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Accelerated material design of Mn-Zn ferrite toroidal core using artificial neural network based surrogate model

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Abstract

This paper presents an effective framework for predicting magnetic properties and optimizing the material design of Mn-Zn ferrite core. The objective of the current work is to construct a high-accuracy machine learning-based surrogate model correlating the configuration parameters of ferrite core and its electromagnetic performance according to the various material composition. The finite element method (FEM) combined with a model that considers the dielectric effect was developed to analyze dimensional resonance by magnetic simulation. The dielectric effect was treated as the equivalent circuit and was formulated by coupling with Maxwell's equations. To accelerate evaluating performance, we construct an ANN-based FE surrogate model. Training data is generated through the FEM-based electromagnetic analysis framework, and analysis-based data is added to the previous experimental-based data. ANN models were trained to predict microstructure parameters, magnetic properties, and core loss using expanded data. Finally, the Mn-Zn ferrite core performance for various compositions can be mapped through the effective surrogate model and identifies material compositions with optimized magnetic properties. Therefore, the magnetic properties are effectively calculated by the trained neural network, and the optimized composition of the ferrite core shows that the proposed framework can significantly improve the efficiency of material design.

Keywords: material design, optimization, surrogate model, artificial neural network, ferrite core, electromagnetic, finite element analysis

1 Introduction

Power electronic devices have been widely applied to consumer devices and electric vehicles, and their efficiency improvement is strongly required to reduce energy costs. One of the primary energy loss factors in the devices is the magnetic core loss in inductors and transformers. To accurately estimate the magnetic loss, it is important to consider the dielectric constant caused by a thin high-resistive layer at the grain boundary of magnetic material. In recent years, particularly in the development of high-frequency power electronics devices, an increasing need has emerged for a highly accurate simulation methodology to reduce energy loss. Therefore, we have endeavored to develop a micromagnetic field simulation considering the dielectric constant and finite element method.

Material optimization is important to construct Mn-Fe ferrite core to reduce energy loss. However, long hours are required to optimize the material compositions of the core with a complicated composition ratio. In addition, it is difficult to judge whether the designed shape is sufficiently optimized. Metaheuristic algorithm has been widely used in various optimal design problems for its excellent global search capabilities [1]. However, it generally requires a large number of finite-element analyses for fitness evaluation, and thus it leads to a high computational cost to search for the optimal solution. To solve this problem, an artificial neural network (ANN) has been used as the surrogate model, which works much faster than FEM in some previous works [2]-[5].

2 Methods

In this paper, magnetic loss and permeability are set as the objective functions under various inductance values (lower limit) and constraints of the external dimensions and minimum coil winding space. As the operating condition of the inductor, the frequency is set to 100-300 kHz, and the average magnetic flux density in the central section of the core is set to 200 mT.

The Mn–Zn ferrite core has a complex microstructure that the crystalline grains are wrapped in thin high resistance oxide layers to suppress the eddy current. To calculate the dielectric effect, the model equations were established using an equivalent circuit on a simplified microstructure. The crystal grains, which have a high conductivity (σ_1), are separated by thin layers, which have a low conductivity (σ_2), and a dielectric constant (ε_r). These considerations were implemented in our magnetic simulator based on the finite element method using the magnetic field equations of the A-φ method with the magnetic vector potential (A) and the electric scalar potential (φ). In our analytical method, magnetic field equations can be written as

$$\sigma_1\left(\frac{\partial A}{\partial t}+\nabla V+\frac{r}{\varepsilon}q\right)+\nabla\times\left(\nabla\times\left(\frac{1}{\mu}A+\frac{c_\beta}{\mu_0}\frac{\partial A}{\partial t}\right)\right)=J_{ex}+\nabla\times M_s \tag{1}$$

$$\nabla\cdot\sigma_1\left(\frac{\partial A}{\partial t}+\nabla V+\frac{r}{\varepsilon}q\right)=0 \tag{2}$$

where L is the diameter of the grains, and the thickness of the boundary layer is D. μ_0 is permeability in the vacuum. q and J_{ex} are expressed as vectors and represent the charge density accumulated in the surface of the grain boundary and an exciting current, respectively.

In magnetic field equations, the excess loss could be occurred by microscopic magnetization process such as domain wall motion. A relation between magnetic field (H) and magnetic flux density (B) was given by the following equation,

$$H=\frac{B}{\mu}+\frac{c_\beta}{\mu_0}\frac{\partial B}{\partial t}\,. \tag{3}$$

We assumed that the effective field due to the excess loss was proportional to the time derivative of the magnetic flux density (dB/dt) and confirmed that the core losses were well estimated by introducing a coefficient of excess loss (c_β) which considers the role of the domain wall motion.

We optimize manganese–zinc (Mn–Zn) ferrite core using ANN-based surrogate models. An ANN is a field in machine learning, which mathematically models the mechanism of human nerve cells. It assumes an appropriate model between the input and output. It adjusts the parameters of the model by learning a large number of data sets to perform an accurate regression and classification. To design an ANN model, training data sets of magnetic properties and core loss were obtained from the magnetic field FE analysis in advance by combining the randomly generated material parameters of the core. For the ANN activation function, we applied the rectified linear unit, which is advantageous in terms of performance.

3 Results

To design an ANN model, 1000 data sets of ferrite core and magnetic loss were obtained from the magnetic field analysis in advance by combining the randomly generated material parameters of the core. Of the data sets obtained by the calculation, 70% were used for updating the weighting coefficient, and the remaining 30% were used for verification or evaluation. The number of intermediate layers of both NNs was set to 1, and the size of the middle layer was set to 10 after a few trials. For the ANN activation function, we applied the rectified linear unit, which is considered to be advantageous in terms of performance. As a result of the NN design, we obtained a coefficient of determinations (R2) of more than 0.999 between the magnetic simulation results and the NN results. These results show that the designed NNs can be applied as highly accurate surrogate models.

The magnetic loss is minimized by solving the optimization problem. In this paper, we solve optimization problems to obtain optimal material compositions for various Mn, Zn, and Fe values. The two optimized cases were compared for twelve experimental cases that minimized core lo under permeability conditions for optimal results. The experimental groups were selected by adjusting the material variable values of the optimal case. In addition, we changed variables for comparing the result of the objective function and constraint condition; the Mn, Zn, and Fe were changed. As a result of optimal cases, if material values were changed, the core loss of ferrite core did not reach the minimum value or could not satisfy the permeability constraint.

4 Conclusions and Contributions

We applied the surrogate models of the ANN designed based on the calculation data by magnetic simulation considering dielectric constant. This paper aims to develop an efficient design method of the material compositions of Mn-Fe ferrite cores in which the trained ANN fast solves optimization problems. By applying the ANN surrogate models in the optimization, the calculation time is significantly shortened, and the difference between the results obtained from FEM and ANN is shown sufficiently small. The ferrite core with one of the optimum material compositions is manufactured. Its measured magnetic loss and permeability are shown to be in good agreement with the simulation and ANN results (within 10%). For future works, we plan to further improve the simulation accuracy, increase the number for the parameters to be optimized, and apply this method to other devices.

Acknowledgments

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