3 Numerical Simulation

To evaluate different settings of the rotor and stator geometry parameters with respect to the resulting power losses, we used the commercial ANSYS finite-element method simulation package [1].

3 Optimization Methods

There are a variety of stochastic optimization methods and selecting an appropriate one is part of a challenge in solving real-world design optimization problems.

In this section, we present two stochastic methods on optimizing the universal motor rotor/stator geometries to eventually draw conclusions on their suitability for this problem. Two recently proposed global optimization techniques were used, electromagnetism-like algorithm [2] and multilevel ant stigmergy algorithm [6].

Both methods use real vector representation of candidate solutions where each vector component represents one geometry parameter of the electric motor rotor and stator. The parameter search space is discretized and the stopping criterion is given by the number of solutions to be evaluated.

We had previously applied the genetic algorithm (GA) [4, 5] to the same optimization problem [7] and wanted to compare it with novel techniques in this study.

The applied optimization methods, the EMA and the MASA, are described in the following subsections.

3.1 Electromagnetism-like Algorithm

The *electromagnetism-like algorithm* (EMA) [2] is optimization heuristic, which was proposed for unconstrained global optimization problems, i.e., the minimization of non-linear functions.

Having a multi-dimensional solution space where each point represents a solution, a charge is associated with each point (calculated upon the objective function value of the solution). A population of solutions is created, in which each solution point exerts attraction or repulsion on other points, the magnitude of which is proportional to the product of the charges and inversely proportional to the distance between the points (Coulomb's Law). The overall move of a point depends on the influence of all other points of the population (i.e., the move is calculated by vectorially adding the forces of all the other points in each direction).

The dimension of the vector is equal to the dimension of the problem, i.e., the number of parameters to be optimized.

The principle behind the algorithm is that worse solutions prevent a move in their direction by repelling other solutions in the population, while better solutions facilitate moves in their direction.

The EMA pseudo code is shown in Fig. 1.

1: Evaluate the initial population S of random solutions
2: **while** stopping criterion not met **do**
3: Optionally perform local search on some solutions
4: Calculate the force of solutions $\boldsymbol{s}_j$ ($j \neq i$) on solution $\boldsymbol{s}_i$
5: Move each solution $\boldsymbol{s}_i$ according to the forces
6: Evaluate each new solution
7: **endwhile**

Figure 1: Electromagnetism-like algorithm.

If the local search procedure (line 3) is enabled, it explores the immediate (Euclidean) neighborhood of individual points (either all points or only the best one). Then the total force exerted on each point by all other points is calculated (line 4). It depends on the charge of the point under consideration as well as of the points exerting the force, and the Euclidean distance between them. The charge of each point $\boldsymbol{s}_i$ is determined by its objective function value $f(\boldsymbol{s}_i)$ in relation to the objection function value of the current best point $\boldsymbol{s}_{best}$ in the population, with better objective function values resulting in higher charges. For a minimization problem, the charge q_i of the point $\boldsymbol{s}_i$ is determined according to equation:

$$q_i = \exp\left(-d \frac{f(\boldsymbol{s}_i) - f(\boldsymbol{s}_{best})}{\sum_{k=1}^{m} (f(\boldsymbol{s}_k) - f(\boldsymbol{s}_{best}))} \right) \quad (2)$$

The parameter m represents the population size, d is the dimension of the solution space. A set of force vectors $\boldsymbol{F}_i$, i = 1, ..., m, that are exerted on the point $\boldsymbol{s}_i$, is determined:

$$\boldsymbol{F}_i = \begin{cases} \sum_{j=1, j\neq i}^{m} (\boldsymbol{s}_j - \boldsymbol{s}_i) \dfrac{q_i q_j}{\left\| \boldsymbol{s}_j - \boldsymbol{s}_i \right\|^2} & if\ f(\boldsymbol{s}_j) < f(\boldsymbol{s}_i) \\ \sum_{j=1, j\neq i}^{m} (\boldsymbol{s}_i - \boldsymbol{s}_j) \dfrac{q_i q_j}{\left\| \boldsymbol{s}_j - \boldsymbol{s}_i \right\|^2} & if\ f(\boldsymbol{s}_j) \geq f(\boldsymbol{s}_i) \end{cases} \quad (3)$$

In this way, a point with a relatively good objective function value attracts the other points, while the point with an inferior objective value repels them. The forces exerted on $\boldsymbol{s}_i$ by each of the other points are combined by means of vector summation.

The movement according to the resulting forces is then performed (line 5), which generates a new population. The imposed force is normalized by division with its norm and therefore only identifies the direction of the move, not the magnitude. The magnitude of each move is determined for each dimension separately according to the charges ratio of the involved solutions.

The EMA is a population-based algorithm, since it operates on a population of solutions rather than on a single solution at a time. The convergence properties of this algorithm are analyzed in [2].

3.2 Multilevel Ant Stigmergy Algorithm

The *multilevel ant stigmergy algorithm* (MASA) [6] is a new approach to solving multi-parameter optimization problems. It is based on stigmergy, a type of collective work that can be observed in ant colonies. The MASA operates as follows (see pseudo code in Fig. 2).

First, the problem parameters are transformed into a search tree where vertices represent discretized values of parameters (line 1). A vertex representing a parameter value is connected to all vertices representing the values of the next parameter. In this way, the multi-parameter optimization problem is transformed into a problem of finding the cheapest path.

Second, the tree is coarsened to a predetermined size (line 2). Coarsening is merging two or more vertices that represent discretized values of the same parameter into one vertex; this is achieved in L iterations (we call them levels). In the coarsened tree the initial amount of pheromone is deployed in all vertices (line 3).

```
1:  Construct the search tree from all parameters
2:  Coarsen the tree in L levels
3:  Initialize vertices with initial amount of pheromone
4:  for l = L downto 1 do
5:    while current level l stopping criterion not met do
6:      for all ants do
7:        Find the cheapest path
8:      endfor
9:      Update pheromone amounts in all visited vertices
10:     Increase the pheromone amounts on best path
11:     Evaporate pheromone in all vertices
12:   endwhile
13:   Refine the tree by one level
14: endfor
15: Optionally perform local optimization
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Figure 2: Multilevel ant stigmergy algorithm.

Next, the optimization procedure based on ant colony optimization [3] is applied (lines 5–12). All ants simultaneously start from the starting vertex. The probability of choosing the next vertex depends on the amount of pheromone in the vertices. Ants repeat this action until they reach the ending vertex. The parameter values gathered on each ant's path represent a candidate solution, which is then evaluated according to the given objective function. Afterwards, each ant returns to the starting vertex, on its way depositing pheromone in the vertices according to the evaluation result: the better the result, the more pheromone is deposited. If the gathered parameter values form an infeasible solution, the amount of pheromone in the parameter vertices is slightly decreased. When the ants return to the starting vertex, two additional actions are performed. First, following ant colony optimization, “daemon action” is applied as a type of elitism, i.e., additional increase of the pheromone amount on the currently best path. Second, the pheromone in all vertices evaporate, therefore, in each vertex the amount of pheromones is decreased by some predetermined percentage.

Then the coarsened tree is refined by one level (line 13). All vertices created from one vertex have the same amount of pheromone as the original one. When refinement is done, the optimization phase continues. These two phases are repeated until the graph is expanded to its original size and the optimization performed on every level of the expansion (lines 4–14).

Finally, local optimization can be applied. Local optimization has become a mandatory addition to any ant-based algorithm. With the use of local optimization one usually improves the convergence or improves the best solution found so far. In our case, we use it because our basic search technique is oriented more towards finding the best area of the solution space. We can say that the search is more of a broader type, so we use local optimization to improve the best solution.

4 Experimental Results

As explained in Subsection 2.2, we optimize ten parameters of the electric motor rotor/stator geometry. Predefined search intervals for their values are used and the discretization step for all parameters is 0.1 mm. Therefore, the size of the search space can be obtained as a product of the numbers of possible settings over all parameters. It turns out to be approximately 10^{20} points.

The first optimization method—the EMA—is population-based. Therefore, it starts with an initial population of solutions. To assist the population-based method in finding feasible solutions, it was modified to start not with a population of random solutions, but rather a population of solutions that are random perturbations of a predefined solution. For this purpose the engineering solution was used, specifying the universal motor rotor/stator geometry used in practice.

Unlike the population-based methods that gradually improve the solutions, the MASA is a solution-construction method. Initial experiments with the MASA on the electric motor geometry optimization problem have shown this algorithm is capable of successfully navigate the search from infeasible to feasible regions. The multilevel approach significantly reduces the search space in the early stages of exploration. This reduction enables the MASA to perform well without any background information on the feasibility of solutions. Through stigmergy, infeasible regions in the search

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space are found less attractive by the ants, and consequently the search focuses on feasible ones.

The stopping criterion for both optimization methods was given by the number of solutions to be evaluated. It was set to 1400 and this value vas chosen considering the computational complexity of the optimization procedure.

Table 2: Result statistics for the optimization methods (universal motor power losses in watts).

Method	***Best***	***Average***	***Worst***	***St. dev.***
eng. design	177.9	--	--	--
GA	147.0	N/A	N/A	N/A
EMA	134.9	141.9	148.0	3.7
MASA	114.2	128.9	135.9	7.8

The optimization methods were run 20 times. The obtained results in terms of the electric motor power losses are presented statistically in Table 2. The method performance diagrams are shown in Fig. 3; also compared with power losses of the original engineering solution that amounted to 177.9 W.

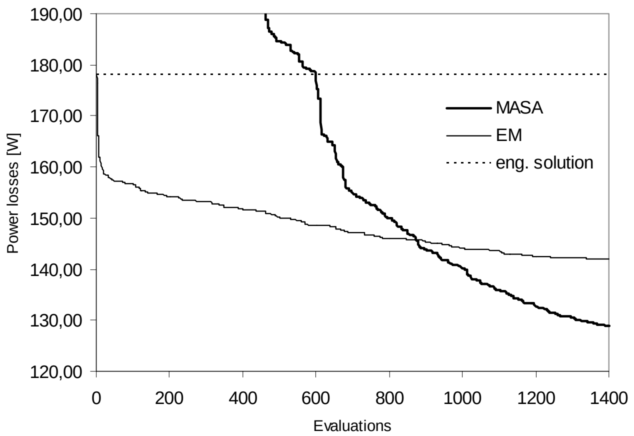

Figure 3: Performance of the applied methods in optimizing universal motor rotor/stator geometry parameters (average over 20 runs).

The results first of all show that applied methods significantly improve the engineering design of the electric motor rotor and stator. While the EMA starts with the engineering solution originally used in motor production and evolve rather slowly, the MASA starts with randomly created solutions that results in high power losses, but rapidly improve during the course of run.

By applying stochastic optimization methods we found various electric motor rotor/stator geometry parameter settings to minimize the power losses. The optimization procedures were however driven according to the results of computer simulation. To provide a more realistic evaluation, we have submitted the resulting designs to an expert designer to analyze them from the technical and production points of view. The expert confirmed the usefulness of the presented results.

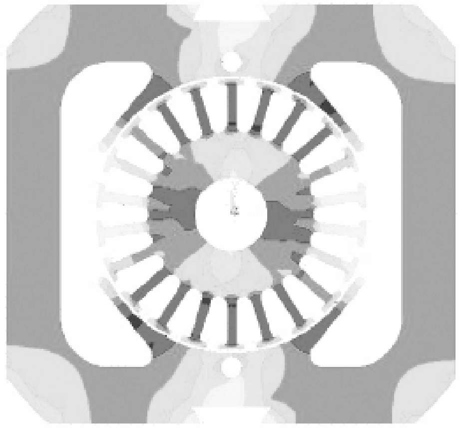

Figure 5: Laminations of the original engineering rotor and stator design with power losses of 177.9 W.

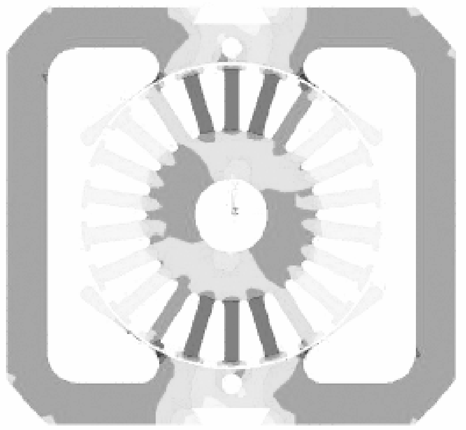

Figure 6: Laminations of the rotor and stator design with minimum power losses (111.1 W) as found in the optimization experiments by the MASA.

5 Conclusion

In this paper, we have performed a comparative study of two stochastic optimization methods in computer-assisted design of universal AC or DC motor rotor/stator geometry. The primary design goal was to minimize the power losses, however, the resulting designs were also evaluated by an expert designer from the point of view of feasibility for use in regular production. The applied methods were the electromagnetism-like algorithm and the multilevel ant stigmergy algorithm. They were applied to optimizing the geometry parameters of a universal motor already in regular production. The optimization procedures were navigated by numerical evaluation of the candidate solutions.

The output of this study can be summarized in several important findings. Above all, both compared optimization methods were able to significantly improve the original engineering design. Comparing the tested methods, a recently proposed optimization technique the MASA generated the minimum power loss designs. Its additional advantage shown on this problem was the capability of successfully performing the optimization from random starting points, which was not the case with the other methods. In our opinion, the superiority of the MASA arises from its multilevel search feature. On the methodological side, the multilevel approach found beneficial with the MASA, is worth of exploration in combination with other optimization methods.

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