Comparison of different meta-model techniques for torque optimization constrained by mechanical strength in automotive high-speed Spoke-type IPM machine

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This paper focuses on the torque optimization of a high speed Spoke-type interior permanent magnet (IPM) machine for automotive powertrain application. The optimization target is to balance the torque performance at low speed and durability of rotor strength at maximum speed. Firstly, torque and mechanical centrifugal force analysis using 2-D finite element method (FEM) are established to obtain the objectives and constraints. Secondly, metamodeling techniques including different kind of design of experiment (DOE) and meta-models are used to construct the design space, objective functions and constraint functions. Comparison of metamodeling techniques is carried out and engineering guidelines on selection for electric machine design optimization are given. Finally, some different optimization methods are applied on the meta-models to determine the optimal design.

Index Terms— **Permanent magnet machines, Finite Element Analysis, Stress, Optimization and Metamodeling.**

I. Introduction

The interior permanent magnet (IPM) machines have been widely used in automotive applications because they have high torque density and a wide speed range. However, there are some mechanically weak locations in rotor at high speed due to centrifugal forces [1]. These locations are concentrated locally in the so-called bridge and rib parts which are relatively thin values in rotor core. At the opposite, these regions should be thin to limit magnetic flux leakage [2]. Therefore, a compromise has to be found for the geometry of these regions. The mechanical stress analyses can be carried out by analytical and approximate methods [3], but this kind of method is useful in the early stage design and does not constitute a substitute for accurate mechanical validation. Therefore, finite element method (FEM) with higher accuracy are used both in electromagnetic and mechanical analyses in detailed design optimization.

On the other hand, it is also well-known that FEM analyses are time-consuming in particular when parametric analyses are required, uncertainty propagation for instance [6]. One solution is to use metamodels to reduce computational time [4]. There are few papers addressing metamodeling techniques in the electric machine optimization including mechanical constraints. In this paper, different kinds of metamodeling techniques are used for comparison of the quality constructing the torque objectives and stress constraints utilized in the optimization.

II. Finite element models of Electric machine

Price fluctuations of rare earth magnets have impact on the design of electric machines. Therefore, a spoke-type ferrite IPM machine is chosen here. The machine structure is not provided here because of confidential reasons. The final version of paper will use a public machine geometry. Three important dimensions related to the bridge parts are selected as design variables.

For electromagnetic analysis, a transient solver is used. The torque performances are simulated at low speed. Average torque and torque ripple rate in one period are obtained from this simulation.

Centrifugal force dominates the stress and strain compared with electromagnetic force and magnetic attraction force [5]. Therefore, the centrifugal force caused by high speed is only considered in the mechanical analysis. From this simulation, the maximum of maximum principal stress (MPS) on the whole rotor and maximum of directional deformation (DD) are obtained.

III. Metamodeling construction

A. Design of Experiment (DOE)

In [4], comprehensive explanations about various sampling methods and their advantages are introduced. The main idea of the DOE, which also could be called sampling is to provide an informative database for building the meta-models in order to represent the knowledge of the objective landscape with less calls of FEM analysis.

Here two methods are used: full factorial design (FFD) and Latin hypercube sampling (LHS). A n-level FFD design contains n^k samples (k is the dimension of variables or factors). The main method of LHS is stratification of the input probability distribution which divides the cumulative curve into equal intervals. Then the samples are randomly taken from each interval. The 3^3, 5^3 FFD and 27, 125 samples of LHS are used.

In our study, the total computational time of 125 samples is 42 hours by using 2.70 GHz Core i7 PC. The samples used in construction of meta-model are completed within a practical computational time. More samples also could be launched to increase the accuracy of meta-models.

B. Meta-models

Meta-models are also called surrogate models which means a model of model. Various meta-models are used in the engineering applications. In this paper, response surface methodology (RSM) and Kriging are chosen.

1) Response surface methodology

RSM represents the relationship between inputs and outputs by a combination of polynomials. Second order polynomials (1) have the ability to represent curvature which includes quadratic terms and two-factor interactions:

$$\hat{f}(x) = a_0 + \sum_{i=1}^{k} a_i x_i + \sum_{i=1}^{k} \sum_{j=1, i \leq j}^{k} a_{ij} x_i x_j \, . \tag{1}$$

2) Kriging

The Kriging method is comprehensively explained in the literature [4]. The form of the Kriging meta-model used in this study is shown in (2):

$$\hat{f}(x) = \sum_{i=1}^{N} w_i \psi^{(i)} \, , \; \psi^{(i)} = \exp\left(-\sum_{j=1}^{k} \theta_j \left| x_j^{(i)} - x_j \right|^{p_j} \right) \tag{2}$$

where N is the number of samples, w_i is the weight of each basis function, $\psi^{(i)}$ is the ith basis function, θ_j is the width of basis function, p_j is the exponent of the variables Euclidean distance. In this paper p is fixed to 2 to reduce the complexity.

C. Model verification and validation

Model verification and validation are of great importance, especially for metamodeling [6]. Cross-validation is the most popular method and two types of different measures of model accuracy are used for validation. The first one is the root mean square error (RMSE) and the second one is correlation coefficient R^2.

IV. Numerical results

Average torque and torque ripple rate are selected for the objective functions. The quality of different quantity of samples and different types of meta-models are shown in TABLE I and II.

TABLE I
AVERAGE TORQUE METAMODELING RESULTS

	RSM (2nd order)		Kriging	
	RMSE	R^2	RMSE	R^2
3-level FFD	0.0187	0.9949	0.025	0.9926
27-point LHS	0.0175	0.9948	0.0206	0.9941
5-level FFD	0.0155	0.9953	0.0123	0.9982
125-point LHS	0.0130	0.9966	0.0152	0.9962

TABLE II
TORQUE RIPPLE RATE METAMODELING RESULTS

	RSM (2nd order)		Kriging	
	RMSE	R^2	RMSE	R^2
3-level FFD	0.0970	0.9175	0.0643	0.9669
27-point LHS	0.0903	0.8826	0.1012	0.9277
5-level FFD	0.0772	0.9266	0.0316	0.9876
125-point LHS	0.0676	0.9288	0.0209	0.9946

Maximum of maximum principal stress (MPS) of the whole rotor and the maximum directional deformation (DD) are selected for the constraint functions. The quality of different quantity of samples and different types of meta-models are shown in TABLE III and IV.

TABLE III
MAXIMUM OF MPS METAMODELING RESULTS

	RSM (2nd order)		Kriging	
	RMSE	R^2	RMSE	R^2
3-level FFD	0.1839	0.7110	0.1708	0.7572
27-point LHS	0.1284	0.8172	0.1600	0.8408
5-level FFD	0.1480	0.7092	0.1501	0.7610
125-point LHS	0.1099	0.7316	0.0785	0.8743

TABLE IV
MAXIMUM OF DD METAMODELING RESULTS

	RSM (2nd order)		Kriging	
	RMSE	R^2	RMSE	R^2
3-level FFD	0.0702	0.9631	0.1191	0.9487
27-point LHS	0.1967	0.5422	0.1516	0.8624
5-level FFD	0.0540	0.9564	0.0694	0.9731
125-point LHS	0.0480	0.9549	0.0430	0.9802

V. Multi-objective optimization

Multi-objective optimization gives more information about the problem than the weighted single objective optimization. But multi-objective optimization needs a large amount of function calls. Here meta-models play a key role.

The best of the four meta-models is used in the construction of Pareto frontiers. The Pareto frontiers with and without constraints are shown in Fig. 1. Torque are normalized in this case which means the one close to 0 is better. The constraints are used in the optimization to prevent rotor to be busted. Here the total function count is up to 6827 and 11832 respectively. The methodology is useful to reduce the burden of computer with a considerable accuracy.

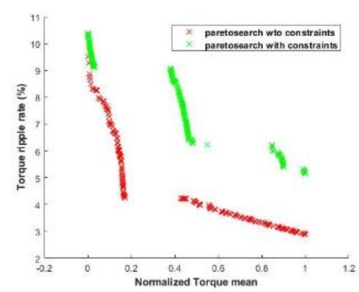

Fig. 1. Pareto frontier of the optimization with and without constraints.

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