

An NDTL-CNN Approach for Accurate Iron Loss Estimation in Permanent Magnet Synchronous Motors

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To precisely calculate iron losses of permanent magnet synchronous motors (PMSMs) under the influence of multiple physical fields, an advanced deep learning based estimation strategy is proposed, which combines convolutional neural network (CNN) with network-based deep transfer learning (NDTL). The advantage of the proposed model lies in its ability to accurately address iron loss calculation challenges across various operating conditions, even with a limited amount of sample data. Specifically, simulation data encompassing various loads and influencing factors are first generated using an analytical iron loss model, followed by designing a pre-trained CNN-based iron loss model to efficiently extract pertinent features from the data. Subsequently, an NDTL algorithm is employed to fine-tune the key parameters of the CNN model enabling it to adapt to novel feature distributions and thereby substantially enhancing model performance. Finally, the effectiveness of the proposed NDTL-CNN approach is tested using data from various states on an actual PMSM applied in electric vehicles. Experimental results indicate that the model using the proposed algorithm achieves high estimation accuracy and good practicality, solving the problem of poor generalization ability of traditional deep neural network approaches.

Index Terms—Convolutional neural network, deep transfer learning, iron loss estimation, permanent magnet synchronous motors.

I. INTRODUCTION

PERMANENT magnet synchronous motors (PMSMs) are highly efficient and power-dense, making them popular in electric vehicles (EVs), aerospace, and industrial automation. Accurate calculation of iron losses is crucial for optimizing the motor design, thus improving system efficiency, and reducing energy waste. However, iron loss calculation usually requires a multidisciplinary approach, considering factors like material characteristics, electromagnetic fields, temperature effects, and mechanical stress, with the key challenge being the creation of an accurate multi-physics coupling model [1].

Our team previously proposed an advanced analytical model that considers the coupling of multiple factors [2], the final iron loss mode can be derived as (1) in which the meaning of each nomenclature can be found in [2].

$$P_{iron_3} = \left(\frac{k_{h_PWM}^T K_h(T_C, \sigma) \cdot \omega_s}{2\pi} \cdot B_{Tm}^2 + 8K_e(T_C, \sigma) N_R N_S \left(\frac{B_{Lm}}{T} \right)^2 \right) \cdot V_T + \left\{ \frac{k_{h_PWM}^Y K_h(T_C, \sigma) \cdot \omega_s}{2\pi} \cdot B_{Lm}^2 + \frac{4K_e(T_C, \sigma) \cdot \omega_s (2 + \beta C_N N_S)}{\pi T \beta} \cdot B_{Lm}^2 \right\} \cdot V_Y + \left\{ \frac{K_e(T_C, \sigma)}{(N_W S)^2} \cdot \sum_{i=3,5,7,\dots}^n \left(\frac{V_n}{2\pi} \right)^2 \right\} \cdot (V_T + V_Y) \quad (1)$$

Although the improved analytical methods for modeling iron losses can describe the loss characteristics of PMSMs with acceptable accuracy, discrepancies still occur in real-world applications due to factors like equipment aging and additional energy losses. In recent years, as artificial intelligence has increasingly permeated industrial applications, researchers have explored the use of machine learning and deep neural network approaches as surrogate models for predicting various motor performances [3]–[5]. However, this approach is deemed inefficient due to the substantial data requirements for training these surrogate models and the considerable computational

expense associated with collecting data for iron loss studies in PMSMs, which take into account multiple physical factors.

Therefore, this paper introduces an advanced convolutional neural network (CNN) model combined with network-based deep transfer learning (NDTL) to accurately predict iron losses in PMSMs using limited data across diverse operating conditions. Initially, simulation data covering different loads and factors like temperature, stress, and magnetic density are generated via an analytical model of (1). A pre-trained CNN then extracts key features, which are further optimized by NDTL to adapt to new feature distributions and enhance model performance. Comparative studies between predictions and experimental results validate the method's effectiveness.

II. IMPLEMENT OF THE NDTL-CNN APPROACH

Transfer learning in deep neural networks involves source and target domain data that share similar yet distinct distributions. Its goal is to transfer knowledge learned from a source domain with abundant labeled data to a target domain with limited labeled data [6].

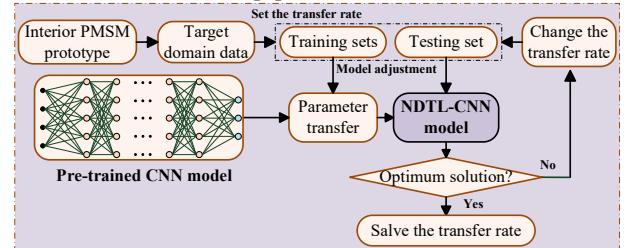


Fig. 1. Principles of iron loss prediction using NDTL-CNN approach

The logical principles underlying iron loss prediction for PMSMs using transfer learning, as illustrated in Fig. 1, revolve around a method that employs sample weights in the transfer learning process. Measuring iron loss in PMSMs is costly and complex, requiring experiments under various conditions. This limits practical iron loss data availability. To solve this issue, an advanced iron loss model [2] is used to simulate and predict data under different conditions, offering low cost, reliability,

and flexibility. By using the parameters of a CNN trained on the source domain, the multi-kernel maximum mean discrepancy method is employed to analyze the differences in deep features between simulation data and measured data. This involves measuring the domain adaptation between these two categories of data and calculating their weighting factors to minimize the loss function, ultimately fine-tuning the last layer of the CNN.

III. RESULTS AND ANALYSIS

A. Data preparations and Parameter Configurations

By configuring iron loss analytical model's parameters, batch computation generates simulated iron loss data across 2500 operating conditions as source domain data. This data is divided into training, validation, and test sets at 60%, 20%, and 20% ratios to pre-train a CNN. Specific CNN parameters are detailed in Table I, with training accuracy results for both training/validation and testing phases shown in Fig. 2.

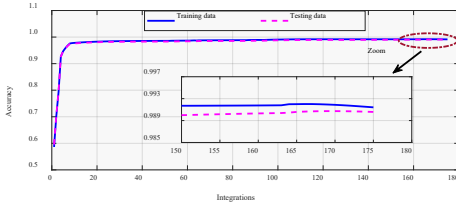


Fig. 2. Magnetization as a function of applied field.

TABLE I
NETWORK STRUCTURE OF CNNs

Parameter	Settings	Parameter	Settings
Optimizer	Adam	Layer_1 kernel Number	32
Initial learning rate	0.001	Layer_2 kernel Number	64
Kernel size	2	Dense_1 neuron Number	64
Dropout rate	0.1	Dense_2 neuron Number	32

Another 700 target domain datasets are collected from an experimental interior PMSM prototype used in electric vehicles. The transfer rate a denotes the fraction of target data used for fine-tuning. In real-world applications, limited target data makes large a impractical. Additionally, higher a increases fine-tuning time, reducing the efficiency benefits of transfer learning. Considering practical constraints and diagnostic accuracy, the study selects $a = 0.3$.

B. Comparative Verifications with the Prototype

Fig. 3 compares iron loss calculations for an interior PMSM, contrasting results with measured data across varying operating speeds and current inputs. The comparison includes three models: the proposed NDTL-CNN model, the pre-trained CNN model, and the analytical model from [2]. It can be observed that the proposed model can maintain high accuracy for loss prediction under various operating conditions. The iron loss models based on the pre-trained CNN and the analytical method exhibit maximum errors of 7.58% and -5.45% respectively across all three input phase currents. In contrast, the proposed model achieves a maximum error of only 3.39% for a 300 A input current, with errors for the other two currents remaining below 3.3%. Moreover, the proposed method shows superior stability in prediction accuracy compared to the others. Across various conditions, the absolute average error of the proposed model stays within 1.06%, which is approximately one third of the error from pre-trained CNN and half of that from the improved analytical method in [2].

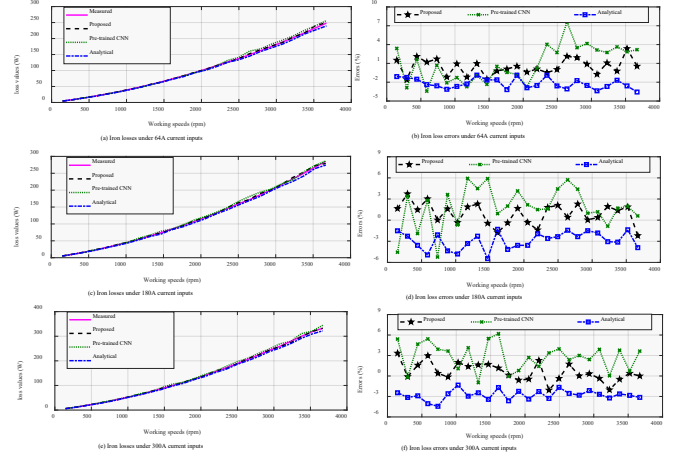


Fig. 3. Comparative results of iron loss prediction using different models.

To further validate the effectiveness of the proposed method, tests are conducted on the same platform with a Core i7-7700 processor, 32 GB memory, Windows 10, and MATLAB R2024a. Each algorithm runs 50 times for average. The comparison results are presented in Table II. As given, the proposed algorithm achieves higher accuracy and shorter computation time for the integration process with the same sample size.

TABLE II
COMPARATIVE RESULTS OF THE EFFECTIVENESS FOR VARIOUS MODELS

Algorithm	Accuracy	Integrations	Simulation time
Pre-trained CNN	0.948	1680	13.3 s
NDTL-CNN	0.991	174	4.8s

IV. CONCLUSION

This paper proposes an improved NDTL-CNN approach to tackle the challenges of low accuracy and exorbitant cost of acquiring experimental data in PMSM iron loss prediction. The method undergoes cross-domain training via transfer learning and has been experimentally validated for both effectiveness and feasibility. The results highlight that, even with the target domain data comprising just one-fifth of the source domain data, the NDTL-CNN with transfer learning achieves a prediction accuracy exceeding 96%. Comparative results indicate that the proposed model can not only enhance prediction accuracy and reduce training time but also address the problems of traditional prediction models in training data limitation. The NDTL-CNN also significantly boosts the model's generalization capabilities.

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