

Characteristics Estimation and Design of SPMSM using Analytic Method-based Transfer Learning

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This paper proposes a transfer learning approach based on an analytic method to efficiently estimate the electromagnetic characteristics of a Surface-mounted Permanent Magnet Synchronous Motor (SPMSM). The characteristics of SPMSM are determined by geometric variables and input current conditions and the methods for calculating these characteristics include analytic methods and Finite Element Analysis (FEA). Analytic methods offer rapid computation and are suitable for large scale data but struggle with nonlinear characteristics, while FEA provides high accuracy but requires longer computation time. To overcome these limitations, this paper proposes a method that utilizes an analytic approach to rapidly generate large scale data, trains a deep learning model based on this data, and then applies transfer learning with a small amount of FEA data to enhance the accuracy of the performance prediction model while reducing computation time. The proposed method has been confirmed to rapidly and accurately estimate the electromagnetic characteristics of SPMSM according to geometric variables and current, and by complementarily utilizing the advantages and disadvantages of both analytic methods and FEA, it significantly reduces computation time during the design process.

Index Terms— Eccentricity, pole angle, surface-mounted permanent magnet synchronous motor, transfer learning

I. INTRODUCTION

SURFACE-MOUNTED Permanent Magnet Synchronous Motor (SPMSM) have electromagnetic characteristics such as no-load back Electromotive Force (EMF), power density, and torque, which are important for evaluating their performance.

The characteristics of SPMSM can be determined through analytical calculations based on motor parameters or using Finite Element Analysis (FEA). Analytic Method (AM) have the advantage of quickly calculating the electromagnetic properties of motor but are limited by low accuracy. In contrast, FEA takes nonlinearities into account and provides high accuracy, but it has the drawback of requiring long computation times [1].

Therefore, recent research has been actively focused on utilizing deep learning to complement the time-consuming drawbacks of FEA and to rapidly derive characteristics under new conditions. Deep learning based approaches show potential for efficiently predicting characteristics by learning from FEA data. However, improving the accuracy of characteristic prediction requires a large amount of high-quality data, and obtaining such data remains a significant challenge [2], [3].

This paper proposes a transfer learning approach to simultaneously address these challenges. This approach minimizes the use of FEA data while maintaining high prediction accuracy and improves the generalization performance of the learning model by generating a large dataset using AM. Additionally, through transfer learning, the pre-trained model can reduce the time required to estimate characteristics under new conditions. This approach demonstrates the potential to be more efficient than traditional method and significantly reduce the time required for characteristic estimation. The entire process of estimating SPMSM characteristics using the proposed transfer learning method is shown in Fig. 1.

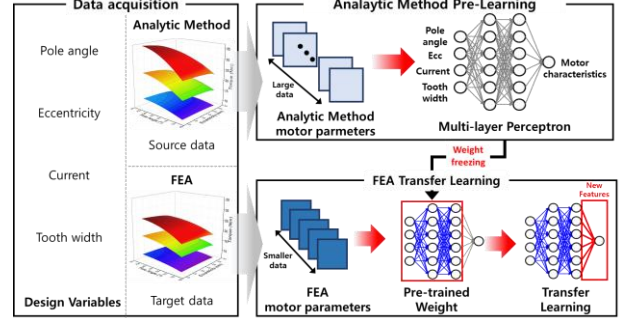


Fig. 1. Concept of proposed method for SPMSMs

II. PROPOSED METHOD: ANALYTIC METHOD-BASED TRANSFER LEARNING

Transfer learning is a technique that applies the domain knowledge of a pre-trained model on a large source dataset to a smaller target dataset [4]. In this paper, the source data, AM enables rapid calculations and allows for the acquisition of large datasets but has low accuracy, while the target data, FEA, provides high accuracy but requires significant computation time. Therefore, the deep learning model is first trained on the source data, and the knowledge gained is used to ensure that the target data follows the distribution of the source data, enhancing the regression performance of the FEA model.

A. SPMSM Model

Table I presents the main specifications of the SPMSM, and the listed parameters are used as baseline values that remain unchanged during the design process. Fig. 2. illustrates the design range of the SPMSM, and these variables significantly influence the electromagnetic performance of the motor.

B. Analytic Method for Pre-learning

AM can rapidly calculate the magnetic field distribution of a motor based on design parameters by utilizing the governing equations of the magnetic field, but they are limited by low

TABLE I
SPECIFICATIONS OF SPMSM

Item	Unit	Value
Number of poles / slots	-	16 / 18
Permanent Magnet	-	N52H
Stator/Rotor Core	-	50PN470
Stator diameter	mm	100
Rotor diameter	mm	64
Air gap	mm	0.5

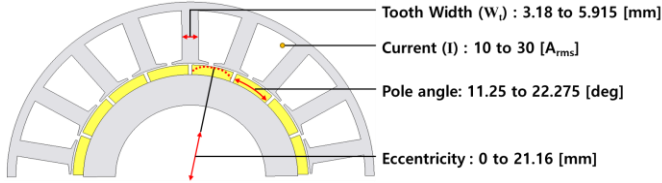


Fig. 2. Design variable of SPMSM

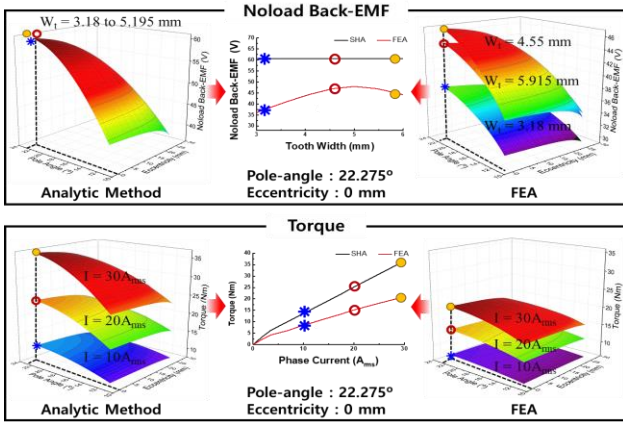


Fig. 3. Comparison of AM and FEA characteristic results

accuracy [5]. In contrast, FEA provides high accuracy by considering nonlinearity, but it requires significant computation time. Fig. 3. compares the characteristic results of AM and FEA according to design parameters. AM does not account for magnetic nonlinearity caused by geometry and input current, resulting in differences with FEA results. To address these issues, this paper proposes a method that integrates AM and FEA for transfer learning.

C. Transfer Learning for Feature Estimation

In this paper, a Multilayer Perceptron (MLP), one of the Deep Neural Network (DNN) architectures, was selected for the research [6]. The perceptron generates output by summing weighted inputs, and the MLP stacks multiple perceptron layers to recognize complex patterns in data [6]. To prevent overfitting, the source dataset was divided into training, validation, and test datasets in a ratio of 7:1.5:1.5 for the training process. The detailed settings of the DNN are presented in Table II, and the target DNN was trained using transfer learning with three of the four hidden layers frozen, based on the training data, and validated through dataset labeling. Fig. 4. shows that transfer learning improves no-load back EMF by 8% and average torque by 6% compared to models without it. While more data enhances performance even without transfer-learning, this approach achieves high accuracy with a small amount of FEA data, demonstrating its effectiveness in data limited situations.

TABLE II
DETAILED SETTING OF TRANSFER LEARNING AND NUMBER OF DATASET

Design variable	Pole-angle, Eccentricity, Current, Tooth Width	
Characteristics	Noload Back-EMF	Torque average
Number of layers	4	4
Number of nodes	25	25
Learning rate	1e-4	1e-4
Activation function	ReLU	ReLU
Optimizer	Adam	Adam
Loss function	Normalized Root Mean Squared Error	Normalized Root Mean Squared Error
Size of mini-batch	32	50
Train data	Case 1	120
	(w/o transfer)	(FEA)
	Case 2	480
	(w/o transfer)	(FEA)
	Case 3	34983 + 120
	(with transfer)	(AM + FEA)

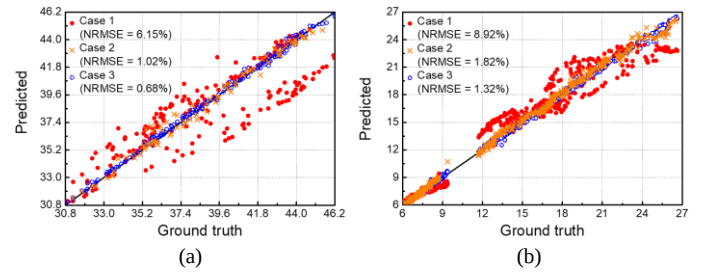


Fig. 4. Comparison of predicted results and actual values on the test dataset with and without transfer learning. Results of comparing (a) Noload back-emf, (b) Torque average

III. CONCLUSION

This paper proposes an analytic method-based transfer learning approach for the design and nonlinear characteristic estimation of SPMSM, achieving high prediction accuracy and reduced computation time by utilizing large-scale AM data and a small amount of FEA data for transfer learning, thus addressing the limitations of traditional approaches. This demonstrates the potential for complementarily utilizing both analytic and numerical methods in motor design.

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