Prediction of IPM Machine Torque Characteristics Using Deep Learning Based on Magnetic Field Distribution

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ABSTRACT This paper proposes a new method for accurately predicting rotating machine properties using a deep neural network (DNN). In this method, the magnetic field distribution over a cross-section of a rotating machine at a fixed mechanical angle is used as the input data for the DNN. The prediction accuracy of the torque properties of an inner permanent magnet (IPM) motor for the CNNs trained by the magnetic flux density distribution and material configuration is compared. It is shown that the proposed method facilitates a more accurate prediction of machine performance than a conventional method in which the cross-sectional image of a rotating machine is input to the DNN. Furthermore, the DNN learned by the proposed method is applied to the topology optimization algorithm. Topology optimization can be effectively accelerated because the number of analyses by the finite element method can be reduced using the proposed method. The total computing cost is reduced by 52.5% compared with conventional optimization without surrogate models.

INDEX TERMS Topology Optimization, Deep Learning, IPM Motor, Finite Element Method

I. INTRODUCTION
Recently, topology optimization [1] has attracted significant attention because of its excellent features such as usefulness for conceptual and initial design, potential to provide a novel structure that might not be found by conventional approach, and lack of need for laborious parametrization of the target materials, unlike conventional parameter optimization. There are two different approaches to topology optimization, which are based on sensitivity methods [2-4] and stochastic algorithms [5-7], such as genetic algorithms. The former approach has a relatively low computational cost, whereas its result depends on the initial configuration. Therefore, this approach is challenging to address multimodal problems that are often encountered in real engineering scenarios. The latter approach can achieve semi-optimal solutions because of the global search ability of the stochastic optimization method. However, it has a relatively high computational cost. When we apply topology optimization to electrical motors, most of the computational cost is paid to the magnetic field analysis by the finite element method (FEM). To reduce the computing cost, surrogate models which work much faster than FEM have been introduced to optimization. Although the conventional surrogate models such as response surface [8], kriging [9], and radial basis function [10] are effective for reducing the computing cost of parameter optimization, they do not work well for topology optimization because of their large degrees of freedom.

As a surrogate model for topology optimization, a convolutional neural network (CNN) for the realization of deep learning has been proposed by the authors [11, 12]. Also, there are studies on the application of CNN to parameter optimization of electromagnetic devices [13, 14] and topology optimization of mechanical devices [15, 16]. In this approach, the RGB images of the material configuration in the cross-section of an electric motor are directly input to the CNN to predict the torque properties such as average torque and torque ripple. It has been shown that the individuals generated in the genetic algorithm (GA) process can be quickly evaluated by the trained CNN, and the requirement of implementing the FEM for highly accurate evaluation can be drastically reduced. The improvement of CNN prediction is essential for further reducing the computing cost and optimization quality.

In the above-mentioned CNN-based topology optimization, it is assumed that the torque properties can be predicted from
the cross-sectional images of the materials. However, the torque properties are greatly affected by the magnetic field distribution in the magnetic steel sheet, which has nonlinear BH characteristics. Therefore, prediction accuracy is expected to be improved by adopting the magnetic field distribution as the input data for the CNN instead of the material configuration. Because the magnetic nonlinearity influences the magnetic flux density distribution, the CNN predicts the torque characteristics considering the magnetic saturation. Additionally, because the magnetic field distribution can be expressed in grayscale, the data size of the input images can be reduced to one-third. Therefore, it is expected to accelerate the learning process.

In this paper, we propose the prediction of the torque characteristics of inner permanent magnet (IPM) motors, which are widely used for traction of electric vehicles, using the CNN which is trained by the magnetic field distribution. To verify the proposed method, its performance is compared with that of the CNN which is trained by the material distribution. We also apply the proposed method to the topology optimization of IPM motors to see how it contributes to the speed up of the optimization.

II. REGRESSION USING CNN

A. Network Model

In this study, we used a CNN that can extract the feature amount corresponding to the output from the input data [17]. Fig. 1 schematically shows the structure of CNN used in this study, which has three layers; convolutional layers extracting the features from the input image data, pooling layers that compress the data volume, and fully connected layers. It has been shown that CNN is superior in accuracy for image recognition over the conventional machine learning methods [18].

The structure of the CNN used in this study is shown schematically in Fig. 2. Although there are various configurations for CNNs, we adopted VGG16 [18] for simplicity. We configured the structure of VGG16 for the regression problem with a single output.

B. Target Rotating Machine Models

In this study, CNNs were applied to the topology optimization of two different IPM motors, as shown in Fig. 3. The specifications of the IPM motors are listed in Table 1. IPM motors have four poles and 24 slots with distributed windings [19]. We characterized the torque performance of the IPM motors based on the average torque $T_{\text{avg}}$ and torque ripple $T_{\text{rip}}$, defined by

$$T_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} T_i ,$$

(1)

$$T_{\text{rip}} = \frac{T_{\text{max}} - T_{\text{min}}}{T_{\text{avg}}} ,$$

(2)
where $N$, $T_i$, $T_{\text{max}}$, and $T_{\text{min}}$ are the number of sampling points, the torque of sampling point $i$, maximum and minimum torques, respectively.

### C. Training data

In [11] and [12], the input data to the CNN are the cross-sectional images, represented by RGB, of an electric motor CNN. We trained the CNN so that from the configuration of the iron core, permanent magnets, and coil windings, it outputs the corresponding torque characteristics. When using this method, it is difficult to consider the spatial differences in the material properties of each material. This means that the difference in the magnetic permeability due to magnetic saturation in the iron core cannot be considered, although it can significantly influence the torque performance. To overcome this difficulty, we input the distribution of the magnetic flux density $B = |\mathbf{B}|$ on the rotor core at a fixed mechanical angle instead of the material configuration. Because the distribution of $B$ reflects the magnetic saturation, the torque characteristics are expected to be predicted more accurately. In this study, we compare the accuracy of the torque characteristics predicted by the CNNs trained by the material configuration and magnetic flux density.

Examples of bitmap image generated during the optimization process which are input to CNN are shown in Fig. 4, where (a) and (b) represent the material configuration and distribution of $B$, respectively. The latter is normalized by 2.3T, which is the saturation level of 50A470, so that $B$ values in the white and black areas are 0T and greater than 2.3T, respectively. The machine parameters of the IPM motors are listed in Table I.

In this study, the training data were generated by performing preliminary topology optimization. The distribution of the flux barrier in the iron core shown by the shaded design region and the material attribute $M_e$ of element $e$ is determined in such a way that $M_e$ is set to iron (air) if $\phi(x_e) \geq 0$ ($< 0$), where $x_e$ is the element center position. The exemplified distribution of $G$ and $\phi$ are shown in (a) and (b) of Fig. 5. We arrange $x_i$ uniformly in the design region.

We solve the multi-objective optimization problem $T_{\text{avg}} \rightarrow \text{max.}, T_{\text{rip}} \rightarrow \text{min.}$ using NSGA-II [21] to obtain the data $\{D_{\text{in}}; T_{\text{avg}}, T_{\text{rip}}\}$, where $D_{\text{in}}$ denotes the input data that are composed of either material configurations or distributions of $B$. The optimization settings are listed in Table II. The data are divided into training and test data, which do not overlap. The number of training data, validation data, and test data are 5222, 1306, and 6528, respectively.

The training conditions are presented in Table III. We used the RMSProp for training [22]. We performed the regression using CNN under the same conditions for the I-magnet and V-magnet configurations.

### D. Calculate Magnetic characteristics

![Figure 4: Bitmaps input to CNN](image-url)

![Figure 5: NGnet-on/off method](image-url)

![Table I: The specifications of IPM motor](image-url)

![Table II: Conditions for topology optimization](image-url)

![Table III: Training conditions for CNN](image-url)
In the multi-objective optimization, we compute the magnetic induction $B$ at each mechanical angle using FEM. We compute the force $f_n$ at node $n$ by the nodal force method [23], that is,

$$ f_n = - \int_T T \cdot \nabla N_n \, dS, \quad (4) $$

where $T$, $N_n$, and $S$ denote the Maxwell stress tensor computed from $B$, the nodal shape function and surface of the finite element, respectively. The torque $T$ is obtained from the moment of $f_n$. In this study, the FEM is performed in five steps at every 10 degrees electrical angle in accordance with the period of the sixth-order torque ripple component, which is the main component of base model motor.

III. ACCURACY IN CNN PREDICTION

A. Comparison of conventional and proposed methods

The CNN predictions of $T_{avg}$ for the I- and V-magnet configurations of the IPM motors are plotted against those computed by FEM in Figs. 6 and 7, respectively, where $R^2$ and MAE represent the coefficient of determination and mean absolute error that measures the accuracy of the prediction. In both results, the prediction accuracy of the proposed method based on $B$ was higher than that of the conventional method using the material configuration.
The CNN prediction of $T_{rip}$ for the I-magnet configuration of the IPM motors is shown in Fig. 8. It can be seen that the accuracy of the proposed method is higher than that of the conventional method. However, the accuracy of $T_{rip}$ was significantly lower than that of $T_{avg}$.

The prediction results of the CNN trained by the material configuration and magnetic flux density for a typical case are shown in Fig. 9. It can be seen that the FEM and CNNs based on the conventional and proposed methods result in $T_{avg} = 1.40, 1.06$, and $1.41$.

The above results reveal that the prediction accuracy for the average torque and torque ripple is improved by using the magnetic flux density distribution as input data. This is because the data in the stator region are enriched using this approach. Important information relevant to torque performance exists in the magnetic field of the stator. In contrast, there was no change in the data of the stator when using the material configuration as the input data. Figs. 10(a) and (b) show the typical motor structures that appear in the optimization process, which have good and poor torque performance, respectively. It can be seen that the stator has a high magnetic field density, as shown in Fig. 10(a).

### B. Effect of training region

To compare the effect of the magnetic field distribution and material configuration on the input data to the CNN, we restricted the input region to the rotor, as shown in Fig. 11. There are changes in the material configuration of the rotor, while there are no changes in the stator. The prediction results are shown in Fig. 12, through which we conclude that there are few differences in the prediction accuracy. This suggests that the magnetic field distribution in the stator has a significant influence on the prediction.
C. Amplitude vs. torque ripple
As mentioned above, CNN has inferior accuracy for $T_{rip}$ compared to $T_{avg}$. This would be due to the fact that there exist different magnetic field distributions that give the same value for $T_{rip}$, while they have different values for $T_{avg}$. That is, a one-to-one correspondence cannot be expected as long as $T_{rip}$ is used to characterize variations in torque. For this reason, we introduce $T_{amp} = T_{max} - T_{min}$ instead of $T_{rip}$. The prediction results are shown in Fig.13. We can see that the coefficient of determination for $T_{amp}$ between the CNN prediction and FEM is much higher than that for $T_{rip}$. Note that we can compute $T_{rip}$ from $T_{amp}$ and $T_{avg}$, the latter of which can be accurately predicted. It is found that $T_{amp}$ prediction results are not significantly improved by introducing the magnetic flux density distribution. For the further improvement of this accuracy, other features, such as gap magnetic flux density distribution, should be added to assist the prediction.

D. Grayscale vs. Color scale
In this study, we use the magnetic field distribution expressed in grayscale because the data size of the input images can be reduced to one-third compare with the color scale. We verify what happens if we use the color image instead of the grayscale image. Both images are shown in Fig.14. Fig. 15 shows the CNN predictions of $T_{avg}$ for the I-magnet configuration of IPM motor using color and grayscale magnetic field distributions. Although there was no change in $R^2$, the MAE was improved for the color scale magnetic flux density. We conclude that the grayscale image is sufficient for the prediction of the torque performance. Of course, when we consider different properties such as iron and copper losses, color images would be suitable.

IV. TOPOLOGY OPTIMIZATION USING CNN

A. Optimization algorithm
When using a CNN for topology optimization as the surrogate model, its accuracy can significantly influence the optimization efficiency and result. We compared the topology optimizations using the CNN trained by the conventional and proposed methods to clarify this point.
An overview of the optimization procedure using a GA is shown in Fig. 16. The setting of GA is shown in Table. IV. In the optimization, $T_{\text{avg}}$ is maximized, and the torque ripple $T_{\text{rip}}$ is minimized. We define the optimization problem as:

$$F = w_1 \frac{T_{\text{avg}}}{T_{\text{avg}}} - w_2 \frac{T_{\text{rip}}}{T_{\text{rip}}} \rightarrow \max.,$$  

where we set the weighting coefficients as follows: $w_1 = 1.3$, and $w_2 = 0.3$. The normalized constants are set to $T_{\text{avg}} = 2.1$ Nm and $T_{\text{rip}} = 0.57$, which the original model before optimization has.

Individuals with higher values of $F_{\text{CNN}}$ evaluated by the trained CNN would have a more significant influence on the evolution in the GA process. For this reason, it would be better to re-evaluate them using FEM at high accuracy. In this study, we tested three cases: (i) FEM analysis was performed for all individuals, (ii) FEM analysis was performed only for individuals with $F_{\text{CNN}} \geq 1.0$, and (iii) all the individuals were evaluated by the CNN without FEM computations. It is noted that the $B$ distribution is computed at a fixed mechanical angle for the prediction of the CNN in the proposed method. In contrast, we perform many FEM computations by changing the mechanical angle of the rotor to obtain the torque performance. FEM is used to obtain the magnetic flux density. Hence, the former computing cost is much lower than the latter.

### B. Optimization results

The optimization results for the IPM motor obtained using the CNN trained by the conventional and proposed methods are shown in Fig. 17. The evolutionary histories are shown in Fig. 18, where the vertical axis represents the evaluated value of $F$. The $F$ values obtained by the proposed method after 100 generations were better than those obtained by the conventional method. Without performing evaluations by FEM during the GA processes for case (iii), the proposed method improves $F$ by approximately 25%. The shapes shown in Fig. 17 have thin bridges in the iron core which might be concerned for mechanical weakness. It would be possible to avoid thin iron bridges and small holes by introducing the constraints on the stress in the optimization problem.

The number of FEM analyses executed during the GA process for case (ii) is shown in Fig. 19. The proposed method has approximately 1.09% and 7.28% fewer FEM analyses compared to the conventional method. The number of FE computations for the proposed method is greater than that for the conventional method because the former tends to generate individuals that have better values in $F$ compared with the latter. The total optimization computing times using an Intel Xeon CPU (3.5 GHz, 16 threads) and an NVIDIA GPU (Tesla V100 PCIE 16GB) are shown in Fig. 20. The computing time for case (iii) using the material configuration and magnetic flux density are reduced to 27.3% and 47.5%, respectively, compared to case (i). It took approximately 40 min to train the CNN. The proposed method works faster than the conventional method without the surrogate model, even considering the training time of the CNN. The computing time to evaluate the average torque using FEM is about 1000 times longer than that required for CNN.
computations. The trained CNN can be reused for different optimization problems for the torque performance and other motor characteristics such as loss and induced voltage [11]. For example, the trained CNN can be conveniently reused for optimization, sweeping the values of $w_1$, $w_2$ in (5), and for the multi-objective problem with respect to $T_{avg}$ and $T_{rip}$.

It is important to predict the torque performance of motors for different current conditions. It has been shown in [24] that CNN can predict d- q- inductance and magnet flux. Using these results, we can predict the average torque under various current conditions. This function can be included in our method in principle.

C. Discussion about Optimized shape

To obtain the physical insight of the optimization results, we modify the optimized core shape shown in Fig. 21(b), where the thin core bridge is changed to air. The torque waves before and after the modification are shown in Fig. 22. The average torque and torque ripple become worse by about 2.25% and 12.8%, respectively, due to this modification. We conclude that the thin bridge obtained by the proposed method is important to improve the torque performance. We would
introduce the constraints on the mechanical strength in the future optimization.

V. CONCLUSION
The use of the magnetic field distribution for the input data to the CNN has been shown to effectively improve the accuracy of prediction of the torque performance of IPM motors. The result of the topology optimization can also be improved by evaluating the individuals using the CNN to which the magnetic field distribution is input. The total computing cost is reduced by 52.5% compared with conventional optimization without surrogate models.

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