Multiobjective Electric Machine Optimization for Highest Reliability Demands

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Abstract—This article is about illustrating a workflow for incorporating reliability measures to typical electric machine design optimization scenarios. Such measures facilitate comparing designs not only for rated conditions, but also allow to analyze their performance in the presence of inevitable tolerances. Consequently, by additionally considering reliability or robustness as objectives compared to conventional optimization scenarios, designs featuring low parameter sensitiveness can be obtained.

The analysis of the design’s reliability as part of solving optimization problems involves a significant increase in required numerical evaluations. To minimize the associated prolongation of the runtime, an approach featuring a design of experiments based reduction of required computations and a consequent surrogate modeling technique is presented here. After successful training, the metamodel can be applied for fast evaluating lots of different parameter combinations.

A test problem is defined and analyzed. Based on the observed findings, the necessity of incorporating robustness evaluations to machine design optimization becomes evident. In addition, the derived models allow for studying the impact of any tolerance-affected parameter on the machine performance in detail. This facilitates further beneficial studies, as for instance the analysis of selected changes of tolerance levels rather than a general minimization of the respective ranges which usually is associated with high production cost.

Index Terms—electric machine, optimization, reliability, robustness, sensitivity, six sigma, tolerance analysis

I. INTRODUCTION

Electric machine design optimization has become a major field of research in the recent past. Special sections in high-quality journals [1]–[3], as well as numerous research papers [4]–[8] and state-of-the-art reviews [9] prove this fact. On the one hand, finding the ‘best’ solution for given problem settings is always attracting researchers. On the other hand, a further reason is that through the last years a lot of regulations dealing with minimum efficiency requirements were concluded, e.g., by the European Union or other national or transnational institutions [10]–[12].

Besides the energy efficiency, several additional performance measures are considered for optimization, e.g., the cogging torque, or the torque ripple at load. Consequently, researchers typically face multi-objective optimization scenarios. By introducing weighting factors, such problems can be considered as single-objective problems and classical optimization techniques can be applied. However, as many design parameters are analyzed at once and the unknown performance characteristics are typically nonlinear and feature multi-modality, applying evolutionary algorithms can provide many benefits for approaching such scenarios. Consequently, multiple objectives can be studied at once, facilitating to investigate the tradeoff of conflicting objectives. Prominent algorithms frequently applied are genetic algorithms [13], [14], particle swarm based techniques [15], as well as differential evolution [16]. Moreover, many authors consider hybrid optimization techniques, e.g., in [17].

As manufacturers are further interested in minimizing the (material) cost, highly utilized designs are obtained during optimization. Such designs often are very sensitive regarding tolerances. This follows significant changes in performance when dealing with inevitable inaccuracies of material characteristics and dimensions compared with the ‘ideal’ rated conditions assumed for simulation purposes. A classification of tolerances related to electric machines can for instance be found in [18].

As a consequence, evermore researchers investigate the tolerance sensitiveness of machine designs. Robustness or reliability based measures are defined to compare different design variants in terms of how tolerances impact their performance [19]. As cogging torque of permanent magnet machines is significantly affected by tolerances, a big share of the work is dedicated to this performance measure. For instance, some authors investigate how non ideal magnet characteristics or magnet arrangements modify the cogging torque characteristics [20], [21]. Others focus on changes of the positioning and shape of the rotor lamination [22], [23]. Various different tolerances are considered in [24] by applying analytical models for their evaluation. In [25], the focus is on minimizing the computational effort for deriving probability or cumulative distribution functions for machine performance measures as function of multiple tolerance-affected parameters.

Besides single design analyses, usually performed as post-processing activity, recent work is about incorporating tolerance analyses to optimization scenarios [26], [27]. While many authors focus on expected value and variance and related six sigma based approaches [28]–[30], others derive alternative

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measures, e.g., regarding the hyper volume associated with tolerance ranges [31]–[33] or a local topological derivative [34] or gradient-free local measures [5]. The focus is on maximizing the information gain through the selected measure and facilitating to consider robustness measures as objectives. Consequently, the tradeoff robustness versus rated performance can be studied.

This paper is organized as follows: Section II is about the applied approach for considering the impact of tolerances on the designs’ performances during optimization runs. The focus is on minimizing computational cost while guaranteeing a decent model accuracy. Therefore, design of experiments and surrogate modeling techniques are applied. A test problem is defined within Section III. A similar problem was analyzed in [35]. However, in that work, the focus was on the cumulative distribution function and no additional constraints were considered besides the three objectives. The results of the here focused test scenario are presented in Section IV, highlighting the importance for incorporating robustness measures to modern machine design optimization. This is followed by an even more detailed investigation of the tolerance sensitiveness of selected machine designs in Section V. By making use of the derived models for analyzing the designs’ sensitiveness, the impact of different tolerances can be studied and advantageous conclusions can be drawn regarding which tolerance ranges are beneficial to minimize following a steep increase of the design’s overall reliability. Section VI summarizes this work and gives an outlook about planned future activities.

II. SURROGATE MODEL ASSISTED DESIGN EVALUATION

An initially in [35] introduced similar approach for minimizing the computational cost associated with evaluating a machine design in the presence of tolerances is illustrated in Fig. 1. The overall analysis of the impact of tolerances on performance measures of an electric machine design and thus its reliability is subdivided into 5 steps.

The first step is done offline, it is about defining parameters featuring relevant tolerance levels by considering either a discrete or continuous distribution of the parameters. Based on the selected modeling and on the characteristics of the distribution, descriptive coefficients, e.g., the mean value and the standard deviation, are further required.

The second step is about selecting a reasonable number of parameter levels for modeling the impact of each tolerance-affected quantity. While the more levels give a better modeling accuracy, they also follow an increase in computational cost. Especially when considering many tolerance-affected parameters, the curse of dimensionality takes effect. Based on the selected parameter levels, a full grid analysis could be performed. However, the therewith associated evaluations, usually performed by making use of finite element simulations, have to be individually performed for any design variant considered. As a typical optimization run involves the analysis of thousands of designs, it is advantageous to further reduce the number of required computations. Thus, a design of experiments technique is applied to decrease the number of necessary simulations while acquiring as much information about the design’s characteristics as possible. Obviously, there is a tradeoff.

All the finally defined parameter combinations are evaluated by making use of a computer cluster. As due to network errors or individual computer shutdowns some results might be missing or erroneous, a threshold is defined how many unavailable results can be tolerated. When all the results finally were determined, a surrogate model is trained. Such a model is used to approximate the machine performance for any combination of tolerance-affected parameters that has not been evaluated by finite element simulations so far. A suitable modeling approach as well as the selection of reasonable training data are key aspects for guaranteeing a good model accuracy. A separate model has to be defined for any objective and any constraint considered for the optimization problem. In the past, surrogate modeling was already successfully applied in the field of electric machine design [7], [36], [37], but very seldom for modeling the impact of tolerances.

After the model has been successfully defined, it is used to evaluate a high number of different combinations regarding tolerance-affected parameters and their respective likeliness.

### Table 1: Tolerance-affected parameters

| Parameter | Distribution | Distribution Parameters |
|-----------|--------------|-------------------------|
| $x_1$     | uniform      | $x_{1_{min}}$, $x_{1_{max}}$ |
| $x_2$     | normal       | $\mu$, $\sigma$         |
| ...       | ...          | ...                     |

Fig. 1. Approach for evaluating the reliability of any design variant.
of certain values to appear. This approach is usually called importance sampling. The evaluations based on the surrogate model can be carried out relatively fast. Making use of a high number of evaluations allows for accurately estimating the probability of failure (POF) for any design considering predefined constraints. Consequently, the design’s reliability can also be estimated and compared with any other solution.

III. TEST PROBLEM

A previously investigated optimization problem [35] is reconsidered for this work. Hence, it can be easily compared with results derived earlier. All the constant parameters, the conventional design parameters, the tolerance-affected design parameters as well as the tolerance-affected material parameter are the same as in [35]. They are listed in Tables I-IV, respectively. A sketch of the general structure of the inner-rotor SPM machine to be optimized is given in Fig. 2.

By contrast to the previous study, here three objectives as well as two constraints are considered. The objectives are listed in Table V. The focus is on a single load point evaluation, specified in Table I and the respective efficiency $\eta$ shall be maximized, as indicated in Table V. Besides the consequent optimization of the energetic behavior, any design featuring an efficiency lower than 80% is considered invalid. This constraint is also applied for the reliability evaluation, as due to a change of, e.g., the magnet residual induction, some designs may feature acceptable efficiency for rated conditions and a not satisfying performance for selected combinations of tolerance-affected parameters. Besides the efficiency, the cogging torque $T_{\text{cogg,pp}}$ in percent of the rated load torque as well as the material cost are optimized. While no constraints are applied for the cost, the cogging torque shall at maximum be 10% of the rated torque. It is defined as

$$T_{\text{cogg,pp}} = \frac{\max_\alpha T_{\text{cogg}}(\alpha) - \min_\alpha T_{\text{cogg}}(\alpha)}{T_{\text{rate}}} \cdot 100\% . \hspace{1cm} (1)$$

The material cost are the sum of the cost for the permanent magnets, the laminated steel, as well as for the copper for the stator coils. The cost of any design are determined by a CAD-based computation of the volumes and the respective specific cost defined in Table I.

![Fig. 2. Considered machine topology for the test problem.](image)

### Table I

**CONSTANT PARAMETERS**

| Name                      | Symbol | Unit   | Value |
|---------------------------|--------|--------|-------|
| number of stator slots    | $N_s$  | -      | 12    |
| number of rotor poles     | $p_s$  | -      | 8     |
| air gap width             | $\delta$ | mm     | 0.7   |
| rotor inner diameter      | $d_{ri}$ | mm     | 16    |
| coils’ temperature        | $\vartheta_{coi}$ | °C | 120   |
| permanent magnets’ temperaure | $\vartheta_{pm}$ | °C | 90    |
| rated torque              | $T_{\text{rate}}$ | Nm     | 5     |
| rated speed               | $n_{\text{rate}}$ | rpm    | 3000  |
| specific permanent magnet cost | $c_{pm}$ | (Euro/kg) | 100.0 |
| specific laminated steel cost | $c_{lam}$ | (Euro/kg) | 2.0   |
| specific Copper cost      | $c_{\text{copp}}$ | (Euro/kg) | 8.0   |

### Table II

**CONVENTIONAL DESIGN PARAMETERS**

| Name                      | Symbol | Unit   | Min. | Step | Max. |
|---------------------------|--------|--------|------|------|------|
| stator inner diameter     | $d_{si}$ | mm     | 40.0 | 1.0  | 90.0 |
| stator outer diameter     | $d_{so}$ | mm     | 75.0 | 1.0  | 140.0|
| axial length              | $l_{ax}$ | mm     | 35.0 | 1.0  | 80.0 |
| stator tooth width        | $w_{st}$ | mm     | 4.0  | 0.2  | 10.0 |

### Table III

**TOLERANCE-AFFECTED DESIGN PARAMETERS**

| Name                      | Symbol | Unit   | Min. | Step | Max. |
|---------------------------|--------|--------|------|------|------|
| magnet radial dimension   | $h_m$  | mm     | 3    | 0.25 | 8    |
| – uniform tolerance distrib. | $\Delta h_m$ | mm | -0.1 | 0.0  |
| magnet pole coverage      | $\alpha_m$ | - | 0.5  | 0.025 | 1 |
| – uniform tolerance distrib. | $\Delta \alpha_m$ | - | -0.01 | 0.01 |
| stator slot width         | $b_{ss}$ | mm | 2.0 | 0.5 | 7.0 |
| – uniform tolerance distrib. | $\Delta b_{ss}$ | mm | -0.01 | 0.01 |

### Table IV

**TOLERANCE-AFFECTED MATERIAL PARAMETER**

| Name                      | Symbol | Unit   | Min.  | Nom. | Max. |
|---------------------------|--------|--------|-------|------|------|
| magnet residual induction | $B_r$  | T      | 1.28  |      | 0.08 |
| – uniform tolerance distrib. | $\Delta B_r$ | T | -0.08 | 0.02 |

### Table V

**OBJECTIVES**

| Name                      | Symbol | Unit   | Min. | Max. |
|---------------------------|--------|--------|------|------|
| efficiency                | $\eta$ | -      | 0.8  | 1    |
| coggging torque           | $T_{\text{cogg,pp}}$ | % | 0    | 10   |
| material cost             | $c_{\text{mat}}$ | Euro | -    | -    |

### Table VI

**CONSTRAINTS**

| Name                      | Symbol | Unit   | Min. | Max. |
|---------------------------|--------|--------|------|------|
| thermal index             | $c_{th}$ | A/cm A/mm² | 0    | 1500 |
| rms current density       | $j$ | A/mm² | 0    | 7    |

Besides the objectives, two further constraints are defined to obtain designs with acceptable thermal characteristics. These are given in Table VI. Besides the constraint for maximum rms current density in the conductors $j$, a thermal index $c_{th}$ is computed based on [38]. The computation is done as follows:

$$c_{th} = \frac{2 n_{\text{coils}} A_{\text{coil}} j}{\pi d_{si}} . \hspace{1cm} (2)$$

The second term defined by the fraction gives a measure for the
rms mmf per unit length of the stator circumference. Therefore, the stator inner diameter \(d_{si}\) as well as the overall number of stator coils \(n_{coils}\) and their net conductor cross section \(A_{coil}\) are considered. Typically feasible maximum values for the expected machine size are defined for the two constraints. More details on these parameters can be found in [38].

Any design variant to be evaluated evolves 6 different \(i_d/i_q\)-combinations to be analyzed for a full electric period by 2-D magnetostatic FE-simulations. The software FEMM is applied for these evaluations [39]. Afterwards, a nonlinear machine model is trained and, consequently, the maximum possible efficiency for the given load point is found by finding optimal values for \(i_d\) and \(i_q\).

The overall analysis of a single design, as explained in Section II and Fig. 1, requires 33x6=198 finite element simulations over a full electric period. To minimize the overall runtime, the software HTCondor is applied for managing a computer cluster [40]. After finishing the FE-based evaluation, a surrogate model can be derived and an importance sampling based determination of the design’s robustness is performed by evaluating \(n_{samples} = 10^6\) quasi-random parameter combinations. The reliability \(r\) of the \(i\)-th design is defined as

\[
    r_i = 1 - \frac{n_{invalid,i}}{n_{samples,i}},
\]

and consequently, a probability of failure \((\text{pof})_i\) measure can be derived by

\[
    (\text{pof})_i = 1 - r_i = \frac{n_{invalid,i}}{n_{samples,i}}.
\]

\(n_{invalid}\) is defined as the sum of all evaluated parameter combinations that either violate at least a design parameter boundary or an objective or constraint minimum or maximum. A fully reliable design thus features \(n_{invalid,i} = 0\) or \(r_i = 1\), respectively.

For the optimization, the first 1000 machine designs are analyzed based on the Latin-Hypercube sampling (LHS) technique. Afterwards, the test problem is solved by applying the NSGA-II algorithm [14] with a population size of 100 individuals. Consequently, 5000 more designs are defined based on this algorithm and are subsequently evaluated.

### IV. Results

Throughout this section, the results of the optimization run are presented. Figure 3 gives the results for the three objectives material cost, efficiency, and cogging torque. Each colored circle represents a particular design variant. Clearly, the tradeoff cost versus efficiency can be observed from Fig. 3(a). Designs indicated by black dots are not reliable, thus \(r = 0\). Gray colored dots give variants featuring a borderline reliability, i.e., \(0 < r < 1\). Finally, the fully reliable designs with \(r = 1\) are given by green color.

As can be seen from Fig. 3, especially designs featuring very low cost are not reliable. The reason is that usually material utilization is minimized too much following designs that feature a too high thermal stress. By considering slightly more expensive designs, the gray colored designs featuring borderline reliability appear. These are usually machine designs that feature an acceptable performance for rated conditions, but fail in case of tolerances. By considering the cogging torque constraint of 10%, a further interesting domain in the most right section of Fig. 3(b) can be observed, where only non-reliable or borderline-reliable designs can be found. Particularly the borderline reliable designs might feature acceptable cogging torque performance for ideal conditions, and violate the constraint in case tolerances appear. Thus, a certain ‘safety margin’ regarding the rated cogging performance compared with the respective boundary is required to fulfill the desired cogging for any change of the tolerance-affected parameters.

By again analyzing Fig. 3(a), the full reliable designs are interestingly placed in the more efficient part of the figure. This can be explained by the fact that more efficiency follows lower losses and this follows less thermal stress, which corresponds to lower current density \(j\) and thermal index \(c_{th}\).
Overall, it can be concluded that a lot of designs located within promising domains of the objective space feature zero reliability. Besides, even if constraints would be considered for rated performance, a lot of designs would violate the requirements in case of tolerances occur, indicated by the gray colored circles. Hence, a reliability assessment during optimization is of utmost importance. Figure 4 gives the evolution of the reliability during the optimization run. As can be noticed, during the initial sampling of the design space, a lot of non-reliable domains are identified. When the optimization algorithm is applied, evermore reliable designs are discovered. However, even then still non reliable variants or designs featuring borderline reliability are among the newly generated machine assemblies, as indicated by the white gaps within the individuals’ indices in the range of 1000 to 6000.

In Figure 5, the two performance measures considered as constraints, i.e. the thermal coefficient $c_{th}$ and the current density in the coils $j$, are analyzed against the material cost. A clear tradeoff can be observed. The considered boundaries’ maximum values are given by blue-dashed lines. As optimization aims on minimizing cost, guaranteeing thermally stable operation in the presence of tolerances can only be ensured by a reliability analysis. Then, the overall optimum for this particular tradeoff can be obtained. Applying (too) conservative limits instead to guarantee that designs do not overheat for any imaginable parameter combination usually follows more expensive designs.

Figure 6 can be used for analyzing material cost versus reliability in more detail. The low cost machine designs all feature zero reliability. Consequently, starting at about 33 Euros, some designs featuring borderline reliability can be observed. After a slight additional cost increase, designs with full reliability can be obtained. Nevertheless, for any cost considered, variants performing unreliable or at least feature borderline reliability are potentially obtained. This is mainly due to the constraint on maximum coggling torque.

While for mass-produced machines cost always matter, it might be different regarding productions featuring small batch sizes. Additionally, many papers dealing with machine design optimization do not take cost into account. However, many authors consider specific power or torque regarding the machine’s volume or mass. Then, similar results like here

Fig. 4. Evolution of the reliability throughout the optimization process.

Fig. 5. The tradeoff thermal stress versus material cost.

Fig. 6. Material cost versus reliability.
might be observed, as designs with highest power or torque density typically feature lowest material usage.

V. TOLERANCE SENSITIVENESS INVESTIGATION

In the following, the tolerance sensitiveness of selected design candidates shall be investigated in more detail. Figure 7 illustrates the cumulative distribution function (cdf) of the cogging torque of three different designs selected for comparison. Thereby, the one million different parameter combinations derived via importance sampling by making use of the surrogate model for any design \( i \) can be defined as a set of cogging torque values \( T_i \). The discrete cdf for a certain cogging torque value \( t_{cogg} \) can then be calculated by using

\[
F_{T_i}(t_{cogg}) = P(T_i \leq t_{cogg}) .
\]  

(5)

For practical application, we define the \( n \)-th element of the set \( T_i \) as \( T_{i,n} \) and compute the cumulative sum as

\[
F_{T_i}(t_{cogg}) = \frac{1}{n_{samples}} \sum_n \begin{cases} 1 & T_{i,n} \leq t_{cogg} \\ 0 & T_{i,n} > t_{cogg} \end{cases} .
\]  

(6)

As the number of samples is the same for any design, \( n_{samples,i} \) was replaced by \( n_{samples} \). As can be observed from Fig. 7, three designs were selected, where one is fully reliable, while two others feature similar rated cogging torque performance but \( r_i < 1 \) and thus borderline reliability. Particular values are given in Table VII.

Table VII

| Design       | Reliability \( r_i \) |
|--------------|-----------------------|
| fully reliable | 1                     |
| borderline A  | 0.9233                |
| borderline B  | 0.0015                |

Besides comparing the reliabilities of different designs, the surrogate model based evaluation of lots of parameter combinations further allows to in detail investigate the correlation of changes in tolerance-affected parameters with the change in some performance measure. Thereby, both the sensitiveness of
the output quantity with regard to the parameters as well as the likeliness of the parameters to change is evaluated.

For instance, Fig. 8 gives the correlation of the four considered machine parameters featuring uncertainties (tolerances) with the cogging torque value for the borderline design A from Fig. 7. As can be noticed, the change of the pole coverage is most (negatively) correlated with the change in cogging. An automatized evaluation of the correlation \( \rho_{XY} \) of two cohesive sets \( X \) and \( Y \) can be performed by using

\[
\rho_{XY} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y},
\]

(7)

where \( \text{cov}(\cdot) \) represents the covariance, given by

\[
\text{cov}(X, Y) = \frac{1}{n_{\text{samples}}} (X - E(X)) \cdot (Y - E(Y)),
\]

and \( E(\cdot) \) gives the expected value of a set. Table VIII highlights the normalized correlation for the cogging torque with the four tolerance-affected parameters. As can be noticed, the change of the pole coverage \( \Delta \alpha_m \) features the major impact, followed by the change in the remanence induction \( \Delta B_r \).

When not reaching a certain desired quality level in industry, often all tolerance levels are simultaneously decreased in order to guarantee a particular targeted reliability. By studying the here presented analysis, it is possible to understand which parameter affects some output quantity most. Consequently, it is beneficial to specifically change the tolerance levels of selected parameters rather than minimizing all of them.

As an example, the borderline A design from Fig. 7 is reconsidered for a symmetric reduction of the tolerance levels, such that (i) \( \Delta \alpha_m \in [-0.005, 0.005] \), and (ii) \( \Delta \alpha_m \in [-0.0025, 0.0025] \), i.e., 50% and 25% of the original tolerance levels are applied. Besides, all other tolerance-affected parameters remain unchanged. In Fig. 9, the change of the cumulative distribution function is plotted. As can be observed, the reliability is positively affected. While for 50% levels, \( r_c = 0.9988 \), the design featuring only 25% of the initial tolerance levels is fully reliable \( (r_c = 1) \). Obviously, also an asymmetric change of the tolerance levels can be approached. Here, this would be very advantageous considering the change of the pole coverage levels \( \Delta \alpha_m \). By contrast, changing the quality for any other tolerance-affected parameter while keeping the remaining levels constant at least requires a larger reduction of the acceptable range to obtain satisfying reliability. However, for less influential parameters it might even not be possible to gain full reliability if other parameters still feature the originally considered uncertainties. By analyzing all these relationships and incorporating knowledge about respective cost for maintaining particular quality levels, future work can be about optimizing machine designs for certain quality requirements by individually finding the best quality levels and respective overall production cost for any design variant considered. Moreover, the manufacturing impact on the laminated material due to, e.g., punching or laser cutting, shall further be included to optimization scenarios. As was recently highlighted [41], the effect on the optimal electric machine design is significant.

| Performance measure | Tol. affected parameters |
|----------------------|--------------------------|
| \( \Delta T_{cogg} \) | \( \Delta h_m \) \( \Delta \alpha_m \) \( \Delta b_{ss} \) \( \Delta B_r \) |
| \( 0.0078 \) | \( -1.0000 \) | \( -0.0533 \) | \( 0.3976 \) |

VI. CONCLUSION

This paper was about analyzing and applying measures for electric machine design optimization to guarantee a certain performance in the presence of inevitable tolerances. Such tolerances can be with regard to material characteristics, dimensions, positioning, environmental conditions, etc. As could be observed from the test problem, if the designs’ sensitiveness or reliability, respectively, is not considered during optimization, the discovered Pareto-optimal solutions likely feature low robustness in the presence of such tolerances.

Concurrently analyzing the designs’ robustness during optimization runs usually follows an increase of number of designs’ evaluations and thus computational cost by at least one order of magnitude. An advantageous solution based on design of experiments and metamodeling techniques was presented here. This generic approach can also be applied for any other slot-/pole-combination or other types of electric machines, as well as for other tolerances.

Besides studying fixed tolerance levels, it is beneficial to understand the relative impact of tolerance-affected parameters on the change of particular performance measures. Thus, by contrast to reducing all tolerance levels to obtain the desired design’s reliability, an individual most advantageous selection of tolerance levels is facilitated. By further including information about cost associated with particular parameters’ quality levels, a certain design performance can be guaranteed while simultaneously the overall production cost are minimized. Future work will be about gaining more information about which parameter affects which performance measure most for different machine types and respective power levels.
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