Electric Motor Surrogate Model Combining Subdomain Method and Neural Network

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Abstract

This paper proposes a surrogate model for the rapid evaluation of electric machine designs, based on a neural network combined with a semi-analytical subdomain model. Although both analytical physical-model approaches and data-driven approaches have been proposed to construct surrogate models, which can be significantly faster than numerical finite-element simulations, issues still remain. On one hand, simplifications in analytical approaches often cause inaccuracy, especially in the prediction of highly nonlinear phenomena such as cogging torque of permanent magnet synchronous motors; on the other hand, purely data-driven approaches often require a large amount of training data to achieve high accuracy. In our proposed method, the performance of the electric machine is initially approximated by using a semi-analytical subdomain method, and this initial prediction is used as the input of a neural network, together with other design variables, to obtain the final prediction. We test the method to predict the cogging torque of surface-mounted permanent magnet motors. By combining physical-model and data-driven approaches, the proposed method can predict cogging torque with good accuracy, which cannot be achieved with only physical-model; the prediction accuracy is also much improved compared with conventional neural networks, especially when the size of the training dataset is small.

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Electric Motor Surrogate Model Combining Subdomain Method and Neural Network

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This paper proposes a surrogate model for the rapid evaluation of electric machine designs, based on a neural network combined with a semi-analytical subdomain model. Although both analytical physical-model approaches and data-driven approaches have been proposed to construct surrogate models, which can be significantly faster than numerical finite-element simulations, issues still remain. On one hand, simplifications in analytical approaches often cause inaccuracy, especially in the prediction of highly nonlinear phenomena such as cogging torque of permanent magnet synchronous motors; on the other hand, purely data-driven approaches often require a large amount of training data to achieve high accuracy. In our proposed method, the performance of the electric machine is initially approximated by using a semi-analytical subdomain method, and this initial prediction is used as the input of a neural network, together with other design variables, to obtain the final prediction. We test the method to predict the cogging torque of surface-mounted permanent magnet motors. By combining physical-model and data-driven approaches, the proposed method can predict cogging torque with good accuracy, which cannot be achieved with only physical-model; the prediction accuracy is also much improved compared with conventional neural networks, especially when the size of the training dataset is small.

Index Terms—**Machine learning, Permanent magnet motors, Analytical models**

I. Introduction

THE 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 conventional finite-element method (FEM) based design approaches. The neural network (NN) based machine learning (ML) 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], [2]. 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. On the other hand, a lot of physics-based approaches using analytical and semi-analytical models (AM), which require no training data, have also been proposed to predict the electric machine performance in a significantly shorter time than FEM simulations. These physical models, however, often include some simplifications and approximations that lead to inaccurate predictions compared with nonlinear FEM.

In particular, cogging torque is one critical requirement of motor design, especially for precise motion control applications. Both data-driven approach [3] and analytical approach [4] cannot achieve sufficient accuracy because the torque waveform is often nonlinear and extremely sensitive to slight changes in the dimensions around the air gap region, such as slot-opening, tooth shoe height, and shape of the magnets. The idea of analytical-model-assisted surrogate was discussed by Tang et al. [5] for the accurate prediction of magnetic saturation. However, motor performance metrics related to higher harmonics of the waveform such as cogging torque were not considered. In this study, we propose a surrogate model for motor cogging torque prediction based on NN, in which an analytical approximation is used as an additional input to the NN. The trained model can achieve improved accuracy compared with the analytical-model-only approach, as well as the conventional NN approach, especially when the size of the training dataset is not large enough.

II. Materials and Methods

A. Problem setting

The schematic of an example surface-mounted permanent magnet (SPM) motor is shown in Fig. 1. Nine parameters marked in the figure are tunable design variables, while other dimensions, such as outer diameter of the stator and axial length of the motor, are fixed.

For machine learning purposes, a dataset is constructed, with motor design candidates as input, which are generated by tuning the values of the 9 design parameters, and motor performances such as cogging torque as output, which are obtained by conducting FEM simulations.

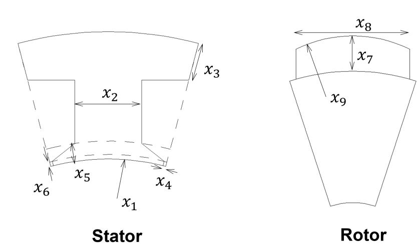

Fig. 1. SPM motor structure with 9 design variables.

B. Semi-analytical subdomain model

We employ a semi-analytical subdomain method [6] to approximate the motor performance with much less computation time than FEM. In this method, the 2D motor geometry is divided into several subdomains and transformed so that they become rectangular shapes in the polar $(r - \theta)$ coordinate. In setting up the problem, we also assume that the iron permeability is infinity. The vector potential distribution is analytically derived by solving Poisson's equation, and the magnetic properties such as magnetic field distribution and torque can be calculated subsequently. However, these assumptions may cause an error in torque calculation because the actual permeability of the iron, in particular at the tooth shoe, can be much lower and varies with the rotational angle of the rotor, depending on the nonlinear B-H relationship of the core material.

C. Neural network with semi-analytical model assistance

The data-driven modeling process is shown in Fig. 2. In a conventional NN-based surrogate model, the design parameters defined in Fig. 1 are directly treated as input to the NN, and the motor performance is output, as shown in Fig. 2 (a). In our proposal, as illustrated in Fig. 2 (b), the motor performance is first estimated using the analytical model, and the estimated value is also used as input for the NN in addition to the original design parameters. During the evaluation of the ML models, training and test data are drawn from the shuffled dataset. To confirm the prediction accuracy with the smaller size of training data, several sets of training and test data are prepared by varying the size of the training data. We also test the purely data-driven NN in Fig. 2 (a) to compare with the proposed method.

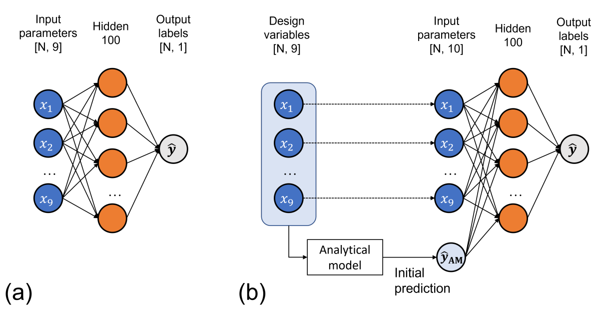

Fig. 2. The flowcharts of the process for (a) NN (b) AM-assisted NN

III. Initial Results

The prediction accuracy of the proposed method in comparison with the analytical model and pure NN is shown in Fig. 3, obtained with training data size of 2000. Here, the root mean square error (RMSE) over the test data is defined as $\mathrm{RMSE} = \sqrt{\frac{1}{n_{\mathrm{test}}} \sum_{i=1}^{n_{\mathrm{test}}} (y_i - \hat{y}_i)^2}$, where n_{test} is the number of test data, $\hat{y}_i$ and y_i are the predictions of the NN and the ground truth obtained by FEM for the i-th test data, respectively, both normalized by the training dataset. Since the training process depends on the initial state of the NN, 20 tests were carried out for each case with the same set of training and test data, and then the mean and standard deviations of the RMSE over the 20 tests were calculated. The proposed method, i.e. the AM-assisted NN, gives the smallest mean value of RMSE.

Figure 4 shows the relationship between the size of training data and prediction accuracy. The RMSE value with the proposed method is smaller than that of the pure NN when the number of training data is 500 or less. When the training data is sufficiently large (1000 or more), no significant difference is observed. This result shows that the proposed method is especially effective with small training data. In the future we will further investigate the effectiveness of the proposed method in the process of multi-objective design optimization of rotating machines. Detailed analysis and results will be presented in the full paper.

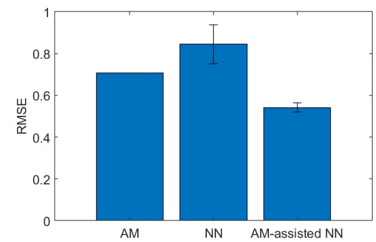

Fig. 3. The values of RMSE with AM, NN, and AM-assisted NN, for the dataset with 500 training data.

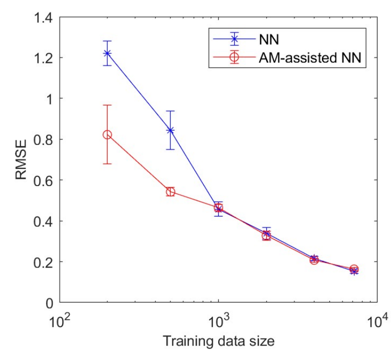

Fig. 4. The relationship between RMSE and the size of the training dataset.

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