Permanent Magnet Motor Torque Waveform Prediction Using Learned Gap Flux

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***Abstract*—In this paper, we propose a surrogate model based on neural networks, for the rapid evaluation of the performance of permanent magnet synchronous motor designs, especially the detailed torque waveform. In the training phase of our proposed method, motor design parameters are taken as input and gap flux density information is taken as output, both fed to train neural networks. In the test phase, gap flux density is predicted with the trained neural networks, the torque waveform is subsequently reconstructed, and a peak-to-peak cogging torque amplitude is estimated from the waveform. We compare the proposed method with conventional neural network based surrogate models, in which torque information is directly used for training, and confirm that the proposed method shows higher accuracy than conventional approaches, especially when the training data size is small.**

***Index Terms*—PMSM, surrogate model, neural network, gap flux density, cogging torque**

I. INTRODUCTION

Design optimization of electric machines using the surrogate model approach is attracting a lot of interests because of its advantage in computational speed compared with finite-element analysis (FEA) based design approaches. The neural network (NN) based machine learning method is one of the promising ways to construct the surrogate model due to its potential in predicting the highly nonlinear performance of the electric machines [1]. However, a large amount of training data is required to train these models with high prediction accuracy, especially for complicated designs determined by a large number of design variables. In particular, cogging torque is one critical requirement for motor design, especially for precise motion control applications. Some studies addressed cogging torque prediction using NNs [3]. In prior studies, torque information, such as peak-to-peak torque amplitude [4] or Fourier components of the torque waveform [5], is often fed as output of the NNs. Normally, those approaches require large number of training data, because torque waveform of slotted motors is often nonlinear and extremely sensitive to slight changes in design parameters around the air gap region, such as slot-opening, tooth shoe height, and shape of the magnets. On the other hand, in principle, torque can be derived from Maxwell stress tensor, which includes the information of magnetic flux density distribution at the air gap. In this study, we propose a surrogate model, in which NNs are used for predicting gap flux, and torque waveform is subsequently reconstructed in order to estimate the cogging torque. We show that this two-step modeling approach achieves better accuracy compared with conventional machine learning models.

II. MATERIALS AND METHODS

A. Training and test data preparation

The design of an example surface-mounted permanent magnet synchronous motor (SPMSM) is shown in Fig. 1. For machine learning purposes, motor design candidates are generated by tuning the values of 9 design parameters marked in the figure. A FEA simulation with no-load is conducted for each design and gap flux density distribution as well as torque is computed at each time step. The gap flux density is divided into space and time harmonics, as

$$B_r(\theta, t) = \sum_{k,l} b_{r,k,l}\, e^{-j(k\theta + l\frac{t}{T})}. \quad (1)$$

$$B_\theta(\theta, t) = \sum_{k,l} b_{\theta,k,l}\, e^{-j(k\theta + l\frac{t}{T})}. \quad (2)$$

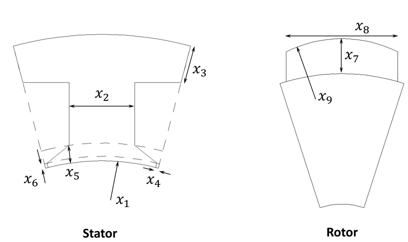

Fig. 1. SPM motor structure with 9 design variables.

The dataset is divided into test data and training data. We prepare plural training datasets with different size corresponding to the unique test dataset, in order to investigate the data size dependence of the proposed method.

B. Surrogate model using neural networks

In a full-connected NN shown in Fig. 2 (a), the design parameters defined in Fig. 1 are treated as input to the NN, and a space/time harmonic component defined in (1) or (2) is output. Each NN has a single output node and in total 546 NNs are independently trained for each of $b_{r,k,l}$ and $b_{t,k,l}$. In the test phase, as illustrated in Fig. 2 (b), B_r and B_θ are reconstructed by using predicted space/time components, and subsequently, torque waveform is computed based on Maxwell stress tensor, as

$$\tau(t) = \frac{r_g^2 l}{2} \int_0^{2\pi} B_r B_\theta d\theta, \tag{3}$$

where r_g and l is the gap radius and the axial length, respectively. Finally, peak-to-peak amplitude of the cogging torque is estimated.

For a comparison purpose, we also test two types of conventional NN approaches using the same training/test dataset: (A) The peak-to-peak amplitude of the cogging torque is directly fed to a NN as training data and it is directly predicted in the test phase; (B) Fourier components of the torque waveform are fed to NNs as training data, torque waveform is reconstructed from predicted fourier components in the test phase, and peak-to-peak amplitude is estimated.

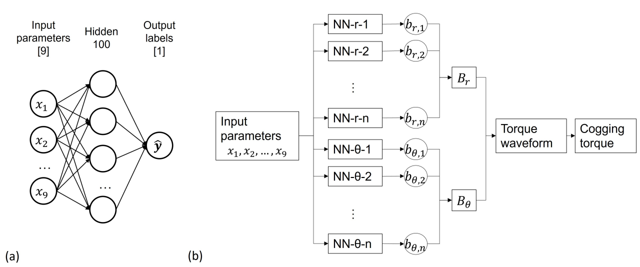

Fig. 2. (a) Structure of a NN for a single output. (b) Surogate model for cogging torque prediction using using multiple NNs for gap flux Fourier components.

III. Initial Results

The reproduced gap flux distribution of three example designs, which are randomly selected from the test data, are shown in Fig. 3. Each predicted curve shows a good fit to the true gap flux computed by FEA. Fig. 4(a) shows a comparison between true and predicted values of peak-to-peak torque amplitude for test data, in which the proposed method is applied with 2000 training data. A good match between the true and the prediction is observed. The root-mean-square errors (RMSEs) of three surrogate models, i.e., two conventional approaches (A)(B) and the proposed method (C), with the dependence on the training data size, are shown in Fig. 4 (b). The proposed method shows smaller RMSEs than conventional approach (A), where the peak-to-peak torque amplitude is directly fed to a NN, for all the training data size. In addition, the proposed method shows smaller RMSEs than conventional approach (B), where the Fourier components of torque waveform is fed to NNs, especially when training data size is smaller than 4000, whereas two approaches show almost the same accuracy when training data size is 4000 or more.

These results show that the proposed two-step method is especially helpful in providing a surrogete model with small training data. In the future we will further investigate the effectiveness of the method in the process of multi-objective design optimization of rotating machines, as well as on-load condition. Details will be presented in the full paper.

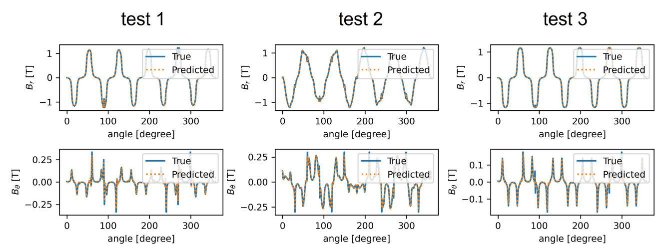

Fig. 3. Examples of predicted and true gap flux of test data.

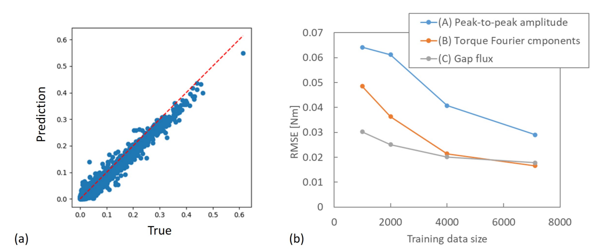

Fig. 4. (a) Prediction vs true plot of peak-to-peak torque amplitude, where the proposed method is applied with 2000 training data. (b) RMSE values with three types of approaches with the dependence on the training data size.

References

[1] T. Guillod, P. Papamanolis and J. W. Kolar, "Artificial neural network (ANN) based fast and accurate inductor modeling and design," IEEE Open Journal of Power Electronics, vol. 1, 2020, pp. 284-299.

[2] A. Reales, W. Jara, G. Hermosilla, C. Madariaga, J. Tapia and G. Bramerdorfer, "A machine learning based method to efficiently analyze the cogging torque under manufacturing tolerances," 2021 IEEE Energy Conversion Congress and Exposition (ECCE), 2021, pp. 1353-1357.

[3] A. Liu, F. Meng and H. Hu, "Deep-neural-network-based Electromagnetic Analysis and Optimal Design of Fractional-slot Brushless DC Motor for High Torque Robot Joints," 2023 3rd International Conference on Electrical Engineering and Mechatronics Technology (ICEEMT), 2023, pp. 715-719.

[4] Y. Xu, B. Wang, Y. Sakamoto, T. Yamamoto and Y. Nishimura, "Comparison of Learning-based Surrogate Models for Electric Motors," Conference on the Computation of Electromagnetic Fields (COMPUMAG), 2023.

[5] L. Hadjout, N. Takorabet, R. Ibtiouen and S. Mezani, "Optimization of instantaneous torque shape of PM motors using artificial neural networks based on FE results," IEEE Trans. Magn., vol. 42, no. 4, pp. 1283-1286, 2006.