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Recent Design Optimization Methods for Energy-Efficient Electric Motors and Derived Requirements for a New Improved Method—Part 1 †

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Abstract: Energy-efficient electric motors are gathering an increased attention since they are used in electric cars or to reduce operational costs, for instance. Due to their high efficiency, permanent-magnet synchronous motors are used progressively more. However, the need to use rare-earth magnets for such high-efficiency motors is problematic not only in regard to the cost but also in socio-political and environmental aspects. Therefore, an increasing effort has to be put in finding the best design possible. The goals to achieve are, among others, to reduce the amount of rare-earth magnet material but also to increase the efficiency. In the first part of this multipart paper, characteristics of optimization problems in engineering and general methods to solve them are presented. In part two, different approaches to the design optimization problem of electric motors are highlighted. The last part will evaluate the different categories of optimization methods with respect to the criteria: degrees of freedom, computing time and the required user experience. As will be seen, there is a conflict of objectives regarding the criteria mentioned above. Requirements, which a new optimization method has to fulfil in order to solve the conflict of objectives will be presented in this last paper.

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

1. Introduction

The design of electric motors is a challenging task since various variables have to be taken into account and simultaneously different requirements have to be respected. In the past, the design process was characterized by iteratively optimizing the design proposal until the goals were achieved. This process was mainly influenced by the experience of the user, his knowledge of other motors which had to fulfil comparable requirements and was therefore a tedious task. The main steps in the design process were performed manually. Only the detailed analysis of the design proposal was executed with the help of software for numerical calculations [1]. Nowadays, with increasing computing capacities, it is possible not only to use numerical calculations for the verification of a design proposal but also as an essential component in the design processes. In recent years, different approaches to the design optimization problem of electric motors using numerical calculations have been developed. Their common goal is to determine the best design possible regarding some objective functions under consideration of boundary conditions. Typical objective functions are: efficiency, torque, cogging torque, torque ripple, motor weight, material costs, etc. In addition, for valid design proposals, boundary conditions have to be respected, like: motor diameter, motor length, motor weight, minimal airgap or maximum allowable current density in the coils.

All approaches to the design optimization problem have in common that they are handling the search for the best geometry as a mathematical optimization problem.

This paper is divided into two main sections. In the following section, the distinct characteristics of the design optimization problem are stated. Section three is dedicated to give an overview of general optimization methods. The closing section of this paper is used for a summary of the findings.

2. Essential Characteristics of the Design Optimization Problem

The design process of electric motors can be seen as an optimization problem, where certain requirements have to be met and boundary conditions have to be respected. Consequently, these problems can be solved with mathematical means.

Optimization problems can depend on one or multiple variables. In the following, only multidimensional optimization problems with n independent design variables are considered. The individual design variables are combined in the design vector $\boldsymbol{x}$.

The first distinctive feature of such an optimization problem is the number of objective functions. In its simplest form, there is one objective function $f(\boldsymbol{x})$, which has either to be maximized or minimized [2].

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} f\,(\boldsymbol{x}) \tag{1}$$

If there are two or more objective functions, for instance efficiency, weight and torque ripple, multi-objective optimization problems with m objective functions have to be solved [3].

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} \big(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots, f_m(\boldsymbol{x})\big) \tag{2}$$

Another distinctive feature of optimization problems is the behaviour of the objective functions. Typically, in engineering respectively modelling of physical systems, there is no linear correlation between its design variables and its objective functions. Therefore, they are called nonlinear optimization problems [4].

Further, optimization problems differ with respect to the type of design variables. Continuous design variables allow infinite steps between a lower and upper bound. Contrary to this are discrete variables, where only distinct values are permitted.

Additionally, optimization problems are to be distinguished in terms of whether there are boundary conditions to be respected or not. Typically, multiple boundary conditions have to be taken into account, limiting the feasible sets of possible solutions by employing mathematically linear or nonlinear equality respectively inequality constraints [5].

The resulting general optimization problem takes the following form. It consists of m nonlinear objective functions $f(\boldsymbol{x})$, i equality constraints $g(\boldsymbol{x})$, j inequality constraints $h(\boldsymbol{x})$ and k of the n design variables are integers.

$$\begin{aligned}
&\min_{\boldsymbol{x}\in\mathbb{R}^n} \big(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots, f_m(\boldsymbol{x})\big)\\
&w.r.t.\\
&g(\boldsymbol{x}) = \big(g_1(\boldsymbol{x}), g_2(\boldsymbol{x}), \dots, g_i(\boldsymbol{x})\big)\\
&h(\boldsymbol{x}) = \big(h_1(\boldsymbol{x}), h_2(\boldsymbol{x}), \dots, h_j(\boldsymbol{x})\big)\\
&x_3, x_4, \dots x_k \ are\ integers
\end{aligned} \tag{3}$$

The mathematical description of the objective functions is another distinctive feature characterising the design optimization problem. Generally, there are two different approaches. The first approach is to directly describe the physical properties with Maxwell’s equations, mainly using finite element analysis (FEA) or analytical models [6,7]. The other approach is to use surrogate models, approximating the physical properties. Different surrogate models have been developed, for instance response surface models, radial basis function models or kriging models [8,9].

In order to solve optimization problems efficiently, deterministic or stochastic algorithms can be used. Deterministic algorithms solve optimization problems in a mathematically exact way. But the solution found does not necessarily have to be the global optimum [10]. If probability is a crucial factor for the working principle of optimization algorithms, they are called stochastic methods. These algorithms might not find the exact best solution but they are able to determine the global optimum with a certain probability [11].

3. Recent Design Optimization Methods

Over time, different approaches to the design optimization problem of electric motors have been developed. The common goal of the design processes is to determine a geometry of stator and rotor, which meet certain requirements and boundary conditions. A general overview of different procedures regarding the design optimization problem can be found in [12–14]. In the upcoming sections a deeper insight into deterministic and stochastic methods will be given.

3.1. Deterministic Methods

The core principle of deterministic methods is to solve optimization problems in an iterative but mathematically exact manner. In each iteration step, a new point, which is closer to the optimum than the preceding one, is computed. Dependent on what information of the mathematical properties concerning the optimization problem is used, different types of algorithms can be distinguished. If only the actual value of the objective function is used, these types are called zero-order methods. Accordingly, methods which make use of the first and second derivative, are named one- respectively second-order methods. For multi-objective optimization problems, diverse procedures are used to deal with the multiple objective functions. A possible approach is to combine the multiple objective functions into one objective function. Other approaches use boundary conditions int order to account for the different objective functions. Generally, the consideration of boundary conditions is another important aspect of deterministic methods. Their presence in an optimization problem has to be especially considered in the solution process. To cope with this additional complexity, various techniques to implement the boundary conditions into the problem formulation are used. The downside of deterministic methods is that they are not able to distinguish between local and global optima. Dealing with this is possible in different ways, but a practical and most common approach is to rerun the optimization with different starting values. A deeper insight into various deterministic optimization methods is given in [15–17].

3.2. Stochastic Methods

The most significant feature of stochastic methods is probability. There is no absolute certainty that the optimum will be achieved nor that the exact same solution will be calculated even with the same starting values. However, the chance to achieve a global optimum is very high, which is a major advantage. Mimicking natural phenomena is the main principle of these methods. One of the most popular types are genetic algorithms. Their functional principle is to emulate the process of natural selection. The basis is a population of many individuals. The individuals consist of genes which are the encoded description of the optimization problem. To determine which individuals are better than the others and therefore have a higher probability to survive, the objective functions are used. The nature-like mechanisms of mutation and breeding are applied onto the population. Breeding of the next generation happens mainly by recombination of two individuals, exchanging parts of their genes. Other individuals proceed to the next generation mainly unchanged, but small random changes to their genes occur with a certain probability. This process of replacing previous generations is carried out until the optimum of the optimization problem is found or other termination criteria are reached. Another important stochastic method is particle swarm optimization. Inspired by the movement of birds or fish, this algorithm tries to determine the global optimum by moving particles around the design space. Furthermore, other methods exist e.g., simulated annealing, where the motion of atoms and the probability of accepting states with higher or lower energy dependent of a temperature is imitated. A thorough overview with detailed information can be found in [11,18–20].

4. Conclusions

In this first part, the general characteristics of the design optimization problem of electric motors were detailed. Based on these attributes, basic methods to solve the optimization problems were presented. In the following part of this multipart paper, these methods are investigated based on the model description used and the fundamental workflows are highlighted.

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

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