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Recent Design Optimization Methods for Energy-Efficient Electric Motors and Derived Requirements for a New Improved Method—Part 3 †

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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: The design of energy-efficient electric motor is a complex problem since diverse requirements and competing goals have to be fulfilled simultaneously. Therefore, different approaches to the design optimization of electric motors have been developed, each of them has its own advantages and drawbacks. The characteristics of these approaches were presented in the previous part of this multipart paper. In this paper, the presented approaches will be assessed with respect to the criteria: degrees of freedom, computing time and the required user experience. A conflict of objectives will become apparent. Based on these findings, requirements for a new design optimization method with the aim to solve the conflict of objectives, will be formulated.

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

1. Introduction

Systematic procedures are a proven concept when it comes to solving complex problems. Such a problem is the design of electric motors, where competing requirements have to be fulfilled. Therefore, various approaches to the design optimization problem of electric motors have been developed. In the previous part of this multipart paper, these approaches have been categorized and presented. Their respective characteristics have been highlighted. The evaluation of these approaches and the deduction of requirements for a new improved design method is the purpose of this paper.

It is divided into two main sections. After this introduction, the different approaches are evaluated and compared according to the criteria mentioned. In the following section, requirements are expressed, which a new improved design method for electric motors should fulfil. The closing section of this paper is used for a summary of the findings and some concluding remarks.

2. Assessment of the Design Optimization Methods

After elaborating the fundamental workflows and their corresponding characteristics in the previous two parts of this multipart paper, the methods shall now be assessed. The criteria to be considered are estimations of the necessary computation time, typical degrees of freedom and the user experience needed for efficient use of the method.

2.1. Computation Time

The computation time necessary to find the optimal solution is dependent on the optimization method, the model description and the number of design variables.

Deterministic methods with physical models are offering rather low computation times. Due to the model description, they are beneficial since gradient calculation is relatively fast. In combination with first-order methods, this leads to fast convergence due to the gradient information and the time efficient solution of the analytic model. If finite element analysis (FEA) is employed, the computation time is not that low anymore and gradient information is time consuming to obtain. Thus zero-order search strategies are applied. Obviously, higher degrees of freedom lead to higher computation times.

Deterministic methods with surrogate models tend to have higher computation times. To establish surrogate models, experimental designs have to be conducted in order to systematically assess the true responses of the objective function. Based on this design of experiment (DOE), the chosen surrogate model description can be adapted based on minimizing the squared errors. Typically, this process has to be performed in each step of the optimization loop.

Stochastic methods with physical models have lower computation times compared to the previous methods. Although the solution process is stochastic and based on groups of individuals, the physical model description is counterbalancing this. Nevertheless, the algorithm of the stochastic method and the model description have to be designed with the computation time taken into account.

The highest computation times are to be expected of stochastic methods with surrogate models. While the calculations based on surrogate models are fast, the determination of them is rather time consuming. Since the solution algorithm approaches the optima iteratively, in each generation a new surrogate model has to be established in order to account for the new design space to be covered.

2.2. Degrees of Freedom

The number of design variables of an optimization problem is mainly influenced by the model description as well as by the algorithms used.

Considering deterministic methods with physical models, the degrees of freedom are comparatively high. Particularly with analytic models since this is not resulting in exceedingly high computation times. Whereas lower numbers of degrees of freedom have to be employed when using FEA to restrict the computation times to comparable values.

Since deterministic methods with surrogate models need to determine the surrogate model in each iteration, the number of design variables is moderate. Higher number of design variables lead to excessively long computation times since in each step a DOE has to be executed.

Stochastic methods with physical models are combining two antithetic properties. Physical models allow for quite high numbers of design variables. But the size of the group to solve the problem is dependent on the number of design variables. So higher degrees of freedom result in increasing computation times. These contradictory properties lead to moderate degrees of freedom.

The most inefficient combination of model description and solution algorithm in terms of degrees of freedom, can be found in stochastic methods with surrogate models. Not only affects the number of design variables the size of the group to solve the problem, but also the determination of the surrogate model is more time consuming. Thus, the degrees of freedom are rather low.

2.3. User Experience

In the creation of physical or surrogate models as well as in designing the solution algorithm, the required user experience is varying significantly.

When deriving the physical models used in conjunction with deterministic methods, user experience is important for accuracy and computation time. The creation of analytic models with few simplifications is hugely influenced by user experience. If FEA is used, user experience is necessary for the identification of relevant design variables and thus lowering computation time. Deterministic methods are more or less standard implementations, where user experience is not very beneficial.

When it comes to the determination of surrogate models together with deterministic methods, user experience is twice as important. Firstly, as pointed out previously, the physical model has to be determined, which is the foundation for the computation of the surrogate model. Here, user experience can decrease simplifications and computation time. Secondly, the approach of modelling the surrogate model is greatly influenced by user experience. Identifying relevant design variables and choosing an appropriate approximation function is the main task of the user.

Stochastic methods with physical models are less dependent on user experience. Since stochastic methods are well established, in this case user experience is important for the identification of important design variables and the appropriate specification regarding the size of the group.

User experience is relevant for stochastic methods with surrogate models, since the choice of the group size and the surrogate model are influenced by experience. The choice of important design variables is affecting the optimization process when it comes to the creation of the surrogate model itself as well as the size of the group. Lower numbers of degrees of freedom are important for manageable computation times.

2.4. Comparison

To clarify the previously described characteristics according to the criteria mentioned, their respective rating is summarized as a point rating system in Table 1.

Table 1. Summary of the properties referring to the methods presented. The convention of the symbols is: "+" meaning lower computation time, higher degrees of freedom and less user experience. The inverse applies to "-". Intermediate values are indicated with "o".

Method	Model	Computation Time	Degrees of Freedom	User Experience	Ranking
deterministic	**physical**	+	o	+	1
deterministic	**surrogate**	-	o	o	3
stochastic	**physical**	+	o	o	2
stochastic	**surrogate**	-	-	-	4

In Table 1, it can clearly be seen that some approaches are more suitable to the criteria considered than others. The least optimal approach is a stochastic method with surrogate models. Deterministic methods with surrogate models are achieving better ratings. They benefit from higher ratings in terms of degrees of freedom and user experience. The second-best rating is dedicated to stochastic methods with physical models since the computation time is lower compared to the previous methods. The best method in terms of these criteria are deterministic methods with physical models. Here, the computation time is rather low, the degrees of freedom are moderate and the required user experience is not as important as it is for the other methods. Consequently, this method is used as a starting point for the deduction of requirements for a new design optimization method.

3. Requirements for a New Improved Design Method

In the previous section, the different approaches to the design optimization problem were assessed. Considering the criteria computation time and degrees of freedom, a conflict of objectives is obvious. Higher degrees of freedom lead to higher computation times and if lower computation times are required consequently, the degrees of freedom have to be restricted. This section presents requirements which a new approach to the design optimization problem based on deterministic methods with physical models has to fulfil.

- The new approach should be able to cope with higher numbers of design variables than the methods presented. Even the approaches with high numbers of design variables found in literature state that these numbers have to be chosen wisely. However, with lower degrees of freedom than the number of design variables of the optimization problem, the design space is restricted. Therefore, it might not be possible to determine the optimum of the objective function and the resulting geometry of the electric motor is inferior to an ideal geometry. To achieve a global design scope of the new method, not only geometric variables should be considered but also the types of materials and magnets.

- User experience should be as less relevant for the new design method as possible. Since analytical models of electric motors are challenging to set up, especially with few simplifications, FEA should be used instead. Therefore, the experience required by the user can be minimized and the new method could be employed by users who do not possess the expert knowledge which would be necessary for other methods. Additionally, FEA can lead to more precise models and thus the influence of the various design variables could be assessed in more detail.
- A low time to determine the optimal geometry of the electric motor regarding some objective functions is another requirement for the new method. Although the number of design variables ought to increase and FEA is used as the model description, the computation time should not increase exceedingly. Therefore, the solution algorithm has to be defined with special remark to the computation time and appropriate methods are to be adapted. In addition, intelligent computation schemes should be used, in order to reduce the time necessary for FEA.
- Since it is often not sufficient to optimize the design of an electric motor regarding one target variable, multiple objective functions should be regarded. Certainly, other methods do employ multiple objective functions, but frequently they are not treated as a true multi-objective problem. This means that either objective functions are converted to boundary conditions or that the objective functions are combined into one objective function and thus treated as a single-objective problem. For this reason, it is not certain that the optimal compromise between the objective functions is determined. Therefore, the new design method should treat the objective functions as a true multi-objective problem, where the pareto-optimal solutions are calculated.
- External requirements are common in the design optimization problem, since electric motors have to fulfil various conditions concerning the available design space, manufacturing tolerances and dynamics. These requirements have to be considered in the design optimization process already. Therefore, it is essential that these requirements are entirely taken into account.

4. Conclusions

In this multipart paper, recent design optimization methods of electric motors were presented. They were categorized whether deterministic or stochastic optimization methods were used. Furthermore, it was distinguished if physical or surrogate models were employed as the mathematical description of the electric motor. For each category, the fundamental workflows were identified and presented in detail. Additionally, the distinct features of these workflows were highlighted. It was shown that, according to the criteria computation time, possible degrees of freedom and required user experience, none of the methods were fully convincing. The most promising approach were deterministic methods with physical models since little user experience is necessary, the number of design variables is moderate and the computation time is rather low. Based on these results, requirements were presented, which a new design method should fulfil. The new method should be able to deal with higher numbers of design variables and also include the material selection of the laminations as well as the magnets. Almost no user experience ought to be relevant for the course of the design process. Although the number of design variables is to increase, the time to compute the best design proposal possible should not increase greatly. Therefore, new computational approaches for efficient FEA calculations as well as deterministic optimization schemes have to be applied. For a comprehensive approach, the new design method is to treat the optimization problem truly as a multi-objective problem with respect to various boundary conditions.

Based on these requirements, a new approach to the design optimization problem of electric motors will be detailed in the future. For this purpose, further research is necessary in order to cope with the requirements the new method has to fulfil.

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