Data-driven neural network for calculating iron loss of soft magnetic materials

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The iron loss is an important specification for SMMs and electric motor, but the grain structure and properties of new SMMs change, and there is the absence of an accurate, generalized method for calculating the iron loss. In this paper, a Data-Driven Neural Networks (DDNNs) iron loss calculation method based on Bertotti's model is proposed, which can consider the excess loss of SMMs and calculate nine coefficients of three types of iron losses based on measurement data. In order to verify the generality and accuracy of the method, tests are conducted using ultra-thin Non-Grain Oriented Electrical Steel (NGOES), NGOES with 6.5% Si content, Grain Oriented Electrical Steel (GOES) and Amorphous Magnetic Materials (AMM). The results show that the calculated and measured iron loss values for the four materials agree well with the root-mean-square error of less than 1%, which confirms the high accuracy of the proposed method.

Keywords: iron loss; data-driven neural networks; soft magnetic materials; electric motor

1. Introduction

Although the Bertotti's model can accurately simulate the core loss of silicon steel material, but it has more parameters and complicated calculation. Researchers tend to neglect the excess loss when calculating the electric motor performance by modeling the core loss of the material [1-2]. Some researchers have already realized the importance of excess losses and used the Bertotti's model to calculate iron loss, but due to the complicated parameter calculation process they only consider a few key coefficients, resulting in poor model generality [3].

2. DDNNs based on Bertotti's model and results

The DDNNs based implementation process is:

(1) Interpolate the iron loss curve of the material based on the test data. (2) Construct the neural network by taking frequency and flux density as variables, core loss as reference value, and model parameters as hyperparameters. (3) The optimization algorithm is used to find the best hyperparameters by minimizing the error between the calculated iron loss value and the measured value. (4) Finally, the hyperparameters are used as coefficients of the Bertotti model to accurately calculate and predict the iron loss of the SMMs. The computational workflow is illustrated in Figure.1.

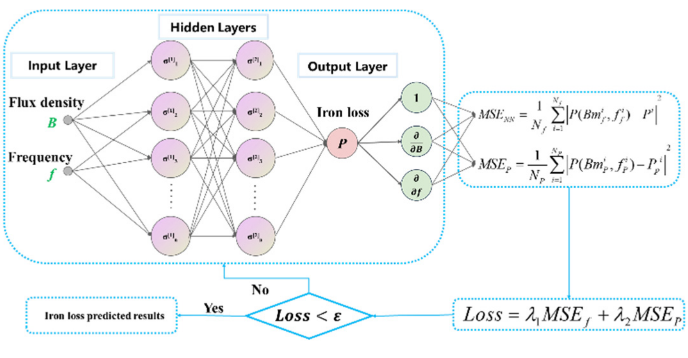

Figure. 1. Neural networks model of iron loss information.

In figure.2, a shows grade T-100, a NGOES with a thickness of 0.1 mm. Due to its thinner nature, it has a lower percentage of eddy current loss and a higher percentage of hysteresis loss and excess loss compared to conventional NGOES. The results show accurate predictions even when the proportion of iron loss components varies. Moving on to b, the material tested is 10JNEX900 with 6.5wt% Si content (0.1mm). This material has a higher percentage of excess loss, but the calculated and measured values are still in good agreement. In c the material is GOES 23R080, which is characterized by a distinct grain arrangement compared to NGOES. Despite the minimal hysteresis loss due to the regular grain arrangement, the DDNNs method still gives the expected results. The d shows an AMM, a new type of material with a thickness of 0.02 mm and no grain structure, demonstrating the continued applicability of the method proposed in this paper. In addition, the DDNNs model not only calculates iron loss from real data, but also predicts values which are difficult to measure with magnetic measuring instrumentation.

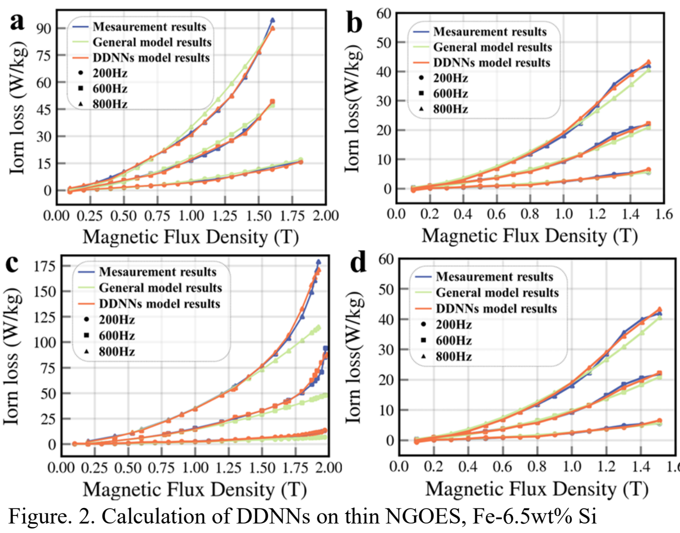

Figure. 2. Calculation of DDNNs on thin NGOES, Fe-6.5wt% Si NGOES, GOES and AMM.

References

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