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Ferrite Core Loss Prediction with Direct Data Interpolation Method

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***Abstract*-This paper proposes a direct data interpolation method for predicting ferrite core loss in power electronics. The core idea is to accurately construct the B-H loop shape given arbitrary H-field waveforms. Unlike conventional loss models like the Steinmetz equation and its variations, or recent neural network methods like MagNet that leverage periodic B-H waveforms and frequencies, this method employs a data segmentation and reconstruction process to fully exploit the distinctive features of the B-H loop under varying conditions. The source data is from Princeton University's MagNet open-source datasets.**

I. Introduction

The magnetic components used in the power electronic systems are considered to have periodic flux waveforms in the core only. Current loss prediction methodologies are all based on this concept. In some variations, such as MSE/GSE, the flux waveform and its first-order derivatives are considered, based on the theory of the domain wall shifting [1, 2] that would well cover the hysteresis and eddy current losses. A third phenomenon of residual loss [2] has been picked up in i^{2}GSE [3]. In the development of these models, most formations, especially the first principles, are from observations of empirical relationships such as power law and exponential law, whilst some are from fundamental mathematical derivations such as harmonic analysis. However, the link between mathematical models and real-world materials is never accurate and reliable. At the time being, scientists are still not capable of predicting materials' physical properties on the macroscopic scale from knowing the formation of the matter. Not to mention the difficulties in controlling production. Practical materials, despite how much care has been provided, come with matter impurities and nonuniformities. These will add uncertainty to the applicability of traditional analytical formulae for core loss predictions.

The core loss prediction problem, from a generic engineering point of view, can be modeled as a canonical function depicted in Fig. 1, where two inputs, the time-varying waveform of $\boldsymbol{B}$, and the material's properties $\boldsymbol{m}$, are taken as the input and a single scalar value P_v, the volumetric loss power, is the output. Both $\boldsymbol{B}$ and $\boldsymbol{m}$ are not simple quantities but abstractive information packs, and in any implementation of this canonical function will have to discretize or summarize them. For instance, the original Steinmetz equation

$$P_v = kf^{\alpha}\hat{B}^{\beta} \tag{1}$$

is a simplification of

$$\begin{cases} \boldsymbol{B} = \{f, \hat{B}\} \\ \boldsymbol{m} = \{k, \alpha, \beta\} \end{cases} \tag{2}$$

With the advancement of more and more powerful and inexpensive computing devices, large-scale databases and data-driven predictions are both economically and timewise viable. One of the emerging methods is neural network (NN) and deep learning solvers such as MagNet [4-7]. An NN evaluator can also be modeled as such.

$$\begin{cases} \boldsymbol{B} = \{\{B_1, t_1\}, \{B_2, t_2\}, \dots \{B_n, t_n\}\} \\ \boldsymbol{m} = \{\text{pretrained NN}\} \end{cases} \tag{3}$$

The waveform is normally represented by discrete samples over a periodic cycle, whilst the material property is the pretrained NN – where the topology and selection of activate functions are manually designed, which is not straightforward, and the behavior may be unpredictive; and the individual cells' weight vectors are trained from a wide range of sampled data.

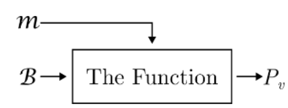

Fig. 1 The canonical function for the core loss prediction.

In [8], the authors asserted the two axioms for a plausible solution, which are adopted in this proposal:

Axiom 1: The loss must be a continuous function of parameters describing the waveform.

Axiom 2: If there are two equivalent descriptions of a waveform, calculations of loss based on either must give the same result.

Axiom 1 is difficult to strictly proven for a NN method, also can be seen from the unsmooth curves in [4]'s Fig. 17; but for axiom 2, any generic data presentation by sampling points should be naturally abiding.

This paper proposes a method that is similar to MagNet but can be formed more predictably and determined, whilst fully utilizing the sampled datasets. This results in a method that combines both the direct data interpolations and the database techniques. Data segmentation methods are used to determine the values in the database. In this paper, the methodology with detailed ideas and assumptions is described in Section II, Section III studies some cases in the Magnet datasets and shows the prediction results using the innovative data interpolation method. The conclusions are summarized in Section IV.

II. Methodology

A. Ideas and Assumptions

To accurately predict the ferrite core loss in power electronics, this paper implements a direct data interpolation method for constructing the related B-H loop shape with either arbitrary H-field or B-field waveforms. As mentioned in [4-6], the volumetric core losses per cycle can be calculated from the area enclosed by the B-H loop (energy per cycle) times the frequency, which is proportional to the integral of H(t) over B(t), or the integral of B(t) over H(t), as

$$P_v = f \oint H(B)dB = f \oint B(H)dH \quad (4)$$

For simplicity, in this paper, the arbitrary H-field waveforms are regarded as the inputs of the prediction method, since they are always plotted as the horizontal axis in the B-H loop figures.

In more detail, the direct interpolation is based on the hypothesis of dB/dH's dependence on instant B, H, dH/dt, and temperature values, which is the theoretical basis for a series of hysteresis models named history-independent models [9, 10], such as the Duhem models [11]. Therefore, the predicted B-H loops can be constructed from accumulative extracted/interpolated dB/dH values in a database built from the training data segmentation. The growth of the B-H curve may start from an initial state, but eventually will be stabilized. It should be noted that, during the whole process, there are no extrapolation considerations, which means no "prediction" data is used for the B-H curve generation.

B. The Direct Data Interpolation Method

To better describe the developed direct data interpolation method, the following three propositions shall be clarified:

Proposition 1: For a labelled material, i, e. stable formula and production, the derivative of the B field with respect to the H field is dependent on the temperature, B field value, H field value, and the derivative of the H field with respect to time.

Therefore, the fundamental knowledge of core loss in a given material is a set of the following tuple mappings, as

$$\left(T, B, H, \frac{dH}{dt}\right) \rightarrow \left(\frac{dB}{dH}\right) \quad (5)$$

Proposition 2: Accurately measured B-H waveforms can be dismantled (the training data segmentation) to provide tuple mappings and saved in a big database (referred as bDB below). The coverage of the four-dimensional parameter space contributes to the accuracy of the prediction. The envelope should enclose the testing H field waveform to be simulated.

Proposition 3: Numerical integration using the interpolated dB/dH values with respect to the B, H, and dH/dt simulates the physical development of the B field from the H field.

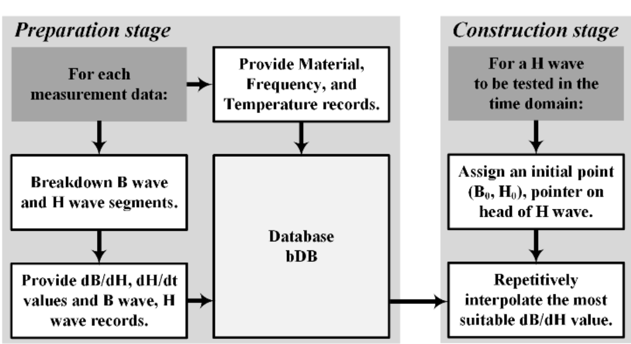

Fig. 2 The flow chart of the data interpolation method.

The flow chart of the data interpolation method is shown in Fig. 2. Overall, this method can be divided into two stages, which are the ***Preparation*** stage and the ***Construction*** stage. The steps in each stage are listed below:

***Preparation*:**

Step 0: Inputs. Material, B wave, H wave, frequency, and temperature records.

Step 1: For each record, breakdown B and H segments, and compute dB/dH and dH/dt values, and store into bDB.

Construction:

Step 0: Inputs. H waveform to be tested in the time domain, repetitive indefinitely.

Step 1: Assign an initial point (B_0, H_0), pointer on head of H waveform.

Step 2: Interpolated dB/dH value w.r.t. current (T, B, H, dH/dt) from bDB.

Step 3: Move to the next step (B, H, dH/dt).

Step 4: Go to *Step 2*, or stop after multiple complete cycles when the B-H loop is stable.

The most basic assumption in this method is that the B-H hysteresis can be piecewise constructed. Therefore, dB/dH is the critical data to be predicted. It is unclear whether it is only dependent on the T, B, H, or dH/dt values, or any combinations of them, but there is no harm to use them all. The four independent variables in equation (5) are called "coordinates", and dB/dH is the "altitudes" to be interpolated from the four dimensional "map". Because all data points are from existing measures, the behaviour should be identical to the real material. This can also be considered as a giant loop-up table (LUT).

However, the data points in most situations are neither evenly distributed, nor evenly covered along all axes. There might be some areas with extreme dense points and some else very sparse. The challenge of this method is really how to effectively extract a number of most close data points near the given coordinates, which will be discussed in the next section with the MagNet dataset analysis and time complexity.

C. Data Analysis

The source data used in this paper is from Princeton University's MagNet open-source datasets. The parameters for each data record are shown in Table I.

TABLE I
THE PARAMETERS FOR EACH DATA RECORD IN MAGNET [5]

Parameter	Data Type	Description
Material	String	Name of material
Temperature	Real	in degree Celsius
Frequency	Real	in Hz
H-Field waveform	Real[1024]	in A/m
B-Field waveform	Real[1024]	in T
P_v	Real	in W/m^3

It is worth noting that the MagNet dataset is enormous. For each of the materials, there are some 40k data records, at four temperatures, having a wide range of frequencies from 49.95kHz to 794.34kHz and various excitation current waveforms. Each record contains 1024 points, therefore, at least 1023 segments can be safely used, and that results in about 40M individual data points for one material (or about 10M points for a measured temperature). Finding the nearest n points normally requires to compute the Euclidean distance between the point and all points in the bDB. Even disregard sorting (that gives n nearest points), going through the whole bDB alone takes O(n) time, which is unacceptable.

Therefore, a method that effectively selects a range of nearest points within O(log n) time is proposed. In *Step 1* in the ***Preparation*** stage when data points are inserted into bDB, an index is inserted at the same time - a composite index of (T, B, H, and dH/dt), in a tree structure (B-Tree) where sorted and ranged queries can be executed in O(log n) time. A modern SQL database is suitable for such purpose. Also, a dynamic range with auto sizing (feedback control) is used to limit the sizes of points to be pulled out from bDB.

D. Loss Analysis

The data acquisition system for MagNet datasets is illustrated in [5]'s Fig. 3 and Fig. 4, in which the testing setup uses a gap-less circular coil with two windings. The temperature of the core is controlled with water/oil bath thermostat, and the frequency is controlled by the function generator. Then, when the core is a simple shape like a doughnut with a uniform cross-sectional area of A and an average circumference length of l, and N turns of the winding, the amplitude of the H-field wave can be projected from the current measured through the first winding (excitation), as

$$H = \frac{N}{l} I_1 \tag{6}$$

The amplitude of the B-field wave can be calculated from the integration of the voltage measured from the secondary winding (capture), as

$$B = -\frac{1}{NA}\int V_2 dt \tag{7}$$

Therefore, it can be considered that the enclosed area by B-H loop is essentially the I_1-V_2dt loop. Assume the I_2 (current in the secondary loop) is almost 0, this loss is recognized as equivalent to the total energy lost in the magnetic core, including the hysteresis loss, eddy current loss, and other losses.

III. Case Study

The measurement data of N87 material in Magnet is studied in this section, which can fully demonstrate the capabilities of the proposed direct data interpolation method for both ferrite core loss prediction and B-H curve construction. For N87 material, there are 40616 training data and 5000 validation data in total. As shown in Table I, during each B-H curve construction, there are at least 1024 interpolation steps to guarantee a complete B-H loop. Then, since in (4), the core loss is proportional to the B-H loop area, the relative error of each time core loss prediction can be defined as

$$E_{cost} = \frac{Area_{BHpred} - Area_{BH}}{Area_{BH}} \times 100\% \tag{8}$$

where $Area_{BHpred}$ is the area of the method constructed B-H loop, and $Area_{BH}$ is the area of the measured B-H loop provided by MagNet. Also, refer to the practical situation, the B-H loop construction are all start from the (0, 0) point.

A. Training Data B-H Loop Recovery

As mentioned in Section II.B, in the method ***Preparation*** stage, a database bDB is built to save all the provided information of the N87 training data, as well as their dB/dH and dH/dt values. Therefore, the direct data interpolation method is first performed on the training data itself, to demonstrate the B-H loop construction effect when having all the curve details.

Three B-H loop recovery results are shown in Fig. 3, with completely different temperature, frequency, and B-H loop shape parameters. It can be seen that, when the B-H loop details exist in the database, through the (T, B, H, dH/dt) coordinates, the interpolation method can well pinpoint the most suitable dB/dH value at each construction step, therefore the B-H loops can be completely recovered.

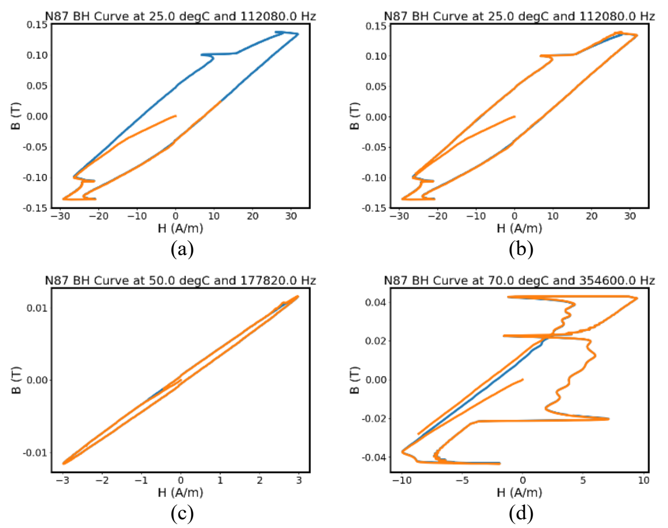

Fig. 3 The recovery results for three different B-H loops belonging to the N87 training data (blue curve represents the measured B-H loop and orange curve represents the constructed B-H loop).

B. Data Validation

Then, the data interpolation method is executed on the 5000 N87 validation data provided by MagNet. The relative error of the predicted core loss is calculated using equation (8). And the error analysis relative to temperature, frequency, and core loss are shown in Fig. 4, respectively.

For time and accuracy considerations, only 4847 out of 5000 data are considered in the core loss error analysis. All of them have finished at least 1100 steps (97% finished over 2100 steps) in three minutes (executed on a laptop having Intel(R) Core(TM) i7-10510U CPU@ 1.80 GHz, 16 GB RAM), and have a relative core loss error below 95%. The average core loss error is 19.42%. As shown in Fig. 4, the errors are uniformly distributed over temperature and frequency, but have clear distribution characteristics relative to core losses: the validation data with lower core losses are more likely to have larger core loss errors.

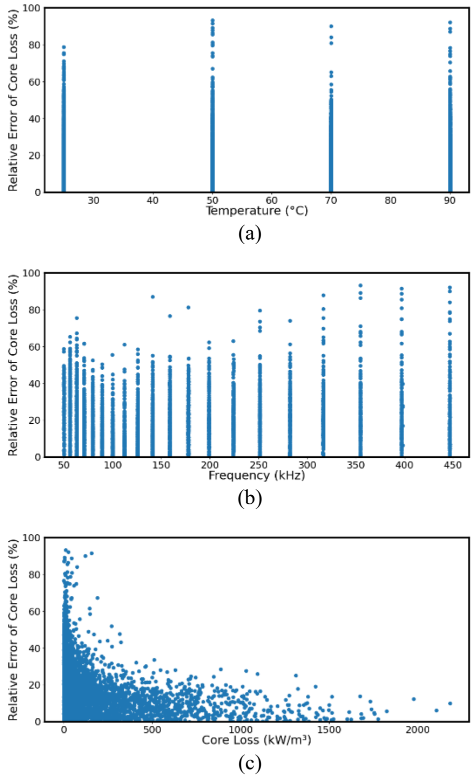

Fig. 4 The relative core loss error analysis relative to (a). temperature, (b). frequency, and (c). core loss.

In more detail, four B-H loop construction results are shown in Fig. 5, with different relative core loss errors. From the smallest to the largest, Fig. 5 (a) (b), (c) (d), (e) (f), (g) (h) show the B-H loops with predicted core loss errors of 1.92%, 12.31%, 24.61%, and 44.83%, respectively. It can be seen that, the core loss error mainly comes from the misalignment of certain envelope segments between the constructed B-H curve and the measured one. Meanwhile, when the B-H loop area is small (the core loss is small) but the envelope misalignment is obvious, the error can become quite large. This is consistent with the error analysis results in Fig. 4.

C. Discussion

During the B-H loop construction, there are two phenomena that need to be discussed. The first phenomenon is shown in Fig. 6, where the constructed curve collapses at the B-H loop's upper edge. This is because at this edge, the theoretical dB/dH value shall be 0. However, in the bDB database, the dB/dH values at this edge which are calculated from the measured training data can have both negative and positive values. Therefore, if there is a large H segment, the B value can then have an obvious change. This discussion is also suitable for the B-H loop's lower edge.

The second phenomenon is shown in Fig. 7, where the constructed curve fails to track the envelope of the B-H loop. This is because there is no required data in the bDB database. As mentioned in Section II.A, in this method, no "prediction" data is used for B-H loop construction.

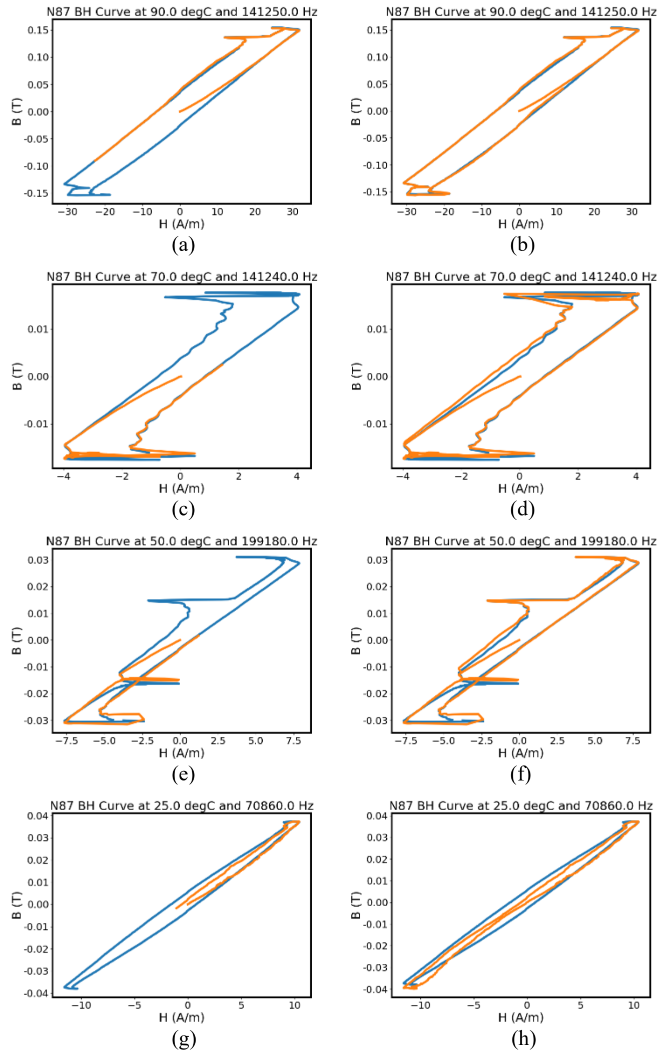

Fig. 5 Four B-H loop construction results with different relative core loss errors. (a) and (b). 1.92%, (c) and (d). 12.31%, (e) and (f). 24.61%, (g) and (h). 44.83%.

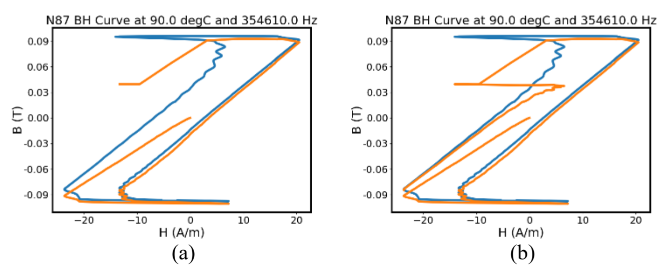

Fig. 6 The first phenomenon: the constructed curve collapses at the B-H loop's upper edge.

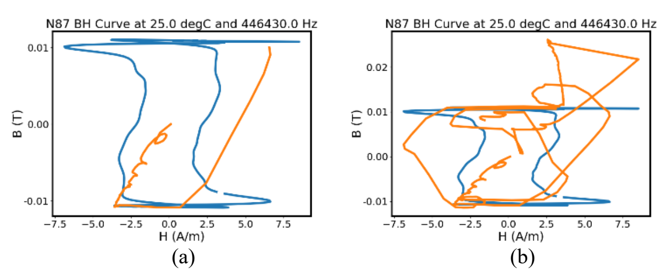

Fig. 7 The second phenomenon: the constructed curve fails to track the envelope of the B-H loop.

IV. Conclusion

A direct data interpolation method is proposed in this paper to predict the ferrite core loss in power electronics, which is based on the accurate construction of the B-H loop shape given arbitrary H-field waveform. Through using Princeton University's open-source MagNet datasets, the data interpolation method is both verified on the N87 material training datasets and validation datasets, and shows good ferrite core loss prediction results under different frequency, temperature, and B-H loop shape conditions.

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