

Study on a Motor Torque Characteristic Estimation Method Using Surrogate Models and Approximation Curves

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In motor design, shape optimization aimed at improving performance constitutes a critical issue. Finite Element Analysis (FEA) is widely used for shape optimization due to the high levels of accuracy it provides, but it can lead to long computation times, thereby reducing the overall efficiency of the design process. To address this issue, recent research has focused on the use of surrogate models to quickly estimate motor characteristics. In this paper, we verified a method for estimating the current-torque characteristics of a motor by estimating the coefficients of an approximation curve using a surrogate model and then calculating the torque. As a result, it was found that estimating the coefficients of the approximation curve resulted in worse levels of estimation accuracy when compared to cases where the torque for each current value was estimated.

Index Terms—permanent magnet motors, optimization, machine learning, curve fitting

I. INTRODUCTION

IN motor design, shape optimization aimed at improving performance constitutes an extremely important task. Finite Element Analysis (FEA) is widely used as a method for shape optimization due to the high levels of accuracy it provides. However, FEA does require significant amounts of computational time, which can reduce the overall efficiency of the design process. To address this issue, recent research has focused on using surrogate models to quickly estimate motor characteristics and achieve efficient optimization.

Previous studies [1-5] have focused on estimating motor characteristics based on data that determines the motor's shape, such as the geometric parameters of dimensions and cross-sectional images of the motor. For example, in prior literature [1], a method was used to estimate the magnetic flux map based on cross-sectional images of the motor and calculate torque characteristics using polynomial approximation. Additionally, other studies [6-8] have involved the construction of surrogate models to estimate magnetic flux maps and torque based on current values. On the other hand, there is no comparison between the methods that use surrogate models to estimate torque, specifically between polynomial approximation and the method that estimates torque for each current values.

In this paper, we constructed a surrogate model with the geometric parameters of motor dimensions being used as inputs and torque as the output, and then verified the estimation of current-torque characteristics. Additionally, as one method used to improve the accuracy of torque estimation, we constructed a surrogate model to estimate the coefficients of the polynomial approximation of the current-torque characteristics and discussed the results of the calculation of torque for each current value.

II. TARGET MODEL AND DATASET GENERATION

The motor model used in this study is shown in Figure 1. This motor is a 10-pole, 12-slot SPM motor. The number of poles, number of slots, outer diameter of the stator, and inner diameter of the rotor were kept constant. In addition to these, eight

dimensional parameters that determine the shape were set as shown in the figure.

We conducted FEA on this motor model and worked on generating a dataset to be used in the surrogate model. In this study, we generated shape data for 13,472 cases by ensuring variance in term of the eight-dimensional parameters. The output characteristics included the amplitude value of the 6th harmonic component of cogging torque at a current of 0A and the average torque at every 10A point spanning from 10A to 100A. Additionally, we calculated the coefficients of the cubic approximation polynomial of the current-torque characteristics based on each shape and added them to the dataset in accordance with Equation (1).

$$Trq = aI^3 + bI^2 + cI + d \quad (1)$$

III. EVALUATION OF THE SURROGATE MODEL

In this paper, we used LightGBM to construct the surrogate model. Based on the dataset created in the previous section, we constructed the surrogate model using 10,000 cases as training data in the following two manners:

- 1) Construction of a surrogate model to estimate torque for each current value based on shape data
- 2) Construction of a surrogate model to estimate the coefficients of the approximation curve of the current-torque characteristics based on shape data and calculation of the torque for each current value using Equation (1)

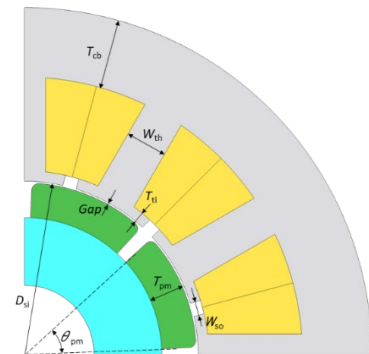


Fig. 1. Motor Model (10-pole 12-slot SPM Motor)

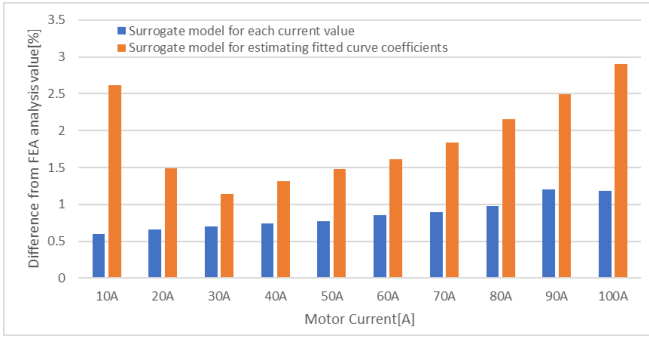


Fig. 2. Comparison of the Error Percentage between Torque Calculation Results from FEA Analysis and Those Calculated Using the Surrogate Model

We verified the accuracy of the surrogate model using the results of 1,500 cases from the dataset. Figure 2 shows the mean absolute percentage error when estimating torque for each current value using the surrogate model and when calculating torque by estimating the coefficients of the approximation curve using the surrogate model, compared to the FEA results for each case. When estimating the coefficients of the approximation curve, the maximum error was 2.9%, which resulted in an increase in error compared to constructing a surrogate model for each current value. When estimating the coefficients of the approximation curve, it is considered that the error increased because the error in estimating the coefficients with the surrogate model and the error in the true torque relative to the approximation curve are compounded.

IV. EVALUATION OF OPTIMIZATION RESULTS

Using the surrogate model that constructed in the previous section, we performed optimization of motor dimensions. In this optimization, we used the NSGA-II algorithm with a population size of 30,000 cases. To achieve high torque output without torque reduction at high current in the current-torque characteristics, it is necessary to set the coefficients of the nonlinear terms (a) and (b) to 0 and maximize the coefficient of the linear term (c) in the cubic approximation polynomial. The coefficients (a) and (b) were set as objective functions to minimize the difference between the values calculated by the surrogate model and the target value of 0. Additionally, maximizing the coefficient (c) was set as another objective function. Furthermore, we created a surrogate model to estimate the amplitude of the 6th harmonic component of the cogging torque and included it as an objective function to be minimized.

Figure 3 shows the results of calculating the torque at 100A current and the Pareto solutions for cogging torque. The blue plots represent the Pareto solutions of the optimization results when estimating the approximation curve, while the orange plots represent the Pareto solutions of the optimization results when estimating the torque for each current value. For torque, there is a maximum error of 3.2% compared to the Pareto solution results, but the estimation is highly accurate. On the other hand, the estimation accuracy for cogging torque is poor, and further investigation is being conducted to improve the accuracy.

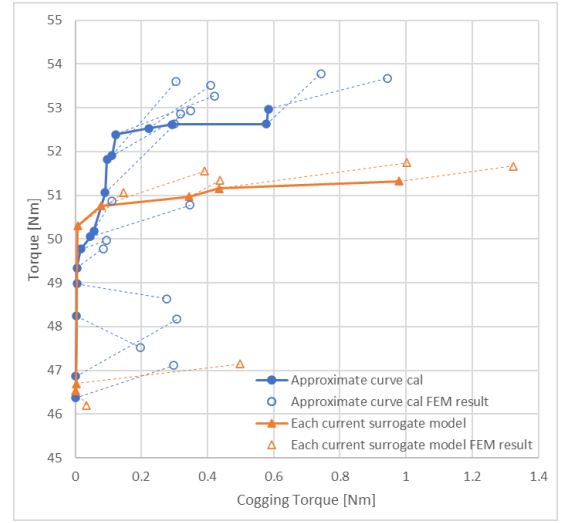


Fig. 3. Pareto Curve for Torque at 100A Current and Cogging Torque.

V. CONCLUSION

In this paper, we investigated a method for estimating the current-torque characteristics of a motor with high accuracy levels using a surrogate model. We verified the estimation of the coefficients of the approximation curve for the motor's current-torque characteristics using a surrogate model. The results, however, showed that estimation accuracy levels deteriorated when compared to the construction of a surrogate model used to estimate the torque for each current value. In the full paper, we plan to include verification results regarding the usefulness of other approximation curves.

REFERENCES

- [1] H. Sasaki, K. Iwata, T. Sato and Y. Sato, "Prediction of Motor Characteristic Maps via Deep Operator Networks for Topology Optimization," *IEEE Trans. Magn.*, vol. 60, no. 12, pp. 1-5, Dec. 2024.
- [2] Y. Xu, B. Wang, Y. Sakamoto, T. Yamamoto and Y. Nishimura, "Comparison of Learning-based Surrogate Models for Electric Motors," 2023 24th International Conference on the Computation of Electromagnetic Fields (COMPUMAG), Kyoto, Japan, 2023, pp. 1-4.
- [3] B. Wang, A. Khaled Ahsan Talukder and Y. Sakamoto, "Topological Data Analysis for Image-based Machine Learning: Application to Electric Motors," 2022 International Conference on Electrical Machines (ICEM), Valencia, Spain, 2022, pp. 1015-1021.
- [4] A. Beltrán-Pulido, D. Aliprantis, I. Bilionis, A. R. Munoz, F. Leonardi and S. M. Avery, "Uncertainty Quantification and Sensitivity Analysis in a Nonlinear Finite-Element Model of a Permanent Magnet Synchronous Machine," *IEEE Trans. Energy Conversion*, vol. 35, no. 4, pp. 2152-2161, Dec. 2020.
- [5] T. Aoyagi, Y. Otomo, H. Igarashi, H. Sasaki, Y. Hidaka and H. Arita, "Prediction of Current-Dependent Motor Torque Characteristics Using Deep Learning for Topology Optimization," *IEEE Trans. Magn.*, vol. 58, no. 9, pp. 1-4, Sept. 2022.
- [6] B. Praslicka, N. Taran and C. Ma, "An Ultra-fast Method for Analyzing IPM Motors at Multiple Operating Points Using Surrogate Models," 2022 IEEE Transportation Electrification Conference & Expo (ITEC), Anaheim, CA, USA, 2022, pp. 868-873.
- [7] D. S. Reay, "CMAC and B-spline neural networks applied to switched reluctance motor torque estimation and control," *IECON'03. 29th Annual Conference of the IEEE Industrial Electronics Society (IEEE Cat. No.03CH37468)*, Roanoke, VA, USA, 2003, pp. 323-328 vol.1.
- [8] M. Tahkola, J. Keränen, D. Sedov, M. F. Far and J. Kortelainen, "Surrogate Modeling of Electrical Machine Torque Using Artificial Neural Networks," *IEEE Access*, vol. 8, pp. 220027-220045, 2020.