

Computationally Efficient Surrogate Modeling of PWM-Induced Iron Loss for Axial Flux Permanent Magnet Synchronous Motors Using Deep Transfer Learning

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Axial flux permanent magnet synchronous motors (AFPMS) have high torque density due to its low magnetic reluctance for stator core, so that AFPMS are used for future mobility. For the traction system in future mobility, high efficiency of AFPMS is required for its long all-electric range. In order to design high efficiency AFPMS, accurate calculation of pulse-width modulation (PWM) induced iron loss is necessary, but it requires high computation cost because of its small time step and complex 3-D magnetic flux path of AFPMS. Therefore, it is hard to construct a surrogate model of PWM-induced iron loss according to the design variables of AFPMS. In this paper, we propose a deep transfer learning-based surrogate modeling process of PWM-induced iron loss for AFPMS with dramatically reduced computation cost. The proposed method incorporates a small amount of PWM-induced iron loss of AFPMS calculated by using 3-D finite element analysis (FEA) and a large amount of sinusoidal current-based iron loss calculated by using 2-D FEA. By using the proposed method, PWM-induced iron loss of AFPMS can be predicted with much reduced computation cost, so that design of high efficiency AFPMS considering PWM harmonics can be allowed. The effectiveness of proposed method will be validated through simulation and experimental results.

Index Terms—axial flux permanent magnet synchronous motors, deep transfer learning, finite element analysis, PWM-induced iron loss, surrogate model

I. INTRODUCTION

AXIAL flux permanent magnet synchronous motors (AFPMS) are considered as a candidate for the traction system of future mobility such as electric propulsion aircraft or electric vehicles with in-wheel drive system due to their high torque density compared to conventional radial flux motors [1]. The efficiency of AFPMS is determined by electromagnetic loss and it consists of copper loss, iron loss, and eddy current loss of permanent magnets. Among these losses, iron loss occurs in electrical steels and varies significantly with the armature magnetomotive force and excitation frequency [2].

In general, iron loss of radial flux motors is calculated using 2-D electromagnetic finite element analysis (FEA) with three-phase sinusoidal armature current for reducing computation cost. On the other hand, the calculation of iron loss for AFPMS requires 3-D FEA because the AFPMS have complex magnetic flux. Furthermore, three-phase pulse-width modulation (PWM) current is required for analysing accurate iron loss since the AFPMS are operated through DC-AC power conversion using PWM. As the PWM current contains synchronous frequency with high frequency harmonics near at switching frequency band, the iron loss of AFPMS vary widely with current vector and rotational speed [3].

In order to simplify the FEA for AFPMS, numerous techniques that approximates the 3-D magnetic flux path as 2-D have been proposed. The simplest way for converting 3-D magnetic flux path of AFPMS into 2-D is to unfolding the stator and rotor of AFPMS into a cross-section in the circumferential direction while maintaining the air-gap volume [4]. While this approach has low accuracy compared to 3-D FEA due to the assumed flux path, it has the significant advantage in computation cost. Recent studies have been proposed the use of

Quasi 3-D techniques to overcome this limitation by dividing the AFPMS into several 2-D FEA model [5]. This method can be expected to have relative high accuracy while having a low computation cost compared to 3-D FEA, but has the disadvantage of requiring the configuration of several 2-D FEA models. Thus, a method to calculate PWM-induced iron loss with high accuracy while maintaining low computing cost is required for the design of high efficiency AFPMS.

In this paper, we propose an computationally efficient surrogate modeling process for predicting PWM-induced iron loss of AFPMS using deep transfer learning (DTL). DTL is a computationally efficient surrogate modeling technique that can predict with high accuracy using small amounts of data which has high computation cost by utilizing transfer learning in deep learning [6]. In the proposed method, a small amount of PWM-induced iron loss for AFPMS according to design variables are calculated with 3-D FEA, and a large amount of sinusoidal current-based iron loss for AFPMS are calculated with 2-D FEA. Then, the PWM-induced iron loss can be accurately predicted with much reduced computation cost by utilizing the proposed method and the datasets for iron loss of AFPMS.

II. PWM-INDUCED IRON LOSS ANALYSIS FOR AFPMS

A. Iron losses in AFPMS considering PWM current

As the iron loss is affected by the magnetic flux density and its frequency, accurate analysis of magnetic flux density is most important in analysis of iron loss for AFPMS. The iron loss of AFPMS can be calculated as follows:

$$W_i = \sum_{n=1} \left(V_n \sum_{m=1} W_{i,m}^n \left| \mathbf{B}_m^n \right|, f_m \right) \quad (1)$$

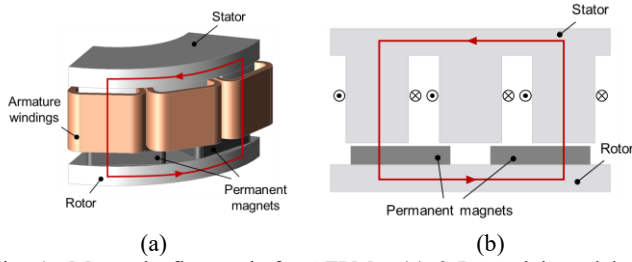


Fig. 1. Magnetic flux path for AFPMs: (a) 3-D partial model, (b) simplified 2-D partial model for FEA.

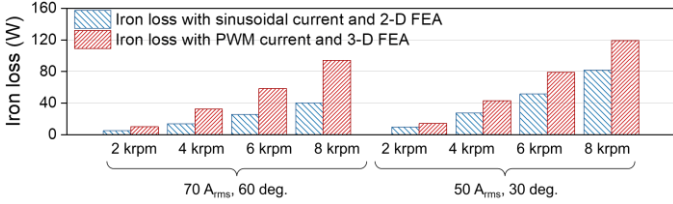


Fig. 2. Comparison of iron loss for AFPMs with 2-D/3-D FEA and type of current source according to current vector and rotational speed.

Therefore, it is necessary to account for the complex 3-D magnetic flux path of AFPMs to accurately calculate iron loss as shown in Fig. 1(a). The magnetic flux density for each element in 3-D FEA can be modeled with magnetic flux density for each axis as follows:

$$|\mathbf{B}_m^n| = \sqrt{B_{x,m}^n + B_{y,m}^n + B_{z,m}^n} \quad (2)$$

However, 3-D FEA requires high computation cost, so that 2-D FEA is used for designing the AFPMs to reduce the computation cost as shown in Fig. 1(b). As a result of ignoring the magnetic flux density of stacking direction, the iron loss of AFPMs can be calculated much reduced computation cost rather than 3-D FEA.

Since the AFPMs are operated by PWM current, the magnetic flux density is also containing high frequency components due to the PWM current. Consequently, the flux density along each axis contains high frequency components near at multiples of the switching frequency. These harmonic components significantly contribute to the increase in iron loss. Fig. 2 shows the comparison of sinusoidal current-based iron loss calculated with 2-D FEA and PWM-induced iron loss calculated with 3-D FEA according to current vector and rotational speed. It can be seen that the iron loss increases as the complex 3-D magnetic flux path is considered, and the effect of high frequency magnetic flux density, but these datasets have similar trends with respect to the input variables. Therefore, we will discuss how to training a surrogate model of PWM-induced iron loss with low computation cost by utilizing the features of these two datasets in the next section.

III. DTL-BASED SURROGATE MODELING FOR PREDICTING PWM-INDUCED IRON LOSS FOR AFPMS

Generally, surrogate-based optimization is widely adopted for designing the AFPMs because of its high computation cost for 3-D FEA. Deep neural networks (DNNs) act as general-purpose surrogate models and are used for predicting

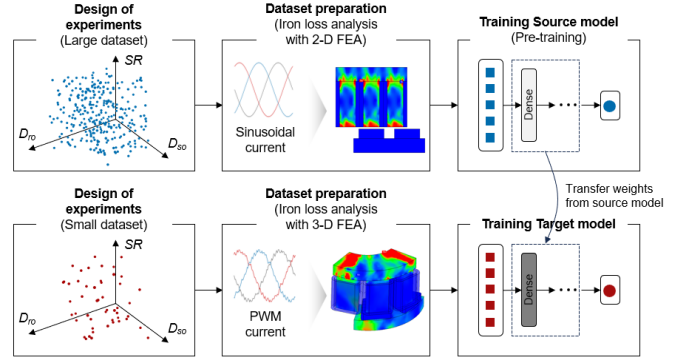


Fig. 3. Concept of proposed DTL-based surrogate modeling for predicting PWM-induced iron loss for AFPMs.

electromagnetic characteristics such as PWM-induced iron loss in AFPMs. In order to increase the accuracy of DNNs, a large dataset is required, but iron loss calculated by 3-D FEA with PWM current consumes high computation cost. Therefore, DTL-based training of surrogate model for the PWN-induced iron loss is proposed in this paper. The detailed process for the proposed method is shown in Fig. 3. The proposed method requires a large number of datasets with low computation cost and a small number of datasets with high computation cost. That is, the source dataset is the sinusoidal current-based iron loss of AFPMs calculated with 2-D FEA and the target dataset is the PWM-induced iron loss of AFPMs calculated with 3-D FEA. Therefore, it is possible to create a DNN surrogate model that can accurately predict the PWM-induced iron loss by utilizing the trained weight transfer from the source DNN to target DNN.

IV. CONCLUSION AND FUTURE WORK

This paper proposes an computationally efficient surrogate modeling process for predicting PWM-induced iron loss in AFPMs using deep transfer learning. Therefore, we will compare the trends and errors for each dataset according to the design variables, and the predicted PWM-induced iron loss using the proposed method will be validated through 3-D FEA and experimental results.

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