

Generation Method of Training Data for Deep Neural Network to Estimate the Magnetization Distribution of Permanent Magnet

S. Nakanishi¹, S. Matsutomo², and Y. Okamoto³

¹Major in Electrical and Electronic Engineering, Graduate School of Science and Engineering, Hosei University 3-7-2, Kajinocho, Koganei, Tokyo, 184-8584, Japan, s.nakanishi2002@gmail.com

²Department of Electronics and Control Engineering, National Institute of Technology (KOSEN), Niihama College 7-1, Yagumocho, Niihama, Ehime, 792-8580, Japan, s.matsutomo@niihama-nct.ac.jp

³Department of Electrical and Electronic Engineering, Faculty of Science and Engineering, Hosei University 3-7-2, Kajinocho, Koganei, Tokyo, 184-8584, Japan, okamoto@hosei.ac.jp

An effective method for training data generation is essential for highly accurate magnetization estimation of permanent magnet using deep neural network (DNN). However, the previous method of generation of training data tended to decrease in accuracy as the number of poles in a multipole magnet is increased, although it could accurately estimate 3D magnetization distribution sequentially. In this paper, we proposed a method for training data generation that combines the Heisenberg model with a 1-D Fourier series expansion. As a result of magnetization estimation using a DNN with this proposed method, it was confirmed that magnetization estimation is highly accuracy for multipole orientation magnet.

Index Terms— deep neural network, Heisenberg model, magnetization estimation, and permanent magnet

I. INTRODUCTION

IN recent years, permanent magnets (PMs) have been used in many electrical devices due to their ability to maintain their magnetic characteristics for long periods of time. If the magnetization distribution (MD) of PM loaded in a device is disturbed, it is difficult to ensure safety of that device. Various numerical analysis methods [1]-[3] have been proposed to evaluate the MD of a PM using the magnetic flux density outside the PM. However, these methods are unable to uniquely solve for MD and might estimate an unphysical MD. On the other hand, magnetization estimation method using deep neural network (DNN) has been proposed to solve these problems and estimate uniquely and physically MD. The input value of DNN is the external magnetic flux density, and the output value is the MD inside the PM. We have proposed a method to effectively utilize magnetization estimation using DNN, which includes the Heisenberg model [4] in generation of training data [5]. But it is difficult to estimate the magnetization with high accuracy for multipole magnets. In this paper, we compare the proposed method, which combines the Heisenberg model and 1D Fourier series expansion, with previous methods [5] for the generation of training data. Then, compared the proposed method with previous method of generation of training data, it was shown that the proposed method achieves highly accurate and fast estimation for demagnetization due to aging and for multipole orientation magnet.

II. PROPOSED METHOD

A. Analysis Model for Permanent Magnet

In this study, the material of the PM used is assumed to be a ferrite. The number of cells in the x -, y -, and z -axis of the PM is 12, 8, and 4, respectively. Fig.1 (a) shows the dimensions of the PM and the mesh division diagrams.

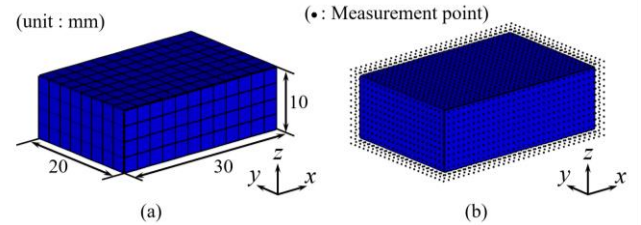


Fig. 1. Target Permanent Magnet. (a) Size of PM. (b) Measurement point.

The measurement points of the magnetic flux density are set 1 mm away from the PM and arranged in a grid pattern with 1 mm intervals, as shown in Fig.1 (b), and the number of measurement points is 2,706.

In this study, the Biot-Savart law [6] is used to calculate the magnetic flux density $\mathbf{B}$ around a PM from the MD $\mathbf{M}$ inside the PM.

B. Generation Method for Training Data

The proposed method prepares a total of 60,000 training data, 20,000 using the Heisenberg model and 40,000 using 1D Fourier series expansion.

Heisenberg model

First, the Heisenberg resizing model is proposed as an adapted model to the Heisenberg model. This model is an improved Monte Carlo simulation of the Heisenberg model of a $7 \times 7 \times 7$ simple cubic lattices, resized to $12 \times 8 \times 4$, the same size as the cells in each axis of the magnet. The spin array of this model is multiplied by the magnetization intensity M_0 to generate a magnetization array, which is the MD. M_0 is the magnetization intensity and a uniform random number of (0.2, 0.5). This method generates 20,000 data.

1D Fourier series expansion

First, the magnetization angle θ is decided using 1D Fourier series expansion.

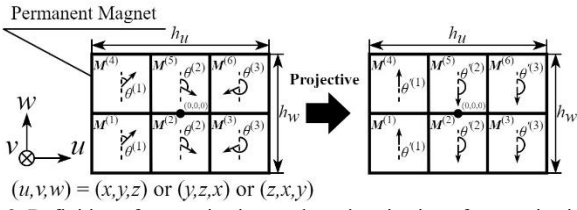


Fig. 2. Definition of magnetization angle and projection of magnetization vector.

$$\mathbf{M}^{(i_c)} = iM_0 \cos(\theta^{(i_c)}) + kM_0 \sin(\theta^{(i_c)}) \quad (2)$$

$$\theta^{(i_c)} = \sum_{m=0}^{N_f} a_m \cos\left(\pi m \frac{u}{h_u}\right) + b_m \sin\left(\pi m \frac{u}{h_u}\right) \quad (3)$$

where, $\mathbf{M}^{(i_c)}$ is the magnetization vector of the PM cell i_c , i and k are unit vectors in u - and w -axis directions, (u, v, w) is one randomly selected from (x, y, z) , (y, z, x) , and (z, x, y) , M_0 is the magnetization intensity and a uniform random number of $(0.2, 0.5)$, N_f is the expansion coefficient and an integer uniform random number of $[0, 15]$, a_m, b_m are expansion coefficients and uniform random numbers of $(-180, 180)$, and h_u is the length of the PM in the u -axis direction.

Next, the magnetization vector is then projected in 2 or 4 directions. Finally, random rotation [7] is performed to orient the magnetization distribution in any direction. In this paper, a total of 40,000 data have been generated, 20,000 in two directions and 20,000 in four directions.

In this paper, we use previous method [5] of generation of training data using Heisenberg model to compare to proposed method.

C. Structure of DNN and Methods of Learning

In this study, the input value of the DNN is the external magnetic flux density and the output value is the MD inside the PM. The structure of the DNN is shown in Table 1. We adopted the mean square error as the loss function of the DNN.

TABLE I
STRUCTURE OF DNN

Layer Type	Input	Hidden Layers			Output
		1st	2nd	3rd	
Number of Neurons	8,118	1,000	2,000	3,000	1,152

III. RESULTS OF MAGNETIZATION ESTIMATION

The magnetic flux density as input to DNN is given a relative error within 3% of the relative error. The mean absolute error rate is used as the evaluation index for each estimation method, and the following formula is used.

$$Error = \frac{1}{N_c} \sum_{i_c=1}^{N_c} \frac{|\hat{\mathbf{M}}^{(i_c)} - \mathbf{M}^{(i_c)}|}{|\mathbf{M}^{(i_c)}|} \times 100 [\%] \quad (4)$$

where, $\mathbf{M}^{(i_c)}$ is the target magnetization vector of the i_c -th cell and $\hat{\mathbf{M}}^{(i_c)}$ is the estimated magnetization vector of the i_c -th cell.

Figure 3 presents the results of magnetization estimation for parallel orientation which is assumed to be caused by thermal demagnetization due to aging. Both previous and proposed methods achieve high accuracy with this estimation. The magnetization estimation results for multipole orientation

magnet are shown in Fig. 4. The previous method has large error in magnetization intensity, but the proposed method is able to estimate very close to the target MD.

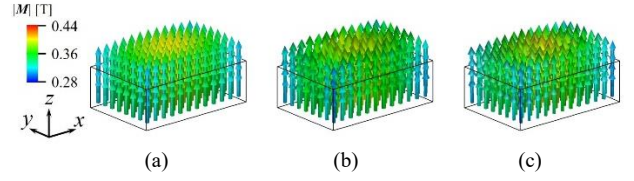


Fig. 3. Demagnetization distribution of parallel orientation. (a) Target. (b) Previous method. (c) Proposed method.

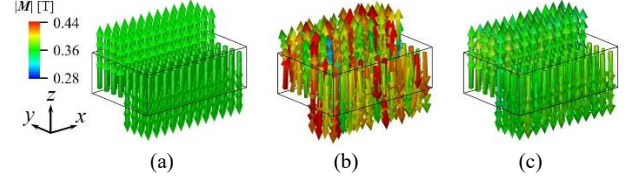


Fig. 4. Magnetization distribution of multipole orientation. (a) Target. (b) Previous method. (c) Proposed method.

TABLE II
EVALUATION BY ACCURACY

Type of MD	Error [%]	
	Previous method	Proposed method
Demagnetization	2.2	2.1
Multipole	10.5	2.0

IV. CONCLUSION

It was proposed method of training data generation using the Heisenberg model and Fourier series expansion for magnetization estimation of PM using DNN. The proposed method improves the accuracy for multipole magnets by 8.5% while keeping the estimation accuracy for demagnetized magnets compared to the previous training data generation method.

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