

Comparative Study of Kriging and Deep Neural Network as Surrogate Models for Performance Prediction of PMSM

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Electric motor design and optimization is a complex process that must simultaneously satisfy various performance indicators such as output, efficiency, and minimization of cogging torque. Finite Element Analysis (FEA) is widely used for this purpose, but its high computational cost and time requirements pose limitations for large-scale design problems. In this study, Kriging and Deep Neural Network (DNN) are compared as surrogate models for predicting the performance of Permanent Magnet Synchronous Motors (PMSMs). Design variables were extracted using Latin Hypercube Sampling (LHS), and FEA was utilized to derive electromagnetic characteristics such as torque, torque ripple, d- and q-axis inductances. The Kriging and deep learning models were evaluated based on data utilization efficiency and prediction accuracy, and the strengths and weaknesses of each method for motor design problems are analyzed. This study proposes practical approaches for effectively utilizing surrogate models to enhance the efficiency of motor design process.

Index Terms— Deep neural network, kriging, permanent magnet synchronous motor, surrogate models

I. INTRODUCTION

PERMANENT Magnet Synchronous Motor (PMSM) design and optimization is a complex process that requires high accuracy and efficient computation, as it must consider various performance indicators such as output, efficiency, and minimization of cogging torque. In particular, Finite Element Analysis (FEA), which is used for designing motors with nonlinear characteristics, provides high accuracy but involves significant computational time and cost, imposing limitations on large-scale designs that include multiple design variables.

To address these issues, Kriging techniques and Deep Neural Network (DNN) have gained attention as surrogate models. Kriging, a statistical technique that has been traditionally utilized, models the relationship between design variables and output values, offering high prediction accuracy even with a small amount of data. It is advantageous for efficiently solving design space exploration and multi-objective optimization problems [1]. On the other hand, DNN, a method that has recently been widely adopted, learns from large-scale data to effectively derive nonlinear characteristics and provides fast and efficient performance predictions after training. This approach is effective in reducing computational burdens and enhancing design efficiency by utilizing high-cost simulation data [2].

This paper compares and analyzes Kriging and DNN as surrogate models for predicting the performance of PMSM. Based on various design variables and output characteristic data, the two models are quantitatively evaluated in terms of prediction accuracy, computational efficiency, and data utilization. Furthermore, the strengths and limitations of each method in motor design and optimization problems are analyzed. This study aims to enhance motor design efficiency and contribute to the establishment of optimization strategies by proposing effective utilization methods for surrogate models. The process for calculating motor design variables and analyzing results by each surrogate model is shown in Fig. 1.

TABLE I
SPECIFICATIONS OF PMSM

Item	Unit	Value
Number of poles / slots	-	8 / 12
Stator/Rotor Core	-	25PNX1250F
Stator diameter	mm	80
Air gap	mm	0.5
Fill factor	-	0.5
Split ratio (α_{split})	-	0.4 to 0.8
Shape ratio (α_{shape})	-	0.3 to 3
Current density	A _{rms} /mm ²	3 to 30
Residual flux density	T	0.4 to 1.4
Pole angle / Pole pitch	-	0.5 to 0.99
Magnet thickness ratio	-	0.05 to 0.15

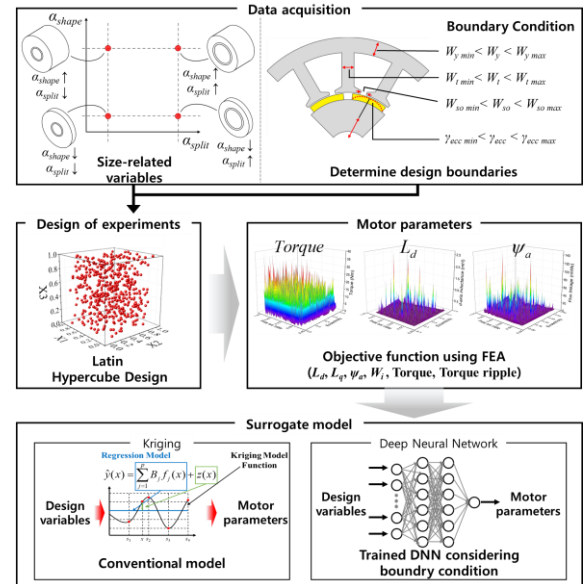


Fig. 1. Concept of the surrogate modeling process for PMSM

II. DNN AND KRIGING BASED SURROGATE MODEL

Kriging and DNN each have their strengths and weaknesses, and the suitability of each method depends on the number of

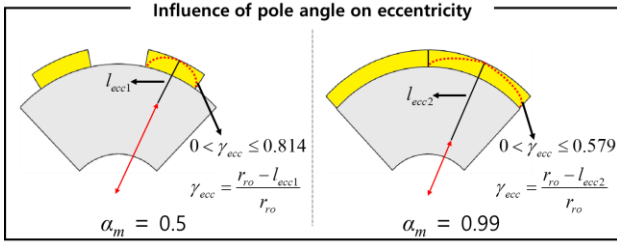


Fig. 2. Determination of eccentricity ratio based on α_m

design variables or motor parameters. Kriging provides high prediction accuracy with a small amount of data, but it is more effective when the number of variables is small and the relationships are relatively simple. On the other hand, DNN excels at learning and predicting nonlinear relationships in large datasets, making it advantageous when the number of variables is high and complex nonlinear characteristics are important.

A. PMSM Design Variables for Surrogate Model

In this study, design variables and boundaries were defined as shown in Table I and Fig. 1. to predict the performance of PMSM and compare various design points. The design variables are key factors that determine the main characteristics and performance of PMSM, forming the basis for performance analysis with surrogate modeling techniques. Table I presents the main specifications and design boundaries of the PMSM. Based on this, the boundaries of geometric design variables such as tooth width W_t , yoke width W_y , slot opening W_{so} , and eccentricity ratio γ_{ecc} can be calculated. These design boundaries are calculated dependently and are significantly influenced by the design variables. Eccentricity ratio is expressed as follows.

$$0 < \gamma_{ecc} < \frac{-2r_{ro}t_m + t_m^2}{2\left(\left(r_{ro}^2 - r_{ro}t_m\right)\cos\left(\frac{\alpha_m\pi}{P}\right) - r_{ro}^2\right)} \quad (1)$$

Where, r_{ro} represents the rotor radius, t_m denotes the thickness of the permanent magnet, and α_m indicates the pole angle / pole pitch. The above equation shows that the boundary value of the eccentricity ratio is greatly influenced by the α_m , and the result determining the maximum value of the eccentricity ratio based on the α_m is shown in Fig. 2. The boundaries of geometric variables such as W_t , W_{so} , and W_y will be discussed in detail in the full paper. These design variables were used in FEA to derive the motor parameters, which serve as the objective function.

B. Surrogate Model for performance evaluation

The Kriging surrogate model models the relationship between optimization variables and the objective function using a random process, providing high-accuracy predictions based on given data. The mathematical expression of the Kriging model is as follows [3].

$$\hat{y}(x) = \sum_{j=1}^p B_j f_j(x) + z(x) \quad (2)$$

The first term represents a deterministic component based on linear regression, while $z(x)$ is a stochastic component defined from data observations and correlation quantification.

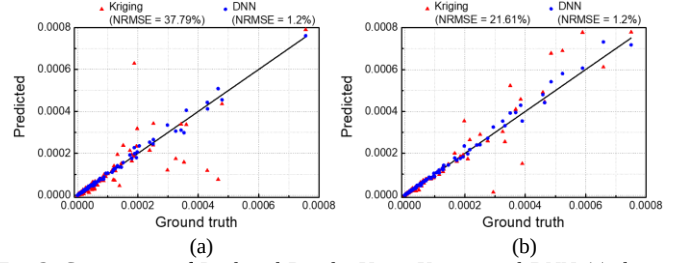


Fig. 3. Comparison of Predicted Results Using Kriging and DNN (a) d -axis inductance (b) q -axis inductance

While the Kriging surrogate model is effective in predicting unknown values with a limited dataset and providing high accuracy in nonlinear problems, deep learning models, such as deep neural networks (DNN), have gained significant attention for their ability to process larger datasets and learn complex, non-linear relationships. In contrast to Kriging, deep learning models can handle vast amounts of data and generalize more effectively, especially in systems with high-dimensional variables and intricate dependencies [4].

Fig. 3. compares the d - and q -axis inductance results using surrogate models, Kriging and DNN, applied under the same dataset and conditions. The inputs are PMSM design variables, and the outputs are the d - and q -axis inductances. The DNN model showed high prediction accuracy, with errors of approximately 4.8% and 1.2%, while the Kriging model showed significantly lower accuracy, with errors of about 37.78% and 21.16%. This difference is due to the ability of each surrogate model to handle the nonlinearity between inputs and outputs. While DNN can effectively learn complex nonlinear relationships, Kriging has limitations, leading to lower accuracy.

III. CONCLUSION AND FUTURE WORK

This study defines the design variables and their boundaries for PMSM and uses Kriging and DNN models to predict performance, comparing the prediction accuracy and efficiency of both models. The performance differences are analyzed based on the nonlinearity between input variables and outputs. The full paper will present detailed equations defining the design variables and their boundaries for PMSM. Additionally, it will include a comparison and analysis of various performance prediction results, along with a discussion on the advantages and applicability of the two surrogate models.

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