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Recent Design Optimization Methods for Energy-Efficient Electric Motors and Derived Requirements for a New Improved Method—Part 2 †

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† Presented at the Economy, Sustainable Development and Energy International Conference (ESDEIC), Edinburgh, Scotland, UK, 25–27 June 2018.

Published: 26 October 2018

Abstract: Designing energy-efficient electric motor is a task where multiple goals have to be achieved at once. To find the best design possible, different approaches have been developed. In part one of this multipart paper, the characteristics of the design optimization problem and methods to solve them have been presented. Part two will deal with the different types of model descriptions and how the fundamental workflows look like. The third and last paper will evaluate the findings concerning the solution methods of the design optimization problem of electric motors. As a consequence, requirements for a new improved optimization method are deduced and presented.

Keywords: electric motor; design optimization; deterministic methods; stochastic methods; physical models; surrogate models; energy-efficient motors; boundary conditions

1. Introduction

To design electric motors, various variables and different requirements have to be dealt with. Recent methods to solve this problem efficiently treat the design optimization problem of electric motors as a mathematical problem. The characteristics of these optimization problems were presented in detail in part one as well as deterministic and stochastic methods. In order to evaluate solutions to the design optimization problem properly, models describing real-world problems and making it accessible for the solution methods, are equally important.

The main part of this paper is dedicated to a thorough literature survey to identify what model descriptions are used and how the resulting fundamental workflows of solving the design optimization problem look like. The last section of this paper is used for a summary of the findings.

2. Models and Recent Design Optimization Methods

Models are used to transform real-world problems into mathematical representations. Together with methods to solve optimization problems, distinct workflows for the design optimization problem of electric motor arise. In the following sections the various approaches are presented in detail. They are categorized according to the optimization methods and model descriptions used.

2.1. Deterministic Methods with Physical Models

Describing the physics of electric motors, Maxwell's equations are crucial. There are two basic approaches to solve them. Analytic approaches derive closed solutions of the magnetic flux density distribution. Despite the rather low computation time, idealizations are necessary. Another approach is finite element analysis (FEA). The magnetic flux density distribution can be modelled more accurately but leads to higher computation times. Detailed information can be found in [1,2].

A literature survey reveals basic information regarding the solution process of optimization problems with physical models [3–5]. The fundamental working steps are depicted in Figure 1.

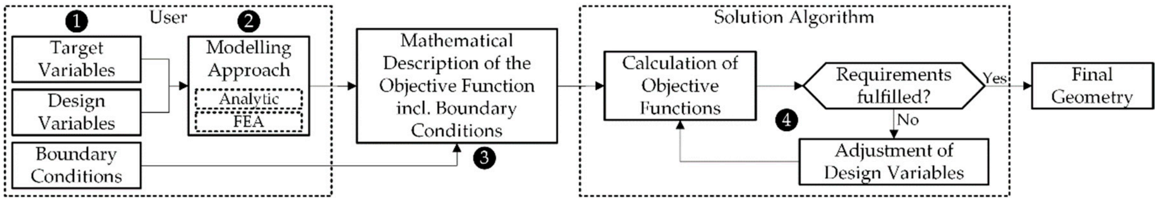

Figure 1. Deterministic method with physical model. Distinct properties are numbered and detailed.

(1) The most influential step is the definition of the target and design variables as well as the boundary conditions by the user. The number of target variables affects the solution algorithm used. Higher numbers of boundary conditions complicate the solution process since the design space gets increasingly restricted. But most important is the number of design variables. They have to be chosen sufficiently high to get an optimal solution, but increasing complexity has to be considered as well.

(2) Modelling the electric motor is the crucial task since the accuracy and the computational speed will be defined. Analytic models offer the possibility of fast computation times, but simplifications are unavoidable, in-depth expert knowledge is required and the models are very specific to the type of electric motor. A more flexible approach can be achieved using FEA, since no simplifications are necessary. The accuracy is high but the drawback are higher computation times.

(3) The objective function has to be computed in dependence of the design variables, the model of the electric motor and the boundary conditions. Subject to the target variables, the objective functions can be trivial to compute or more elaborate calculations have to be performed.

(4) Gradient-free algorithms are used, like pattern search, which try to find the solution by performing a systematic search. Another method is sequential quadratic programming. Here, a quadratic subproblem is constructed, which can easily be solved. Generally, the choice of the algorithm is highly dependent on the model description and the number of design variables.

2.2. Deterministic Methods with Surrogate Models

Surrogate models approximate the physical behavior. To determine the approximation function, the error between measured or simulated test data and the surrogate model is minimized. The most popular approach to surrogate modelling is response surface methodology. Since the area of approximation is typically rather small, simple polynomial functions can be used [6]. Another approach is to use a sum of radial functions with different basis functions and center points [7].

A literature review considering optimization problems with surrogate models yield some general information [8–10]. The workflow of determining the solution can be illustrated as in Figure 2.

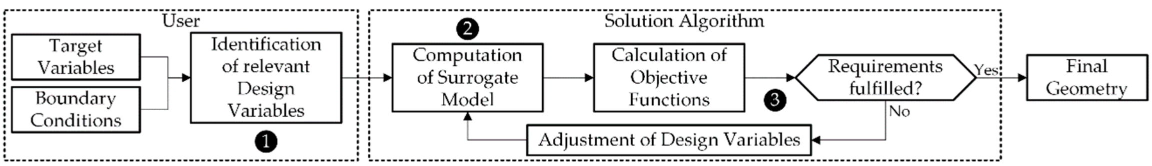

Figure 2. Deterministic method with surrogate model. Distinct properties are numbered and detailed.

(1) The design variables are not arbitrarily chosen by the user. Instead, a screening process is conducted in dependence of the target variables, the boundary conditions and the type of surrogate model. Using a design of experiment (DOE) the statistically relevant variables are identified. Typically, no more than three to six design variables appear statistically significant.

(2) In the actual optimization loop, the surrogate model has to be computed. To determine the approximation function, a DOE has to be performed. Usually FEA is used to compute the true responses at the design points due to its accuracy and usability. Since the surrogate model gives only reasonable values in the observed design space, in each iteration the surrogate model is recomputed.

(3) To determine the optima, literature suggests that often window-zoom-in methods are employed. Starting with a broad design space and a rough estimation of the objective functions, the design space is then decreased and shifted to the assumed optimal design variables. Consequently, more exact surrogate models can be defined, allowing the optimal design variables to be calculated.

2.3. Stochastic Methods with Physical Models

The general workflow of the optimization with stochastic methods and physical models of electric motors is identified as a result of a literature study and depicted in Figure 3 [11–13].

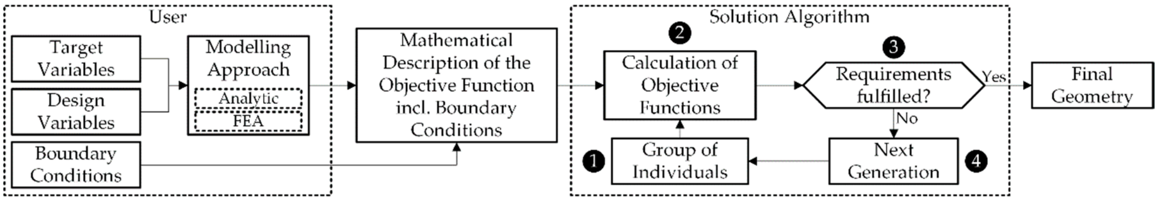

Figure 3. Stochastic method with physical model. Distinct properties are numbered and detailed.

(1) In the initial phase of the optimization process, the initial group has to be created either using expert knowledge or randomly with respect to the boundary conditions. In subsequent optimization steps, the next generation's group is altered based on information gathered in the current one.

(2) Since stochastic methods do not use gradient information, only the value of the objective functions has to be calculated for each member. The size of the group has to be defined with respect to the number of design variables, the computational resources and the model description.

(3) Termination criteria are necessary for stochastic methods, since they will never reach the optimum exactly. An optimality termination criterion is typically the change in objective function of the best member. If the change is below a certain threshold, the optimization is assumed to have converged. Otherwise, usually a fixed number of iterations is used to abort the optimization process.

(4) Depending on their value of the objective function, the members are more or less likely to influence the upcoming generation. In addition, probabilistic noise is added to new members to keep the diversity high, thoroughly inspect the design space and escape local minima.

2.4. Stochastic Methods with Surrogate Models

Depending on a systematic literature survey, the general workflow of the optimization process of stochastic methods with surrogate models can be condensed and is illustrated in Figure 4 [14–16].

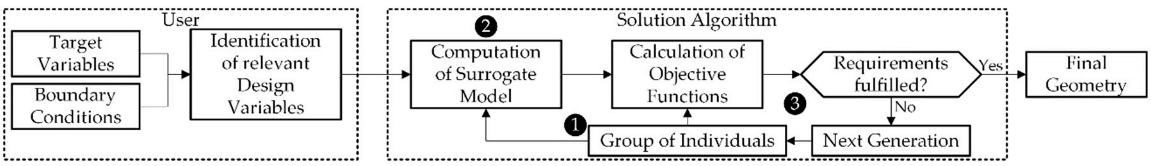

Figure 4. Stochastic method with surrogate model. Distinct properties are numbered and detailed.

(1) The group of design vectors is not only used for the calculation of the objective functions but also for the determination of the surrogate model.

(2) In each iteration, a new surrogate model using a DOE has to be determined. The necessary experimental design is dependent on the number of design variables and can hugely impact the computation time. Afterwards, the objective functions are fast to evaluate due to the simple formulas.

(3) As before, termination criteria have to be checked in order to either successfully terminate or abort the optimization process. While approaching the optimum, the members of the group are resembling each other progressively. To avoid local optima, random changes are applied to the members. Compared to the calculation of the surrogate model, the optimization step is quite fast.

3. Conclusions

In this paper, based on a literature review, the fundamental workflows of different approaches to the design optimization problem of electric motors and their characteristics were presented. The last part of this multipart paper is dedicated to an assessment of these approaches. Based on the findings, requirements for a new design optimization method are formulated.

Conflicts of Interest: The authors declare no conflict of interest.

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