
Publisher's PDF, also known as Version of record

License (if available):
CC BY

Link to published version (if available):
10.1109/OJPEL.2022.3223936

Link to publication record in Explore Bristol Research
PDF-document

This is the final published version of the article (version of record). It first appeared online via IEEE at https://doi.org/10.1109/OJPEL.2022.3223936. Please refer to any applicable terms of use of the publisher.

**University of Bristol - Explore Bristol Research**

**General rights**

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available: http://www.bristol.ac.uk/red/research-policy/pure/user-guides/ebr-terms/
Artificial Neural Network Aided Loss Maps for Inductors and Transformers

Navid Rasekh, Student Member, IEEE, Jun Wang, Member, IEEE, Xibo Yuan, Senior Member, IEEE

Abstract—The non-linear property of magnetics poses challenges for their loss modelling in power electronics due to lacking full physical models. As a practical approach for their loss estimation, the manufacturers can pre-measure the losses in standalone rigs and distribute the "loss maps" as interpolated look-up tables/curves for the end users. However, with more factors discovered that impact the losses, e.g., DC bias and load conditions, the dimensions of the loss maps cannot be solved by conventional surface/curve fitting methods. This paper addresses this problem by applying the Artificial Neural Network (ANN). For both inductors and transformers, Neural Network-aided loss maps (NNALMs) are designed and evaluated with comparisons against conventional loss maps to reveal the limitations of the latter caused by physically intercoupled input variables. The NNALMs not only show superior accuracy throughout the whole datasets, but also enable the loss maps to expand the dimensions to account for more factors (e.g., load conditions in transformers) and generate multiple outputs (e.g., both the winding loss and core loss). The ANN-aided loss maps can be distributed as digitized datasets of standardized magnets, enabling rapid, accurate and user-friendly loss estimations for power electronics engineers.

Index Terms — Artificial Neural Network (ANN), Machine Learning, Loss Map, Inductor, High-Frequency (HF) Transformer.

I. INTRODUCTION

Nearly all power electronics applications involve magnetic components for functionality and filtering purposes. As one of the dominant components in size, weight and power losses, magnetics significantly impact the performance of power converters [1-4]. However, there is no satisfactory first-principle model for core loss in a magnetic component due to the non-linear core loss mechanisms and the intercoupled factors involved, such as the DC bias [5-12]. In addition, similar to the core loss, the winding loss also partly shares the nonlinearity due to the field interactions with the core and complex geometries, which can hardly be captured by the traditional equation-based methods [13-14].

While research on non-sinusoidal waves has been extensively studied in recent years, the most widely used core loss models/datasets are still based-on sinusoidal excitations and simplified operating conditions (e.g., ignoring DC bias) [15-18]. However, the majority of high-frequency magnetics in power converters do not operate with a low-distortion sinusoidal waveform, zero DC bias or room temperature. Therefore, the limited curves and data in a common manufacturer's datasheet cannot factor in all these variables, although some exist models for calculating core losses that factor in temperature based on manufacturer data [19]. Meanwhile, the loss and electromagnetic properties in magnetic materials can vary due to variations in frequency, flux density, DC bias, temperature, and the shape of the excitation waveform, and it is very challenging to measure, store and share all these factors in a manufacturer datasheet [5-6], [14-18]. Moreover, geometry-related, component-specific loss mechanisms, such as the gap losses [3], cannot be reflected in the existing datasheets based on materials.

Numerous research efforts have been made to factor in the additional variables contributing to magnetic losses. For example, [4] proposes to draw the Steinmetz pre-magnetization graphs (SPGs) to reflect the variation of Steinmetz parameters against DC bias levels for core loss. However, this approach does not solve the fitting problem, given that these graphs have no applicable fitting expressions. Moreover, this approach is still limited by the frequency dependency of the original Steinmetz parameters [1] and the dependency on the geometries of individual components (e.g., gap losses [3], ununiform flux distribution [20] and fringing flux effect [21]). To consider the shape of waveforms, an improved generalized Steinmetz equation (iGSE) is proposed in [1], but it cannot solve the non-linear frequency-dependent Steinmetz parameters or the DC bias effect. To consider the gap losses, [3] also proposes to modify the Steinmetz parameters, but it shares the same limitations. In [5] and [8], while the DC bias effect is included, the dB/dt and frequency factors are considered independent factors as a simplification to reduce the dimensions and enable fitting, while in fact, these factors are intercoupled with other variables, i.e. \( H_0 \) and \( \Delta B \).

To address all the above challenges, shifting from material-based to component-based datasets based on empirical measurements is necessary, especially given the growing popularity of standardized magnetics. Subsequently, for the end users to utilize these measurements, it is crucial to realize standardized loss maps with unified frameworks considering multiple inputs (e.g., dB/dt, \( H_0 \), \( \Delta B \), power factor) and outputs (e.g., core loss, winding loss). For this purpose, machine learning has been proven highly effective in solving non-linear multivariable classification and regression problems, especially with Neural Networks (NN) [22-23]. Modelling and designing magnetics in power electronics with the aid of machine learning have been approached in many different ways [15-18], [24-28].

For example, the MagNet projects in [15-18] intend to support data-driven magnetic research using machine learning and neural networks. MagNet stores large quantities of core loss data for many materials measured experimentally under different operating conditions. The input of the MagNet neural network is frequency, voltage/flux-density, duty cycle (single-value), and temperature, and the output is core loss per volume [15-17]. The voltage and flux density (B) inputs are in the form of time sequence waveforms in three shapes, i.e. sinusoidal, triangular, and symmetric trapezoidal. However, the particular challenge in the case of inductor core loss is caused by the PWM operations in DC/AC converters, which involve varying pre-magnetization (\( H_0 \)) and varying pulse widths (duty cycle) [5-7]. As a result, the MagNet NN can only solve the problems in limited cases, e.g., only DC/DC converters with a fixed single duty cycle and \( H_0 \) rather than PWM AC/DC converters.

Moreover, with the composite waveform hypothesis (CWH) [5-7] considered a proven approach to breakdown PWM waveforms and estimating the core loss on a switching cycle basis, the required core loss data only needs to be measured with symmetric 50-50 duty cycle, and there is no need to embed duty cycle as an input variable in the magnetic loss maps. In [18], the input of the NN is a sequence of B (\( \tau \)), temperature, and frequency, and the output is magnetic field intensity, H (\( \tau \)), instead of the core loss per volume. The trained NN obtains the B-H loop and then computes the core loss. The problem with this method, however, is that it might not be suitable to model B-H loops because of its...
extreme phase sensitivity between the measured and predicted $H (t)$, as the relative core loss error due to the phase discrepancy can be very high and reach 200% and above. The shift error for this work does not relate to the core material and is separate from the phase discrepancy caused by the parasitic inductance of the current sensors, e.g., the current probes. Instead, phase shift here refers to the mismatch between the predicted $H (t)$ and the actual one that can be measured from the experiment.

This paper aims to construct loss maps for magnetic components, given the challenge that multiple inputs and outputs are involved in the loss map, where conventional curves and formulas in the device datasheet are not sufficient to express the non-linear relationships with multiple variables. As a contribution, this work implements and evaluates NN to solve the fitting problem in magnetic loss maps, which has a unified framework and expandability for additional input/output variables. In addition, by comparisons, this study reveals significant errors in the conventional core loss maps due to the oversimplification of intercoupled variables as limited by allowable dimensions. The proposed NN-aided loss map (NNALM) is superior and more user-friendly than the equation-based loss models. Beyond the core loss, this work also extends the loss maps to include winding and total losses as the output and an extended range of interlinked inputs (e.g., temperature, load conditions, etc.) as an engineering solution to provide rapid, accurate and complete loss estimations of individual magnetic components. The proposed NNALM estimation model is for already designed inductors and transformers, which is helpful for magnetic component sellers and power electronics designers rather than for magnetics designers. This paper builds on the authors' previous work on accurate core loss and winding loss measurement and estimation for inductors and high-frequency (HF) transformers [5-7], [11-14].

In the following, Section II describes the conventional and component-based loss maps and their limitations in estimating the loss. Sections III and IV present the NN user-friendly loss map for the inductors and HF transformers, respectively, and compare the results with the traditional loss prediction method. This work's practical implementation is also explained in Section V.

II. CORE LOSS MAP APPROACH AND LIMITATIONS

A. Conventional Loss Map

In empirical core loss models, frequency ($f$) and flux density swing ($\Delta B$) are essential factors in determining the core loss. The Steinmetz equation (SE) is widely accepted as an empirically based model for core loss [5] as

$$P_{\text{Core}} = k f^\alpha \Delta B^\beta$$  

(1)

The Steinmetz parameters, $k$, $\alpha$, and $\beta$, are obtained by curve fitting. The SE is, however, limited in accuracy, as the coefficients are only accurate within a specific range of frequencies [2]. Additionally, the SE only applies to sinusoidal excitations, meaning it cannot be directly applied to magnetics driven by other excitations, such as PWM. To solve this problem, the improved generalized Steinmetz equation (iGSE) was developed for calculating any arbitrary flux waveform's loss [1] as ($T$ is the period of one cycle)

$$P_{\text{Core}} = \frac{1}{T} \int_0^{T} k_{i} (\frac{dB}{dt})^\alpha (\Delta B)^{\beta-\alpha} \, dt$$  

(2)

With iGSE, SE parameters are converted from sinusoidal to rectangular excitation. iGSE works by breaking down a complex waveform into individual $B$-$H$ loops. In addition to being widely accepted and proven accurate, the iGSE does not take into account pre-magnetization effects [4].

"Loss map" is an approach proposed in [8] for incorporating DC bias current ($I_b$) effects. Using experimental $B$-$H$ loop measurements, a core loss profile can be constructed covering various magnetic components' operating points [9]. As a result, symmetric square-wave excitation of a closed $B$-$H$ loop is described by three variables, i.e., $H_0$, $\Delta B$, and flux density change rate $|dB/dt|$, without considering the operating temperature. In repetitive symmetric excitation, $|dB/dt|$ can be converted to $f$ [10]. It is, however, more appropriate to refer to this variable as $|dB/dt|$ rather than the frequency for an instant on the $B$-$H$ trajectory. Besides, in power electronics, $|dB/dt|$ is proportional to the square-wave voltage amplitude applied to the magnet component [5]. A loss map, or a database of core loss, are therefore functions of these three variables, as follows:

$$P_{\text{Core}} = F_i (|dB/dt|, (\Delta B), H_0)$$  

(3)

Loss maps generated from finite discrete measurements can be used as look-up tables with interpolations or fitted curves/surfaces [5-10]. In these references, the assumption is that the core loss is correlated $|dB/dt|$ independently of the other two variables (which is not accurate, as will be explained later) and is expressed as similar to iGSE [4], i.e. $P_{\text{Core}} \propto (|dB/dt|)^\alpha$. To specify the coefficient $\alpha$, the factor $dB/dt$ can be determined independently by only one data set (fixed $\Delta B$ and $H_0$). Hence, the loss map is simplified by one dimension. Other variables, $\Delta B$ and $H_0$, affect the core loss in a coupled manner. In view of this, a set of datasets covering the possible operating region of interest formed by various $\Delta B$ and $H_0$ are to be assessed as follows, given a fixed $|dB/dt|$ [5].

$$P_{\text{Core}} = \left( (\frac{|dB|}{dt})^\alpha, \right) \cdot F_2 (\Delta B, H_0)$$  

(4)

To establish the loss maps in this paper, the magnetic structure is excited with a bidirectional half-bridge structure that has been presented in previous studies [5-7], [11-14]. Also, a refined discontinuous test procedure as a triple pulse test (TPT) is performed, offered in [5-6]. Fig. 1 and Table I illustrate the utilized experimental test rig and power circuit built in the form of a two-
winding method for measuring magnetic component's loss using high-bandwidth voltage and current probes. The measured sensed voltage ($V_{\text{Sense}}$) and excitation current ($I_{\text{exc}}$) data are then processed in MATLAB as the following expression for the core loss calculation.

$$P_{\text{Core}} = \frac{N_1}{N_2} \int_0^T I_{\text{exc}}(t) \cdot V_{\text{Sense}}(t) \, dt$$  \hspace{1cm} (5)

$N_1$ and $N_2$ are the numbers of the primary and secondary winding turn, respectively. In the later sections, winding and total losses will also be measured using the methods in [13-14]. In order to reduce phase discrepancy error for measuring the core loss and total loss, the voltage/current probe is aligned using Keysight U1880A deskew tool and calibrated on the oscilloscope with the deskew function. As previously evaluated in [11], the deskew method has acceptable accuracy in the broad frequency range by less than a 5% error. Also, the winding loss results are measured by the methods in [13-14], which are immune to the phase discrepancy error, using the reactive voltage cancellation method.

### Table I: Components and Instruments in the Test Rig

<table>
<thead>
<tr>
<th>Power Supplies</th>
<th>Elektro-Automatik TS 8000 T</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage Probe</td>
<td>Keysight N2862B (150 MHz)</td>
</tr>
<tr>
<td>Differential Probe</td>
<td>Pico TA041 (25 MHz)</td>
</tr>
<tr>
<td>Current Probe</td>
<td>Keysight N27838B (100 MHz)</td>
</tr>
<tr>
<td>Power Device</td>
<td>SiC MOSFET C3M0032120D</td>
</tr>
<tr>
<td>Digital Oscilloscope</td>
<td>MSO-X 3054A (500 MHz, 4 GSa/s)</td>
</tr>
<tr>
<td>DC-Link Capacitance</td>
<td>2025 μF</td>
</tr>
<tr>
<td>Tested Component</td>
<td>92 μH, T184-26, Micrometals©, N1:N2=24:24</td>
</tr>
</tbody>
</table>

Two steps are involved in the loss mapping process. Keeping $|dB/dt|$ constant, various $\Delta B$ and $H_0$ operating points are tested as a first step. Fig. 2 (a) shows the results as a surface interpolated using Thin-plate splines in MATLAB. For fitting surfaces, the Thin-plate Splines method is one of the most powerful approaches in MATLAB. For the results in Fig. 2 (a), the R-square is equal to 1. R-square can take on any value between 0 and 1, with a value closer to 1 indicating that the model accounts for a greater proportion of variance. Also, the sum of squares due to error (SSE) is equal to $4.942 \times 10^{-22}$. An SSE value closer to 0 indicates that the model has a smaller random error component and that the fit will be more useful for prediction. These results are shown that the utilized surface fitting method is highly accurate. Besides, the results indicate that it is challenging to fit a generalized expression to $\Delta B$, $H_0$, and the core loss and problematic to visualize in a datasheet component’s loss profile.

The second step is constructing a set of points with constants $\Delta B$ and $H_0$ and varying $|dB/dt|$. Based on this set of data, curve fitting is performed to define parameter $\alpha$ in (4). As seen from Fig. 2 (b), the measured data are well fitted to a function with exponential growth. The core loss in Fig. 2 (b) is normalized to 11100 T/s (50 V), as the testing voltage and $|dB/dt|$ for Fig. 2 (a) are ±50 V and 11100 T/s, respectively. In summary, the core loss can be obtained from a loss map in two steps: 1) find the energy using $\Delta B$ and $H_0$ in Fig. 2 (a), and 2) scale the energy to the testing voltage using $|dB/dt|$ in Fig. 2 (b).

### B. Component-Based (rather than Material-Based) Loss Map

A precise and convenient loss map can be attained if the loss data is captured from the same core material, shape, and winding arrangement of the aim magnetic device (component-based), as explained previously in [5-6], [14], in contrast to conventional material-based loss maps. This is because, with the same core/winding material, each component built can have different characteristics, e.g., the core gap loss cannot be captured by the material-based dataset. In addition, in power electronics, it is common to use electrical and time-domain variables as opposed to magnetic variables in the loss map. The translation between these variables complicates calculating core losses and loss mapping. Additionally, due to manufacturing tolerances, magnetic components have batch-to-batch variations on their geometries/characteristics, which can subsequently lead to slight loss variations.

In order to simplify core loss estimation and to facilitate a straightforward loss map procedure, a method has been developed in [5] that relies solely on time-domain and electrical variables, replacing the conventional magnetic variables. Using the user-friendly loss map, one operating cycle of a magnetic component can be characterized by three variables: primary voltage ($V_{\text{pri}}$ as $dB/dt$), volt-second product ($V_{\text{pri}} \cdot T$ as $\Delta B$), and DC bias current ($I_0$ as $H_0$). This allows the loss map to be expressed as (6)

$$P_{\text{Core}} = F_3(V_{\text{pri}}, V_{\text{pri}} \cdot T, I_0)$$  \hspace{1cm} (6)

Compared to the magnetic-domain loss map shown in Fig (2), this loss map will not only simplify core loss calculation, but also simplify the loss mapping process that only needs to include the 50% duty cycle with the CWH approach [7]. Using the user-friendly loss map with an aimed operating point, the TPT's electrical and time-domain parameters (pulse width and height) can be derived directly without having to translate from magnetic to electrical domains. This idea is to have a component-based loss map - the tested component should be identical (or at least representative regarding physical structure) to the component to be predicted. This loss map can be a practical idea of what new loss datasheets will look like for the pre-characterized inductors/HF-transformers, analogous to the commercial switching devices' loss data [5-6], [14].

Similar to the core loss, the winding loss characteristic is subject to the large-signal level, as investigated in [13] and [14]. Also, the measured winding AC resistance is found to be correlated with the load level/feature in HF transformers. Hence, on the condition that the experimental measurement carries out on
the specific magnetic component design, and to simplify/improve
the loss extraction process, the measured winding loss, together
with the core loss (total loss), can be distributed in the form of a
user-friendly loss map [6, 14]. As a result, these three variables
also describe the winding loss. DC winding loss can be expressed
with $I_p$. Another two variables as $V_{pri}$ and $V_{ph}$, $F$, demonstrate
individual square excitation and the waveform of current flowing
in a magnetic component, which indicates the ac loss of winding.

C. Limitations

Using the loss map approach developed in previous studies in
practice is not straightforward. It is impossible to provide all
potential scenarios designers may have to deal with in classical
datasheets for magnetic materials. To begin with, a conventional
loss map is usually offered and used as a three-dimensional look-
up table presented in a datasheet [8-10]. Although it will be more
feasible for manufacturers to print the energy loss suggested in [5]
against electrical parameters on datasheets, neither the user nor
the loss map can accurately interpret or cover the full range of possible
data points.

Furthermore, the loss map has limitations regarding the number of variables and how they should be displayed. A datasheet cannot accurately predict the behaviour of magnetic materials under sophisticated operating conditions [18]. Aside from the three variables in the loss map, some other parameters, such as the temperature, also affect the loss value. Besides, when it comes to HF transformers or coupled inductors, the load's type/value, as well as the power factor, contribute to the core and
winding losses [12, 14]. Thus, the parameters will be increased from 3 to 6 as voltage, frequency, DC bias current, temperature, load impedance, and power factor. This detailed loss map cannot be displayed in a graph or look-up table like Fig. 2 in datasheets, and the loss cannot be easily read and obtained by curve/surface fitting.

To show the difference between the most conventional model
and the TPT measurement, the core loss is calculated based on
the magnetic core’s datasheet and compared with measurement results
in Fig.3. The conventional datasheet, such as the one used in [29]
provides a core loss formula based on the sinusoidal excitation
with two input variables: peak flux density and frequency. Also,
the peak flux density should be calculated with a separate equation
based on the excitation voltage, frequency, and magnetic core
properties, i.e. winding number of turns and core cross-sectional
area. This method ignores the DC bias effect and the difference
between sinusoidal and rectangular waveforms. The result reveals
that the datasheet core loss differs significantly from the measured
ones. Increasing the DC bias current increases the error since the
conventional datasheets cannot account for the DC bias effect.
Therefore, as also stated in [4-5], traditional loss datasheets and
methods based on sinusoidal excitation are unreliable tools for
predicting square voltage excitations with DC biases.

![Fig. 4. "dB/dt" scaling models - core loss versus dB/dt and various fixed conditions of ΔB and H0.](image)

As another important limitation in conventional-fitting-based
loss map, Fig. 4 shows that the loss scaling over [dB/dt] is
correlated to the other two variables, which means the three
variables ($H_0$, $ΔB$, and $dB/dt$) are physically intercoupled with
each other. This demonstrates that the conventional loss map
approach ([4],[5]) made an oversimplification to consider the
$dB/dt$ as an independent variable, as in (4) and (6). The four
models shown in Fig.4 are later applied in Section III as examples.

This work aims to overcome these limitations by implementing
neural networks in a user-friendly digital loss map. NNALM can
resolve the problem related to the different and multiple input and
output parameters. NNALM is, therefore, superior to conventional
surface/curve fitting that is prone to error and difficult to display
in datasheets. NN files, which are only a few kilobytes in size, only
need to be trained and provided by the manufacturers to the user
for each magnetic component in a user-friendly loss map format.
The NNALM for inductors and HF transformers will be discussed in
the next two sections, along with the error regarding conventional
loss maps compared to the NNALM.

III. NN AIDED INDUCTOR LOSS MAP

This Section introduces the neural network structure used in
the user-friendly loss map for inductors. A comparison is then
made between the NNALM and the conventional loss maps for the
core loss of the inductors.

A. NNALM Structure

The neural network is the most commonly used
and straightforward method for solving multi-variable non-linear
regression problems [15-18]. Magnetic components can be
designed/modelled more effortlessly with NNs, which have
proven effective in solving problems where precise physical
understanding does not exist [24-28]. This part uses an NNALM
to develop and digitalize a user-friendly loss map model for
inductors. An example of a 5-layer NNALM is shown in Fig. 5.
Specifically, this network has one input layer, one output layer,
and three hidden layers. As a result of using a user-friendly loss
map, the input layer has four input variables: the inductor primary
voltage, excitation frequency, DC bias current, and temperature.
Three parameters are included in the output layer: core loss,
winding loss, and total loss, which can be in different units like
Joule or Watt. The total loss can be obtained simply by summing
the core and winding losses or using the direct total loss approach
using the two-winding method and primary voltage [14]. NNALM
with a total loss is an accelerated option for the power electronics
designers to know the entire loss of the magnetic components
when the separated loss is not of interest.

The hidden layers contain multiple neurons, and the number
of layers and neurons in the hidden part should be optimized. It has
to be noted that the choice of the ANN structure is not unique, and

![Fig. 3. Error of core loss calculated from datasheet against measurement results.](image)
many different structures may give good performances. Also, regarding the number of layers and neurons, there is no general principle to determine their exact numbers [24]. A trade-off between network size and performance needs to be considered when determining the number of neurons in each hidden layer [15-18], [22-28]. A small network may have limited learning capability and cannot provide good predictions, while a large network is more prone to overfitting. ANN designers often use trial and error to find the best performance for their system, which has also been done in this work [24]. Using the trained NN, the user can attain the magnetic component losses based on input parameters. For an accurate NN to be trained, it is essential to have a considerable amount of reliable data, particularly data collected under different conditions. Initially, a large dataset of measurements is collected, and then core and winding losses are calculated, as the data acquisition part described in Section II-A. The NN is trained using these data, and its structure and parameters are saved when the training is complete. The NN can finally be used directly to predict losses for user-defined inputs.

This work uses the built-in MATLAB neural network Toolbox as a NN engine. The NN is designed as a two-layer feedforward network with 15 sigmoid hidden neurons and linear output neurons, which is suitable for regression tasks [25], [30]. Based on the results in the following, a 15-neuron structure per hidden layer is a good balance between performance and computational cost in this work. It is worth mentioning that the use of shallow neural networks may not pose a challenge regarding computational cost. Consequently, overfitting could serve as a better criterion for the network scale of the shallow NN with only one hidden layer. The Toolbox training process determines the weights and biases of the NN automatically. Three subsets are randomly selected from the entire dataset: a training set (70%), a validation set (20%), and a test set (10%). A Levenberg-Marquardt backpropagation algorithm with mean square error as a metric is employed for the training algorithm. To determine if overfitting is occurring, the error metrics of the training and validation subsets are compared in the Toolbox automatically.

For the inductor case, the dataset includes 75 core losses, 75 winding losses, and 75 total losses; in different excitation voltages, frequencies and DC bias currents. Due to the short testing transition (e.g., < 100 μs) of each run, the temperature in the TPT does not cause a temperature rise in the testing. Therefore, all experiments in this paper are conducted at room temperature (e.g., T = 25 °C). Although the temperature is not evaluated as a variable in this work, the ANN-aided loss map can include the temperature effects as one additional input variable, given it can change the loss significantly [15-18]. Though, adding the temperature to the conventional loss maps as one additional dimension is difficult due to the limitation of fitting – in this sense, only ANN-aided loss maps can facilitate this one extra variable considering the possibility that it could be coupled with other variables due to cores' nonlinearity. As a result, the NNALM can include the temperature factor if needed, as indicated in Fig. 5.

Fig. 6 depicts the predicted NNALM results and measured loss for the inductor case. The results demonstrate a solid alignment of the data points around the reference target (Predicted = Measured, \( Y_{\text{NNALM}} = X_{\text{NNALM}} \)). Although the test set is not large and the NNALM results can be improved by enhancing the database, the predicted value has demonstrated acceptable and consistent accuracy. Also, Fig. 7 shows the histogram, a graphical representation of data points and the relative error between the predicted NN and reference values.

Figs. 8 (a-c) compares the NN predicted and measured losses of the inductor core, winding, and total, in different \( \Delta B \) values. In Fig. 8 (a-c), the voltage is selected as 25 V, 50 V, and 75 V, and the frequency is selected as 10 kHz, 15 kHz, 20 kHz, 50 kHz, and 100 kHz. DC bias current in these circumstances is 0 A, 5 A, 10 A, 15 A, and 20 A; therefore, each loss in Fig. 8 has 75 data points. As the \( \Delta B \) is proportional to the inductor voltage and frequency, the data points are scattered, similar to those shown in Fig. 8 (a-c). Results from the neural network demonstrate that it can achieve comparable results to TPT measurements and effectively trace the results. For quantitative analysis of loss prediction accuracy, the relative error between measured losses and predicted losses is calculated as follows and depicted in Fig. 8 (d) for each sample:

\[
\text{Loss Error} \%(\text{predicted}) = \left( \frac{P_{\text{Measured}} - P_{\text{Predicted}}}{P_{\text{Measured}}} \right) \times 100
\]
According to (7), the calculated error can be negative when NNALM predicts a loss that is more than the measured value. Thus, the average error should be calculated using the absolute value of the relative errors. Despite a few data points with errors exceeding 50%, for the core loss, winding loss, and total loss sets, the average relative error (ARE) is 8.32%, 10.14%, and 6.61%, respectively. Hence, the average relative error is within 10% in all three cases.

B. Core Loss Map Comparison

In this part, the results of the inductor NNALM and conventional loss map are compared in various conditions. In the first case, the excitation frequency and DC bias current are fixed to 35 kHz and 0 A, respectively, and the voltage/flux density varies. In this Section, neither the NNALM nor the conventional loss map (surface fitting method) does not include the target test data, so the results should be entirely predicted. Based on the conventional loss map proposed in Fig. 2 and the NNALM results, Fig. 9 illustrates the core loss comparison for the inductor when the curve fitted of core loss versus $dB/dt$ fixed at $\Delta B = 46$ mT and $H_s = 0$ A/m (Model 1).

According to Fig. 9 (b), the calculated error between the reference measured value and the NNALM is much lesser than the surface fitting method, especially in the lower $\Delta B$. Although the data in lower $\Delta B$s are more in number in Fig. 2 (a) compared to the higher $\Delta B$s in the surface fitting, the average error value for the NNALM is around 8.31%; however, the conventional loss map is about 53.70%. Since the core loss is much smaller in the lower $\Delta B$s, surface fitting cannot provide an accurate prediction in this area of the loss map, and only a slight discrepancy can make a considerable error.

Applying the different four models shown in Fig. 4 to factor in $dB/dt$, Fig. 10 displays the core loss results and the calculated error against the reference measured value for each case. As described previously in Section II-C and depicted here, the core loss is closely related to all three parameters in the conventional loss map, and the results are significantly affected by the different core loss scaling models versus $dB/dt$ curves. In comparison to NNALM, this is one of the main disadvantages of the surface fitting. For better comparisons, it is helpful to note that NNALM results are close to measurement results in Fig. 10, as demonstrated before in Fig. 9 (a).

In the next case, the excitation frequency and DC bias current increase to 75 kHz and 2 A, respectively, and the voltage/flux density varies. Fig. 11 shows the core loss results, the error difference between the two methods and the reference value.

Similar to Fig. 9, the error between the reference measured value and the NNALM is lower than the surface fitting method. The average error value for the NNALM is around 9.45%, and the conventional loss map is about 50.86%. Fig. 12 displays the core loss of the measurement and the conventional loss map methods when using different fitted curves for the core loss versus $dB/dt$ curves; and the calculated error between the reference measurement value and various surface fitting results. The average error value for the various curves in Fig. 12 (b), from black to
green, is around 50.8%, 48.4%, 60.8%, and 58.2%, which confirms that different curves resulted in varying accuracy levels in conventional loss maps.

In the following case, the excitation voltage and DC bias current are fixed to 100 V and 0 A, respectively, and the excitation frequency/flux density varies. A comparison of different methods and the reference value is shown in Fig. 13. The error between the reference measured value and the NNALM is lower than the surface fitting method, similar to the results in Figs. 9 and 11. The average error value for the NNALM is around 9.88%, and the conventional loss map is about 65.07%. Similarly to the previous results, error increases when $\Delta B$, as well as the core loss, is decreased in the conventional loss map method.

**C. Summary**

As the results show, surface fitting is incapable of predicting the loss with precision in different situations, especially where the core loss is small and can be significantly changed by a minor wrong prediction. In addition, the obtained loss is remarkably
changed with the conventional loss map method by selecting different fixed sets of $\Delta B$ and $H_0$ for the fitted curve, similar to Fig. 4. This difficulty has therefore been addressed using the NNALM. In every tested case, NNAML could trace the measured loss accurately and predict it, resulting in an average error of less than 10%. By enhancing the database, both the conventional loss map and the NNALM methods can be improved, but the curve fitting problem for the loss map cannot be solved since the core loss parameters are interconnected. Furthermore, even other parameters like temperature can change these fitted curves. Therefore, NNAML can be more practical for estimating the loss, which is easier to be used by the user with the user-friendly loss map inputs. In this way, power electronics designers will no longer have to spend hours extracting and extrapolating parameters from datasheets prone to accessibility or clarity issues.

### IV. NN AIDED HF TRANSFORMER LOSS MAP

NNALM for HF transformers is introduced in this Section, where a greater number of input parameters should be included to ensure accuracy, which is beyond the capabilities of conventional models. Besides the four input variables in the loss map, some other parameters also affect the loss value. In addition to the temperature, the load condition can affect HF transformers’ core and winding losses [12], [14]. Different load conditions change the primary and secondary currents’ amplitude and power factor, resulting in changes in the loss. Hence, it is crucial to include more input parameters in the NNALM than previously proposed ones.

Both the magnitude and phase of the load impedance can affect the loss. There are different ways in which load impedance can be incorporated into the NNALM, depending on the loss map creators or applications of the HF transformer. The impedance magnitude can be expressed with the ohm unit, and the impedance phase can be characterized by the load power factor, as used in this work for input variables. Depending on the application, for example, if the load is in inductive form, the inductance in H or inductive reactance in ohm can be included instead of the power factor in the NNALM for simplification, besides the impedance resistive magnitude. This allows the user to obtain accurate loss values by adding load information, such as magnitude in ohm, alongside the power factor to the NNALM.

As an example, a 5-layer HF transformer NNALM is shown in Fig. 15, with six inputs, three outputs, and three hidden layers. Similar to the inductor NNALM, the NN is designed as a two-layer feedforward network with 15 sigmoid hidden neurons and linear output neurons. A total of three subsets of the dataset are chosen randomly: a training set (70%), a validation set (20%), and a test set (10%). The training algorithm employs Levenberg-Marquardt backpropagation with mean square error as a metric. For the HF transformer case, the dataset includes 375 core losses, 375 winding losses, and 375 total losses; in different excitation voltages, frequencies, DC bias currents, and load conditions. Due to the TPT, all dataset temperatures are at $T = 25\, ^\circ C$ and have the same environment temperature, which means the thermal effects have not been included in this NNALM. Moreover, if the no-load condition for the input values is selected, the transformers NNALM can also be used for the inductor cases as well.

Fig. 16 depicts the predicted NNALM results and measured loss for the transformer case. The results demonstrate a satisfactory alignment of the data points around the reference target ($\text{Predicted} = \text{Measured}$, $Y_{\text{Axis}} = X_{\text{Axis}}$). Additionally, Fig. 17 shows the graphical representation of data points and the relative error between the predicted NN and reference values.

Fig. 15. An example of NNALM structure for the HF transformers with six inputs, three outputs, and three hidden layers.

Fig. 16. NN loss prediction results against the HF transformer’s measured values for (a) training set, (b) validation set, (c) test set, and (d) all the data sets.

Fig. 17. The error histogram of the three different data sets of the transformer.

Figs. 18 (a-c) compares the NN predicted and measured losses of the HF transformer core, winding, and total, in different excitation conditions. NNALM has demonstrated that it can achieve results comparable to TPT measurements and trace them effectively. Despite a few data points with errors exceeding 50%, for the core loss, winding loss, and total loss sets, the ARE is calculated from (7) and shown in Fig. 18 (d) as 7.51%, 7.89%, and 3.48%, respectively. Thus, the average relative error is less than 8% in all three cases.

Table II summarizes different evaluations for the NNALM output of the inductor and HF transformer used. The R-Squared-Error (RSE) closer to one implies a higher prediction accuracy from the NNALM [15], which is defined as follows:

$$ RSE = \frac{\sum(P_{\text{Predicted}} - \hat{P}_{\text{Measured}})^2}{\sum(P_{\text{Measured}} - \bar{P}_{\text{Measured}})^2} $$

(8)
The NNALM is more accurate in predicting transformer losses due to a four-fold increase in the dataset from the different input conditions, compared to the inductor case by roughly 30%. For both the transformer and inductor cases, the ANN structure used in this paper has less than 10% average error for each of the three outputs: core loss, winding loss, and total loss. To illustrate how the error changes across various ANN structures, for instance, with decreasing the number of neurons to 10 from 15, the average error for the inductor case is less than 20%, and for the transformer case, it is less than 18%. For another example, by fixing the number of neurons to 15 and adding one more hidden layer, the average error for the inductor case is less than 17%, and for the transformer case, it is less than 13%. Therefore, as explained, there is no general principle to determine the exact numbers of layers and neurons, and each structure can change nonlinearly.

**TABLE II: PREDICTION RESULTS FOR DIFFERENT TYPES OF LOSS**

<table>
<thead>
<tr>
<th>Magnetic Component Loss</th>
<th>ARE (%)</th>
<th>RMS (%)</th>
<th>RSE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inductor Core Loss</td>
<td>8.32</td>
<td>9.12</td>
<td>1.0062</td>
</tr>
<tr>
<td>Inductor Winding Loss</td>
<td>10.14</td>
<td>10.86</td>
<td>0.9895</td>
</tr>
<tr>
<td>Inductor Total Loss</td>
<td>6.61</td>
<td>7.03</td>
<td>1.0045</td>
</tr>
<tr>
<td>HF Transformer Core Loss</td>
<td>7.51</td>
<td>8.47</td>
<td>1.0013</td>
</tr>
<tr>
<td>HF Transformer Winding Loss</td>
<td>7.89</td>
<td>8.92</td>
<td>0.9947</td>
</tr>
<tr>
<td>HF Transformer Total Loss</td>
<td>3.48</td>
<td>4.50</td>
<td>1.0008</td>
</tr>
</tbody>
</table>

Fig. 19 presents the results of the HF transformer NNALM and conventional loss map in various load impedance magnitudes. DC bias current, excitation voltage, frequency, and power factor are set to 0 A, 50 V, 50 kHz, and one, respectively. The $dB/dt$ fitted curve does not need to be used here as the voltage is set to 50 V.

Similar to the results for the inductor case, the error between the reference measured value and the NNALM is lower than the surface fitting method. NNALM’s average error value is around 7.77%, while the conventional loss map method is about 44.11%. In line with the previous results, the error increases slightly when $\Delta B$, as well as the core loss, is decreased in heavier loads [12] for the conventional loss map method.

In some cases, manufacturers may not be feasible to build a loss measurement platform and collect enough reliable data for model training, especially if multiple factors are included, similar to the HF transformer cases. To overcome the data limitations, transfer learning techniques can be applied [16]. Machine learning techniques, such as transfer learning, use the knowledge gained from solving one problem to solve a related one. In transfer learning, the principal goal is to reduce the amount of new data required. To begin with, a generic model that captures the common characteristics and patterns of magnetic component losses should be created (like the no-load condition or inductor case) and then used to develop loss models for other specifications, such as other load values or power factors, through transfer learning. As a result, many different load conditions do not need to be measured for the HF transformer database, facilitating the data acquisition process.

To sum up, the NNALM is a valuable tool to assist the power electronics designer in estimating the magnetic component losses, particularly for the higher input parameters condition such as HF transformers or coupled inductors, which is challenging or impossible with other methods.

**V. PRACTICAL IMPLEMENTATION**

The ultimate goal is to provide power electronics designers with a tool that will reduce the errors, time and effort spent on extracting and extrapolating parameters from datasheets. In this research, NNALM demonstrates superior accuracy throughout the whole dataset, and it also enables loss maps to account for more factors and generate multiple outputs as both winding and core losses. As a result, the manufacturers can perform all the measurements on representative samples from a batch/design of the component and then generates an NNALM file (e.g., a few kilobytes in size) to distribute to the end-users, which enables rapid, accurate and user-friendly loss estimations. To shift from material-based to component-based datasheets, the NNALM demands large datasets to effectively predict losses of individual components, which is enabled by rapid loss characterization tools/equipment, such as TPT [5-6], MADMIX [31] and the rig applied in [17]. The power electronics engineers can then incorporate this NNALM file in their analytical models or real-time simulation models as interpolated look-up tables in black boxes to estimate the loss of a standardized magnets part in their circuits. In this way, power electronics designers will no longer have to spend hours extracting and extrapolating parameters from
This paper demonstrates using Artificial Neural Networks (ANNs) to aid the generation of user-friendly loss maps as an alternative to traditional datasheets of magnetics. To achieve accurate modelling, an extended range of intercoupled input variables (e.g., DC bias and load conditions) and output variables (e.g., both the core loss and copper loss) can be realized in ANN-aided loss maps. According to the results, the proposed NNALM can achieve consistent and accurate fitting of measured losses under various conditions, which shows less than 10% average error. Comparisons reveal that the conventional loss maps can lose accuracy due to oversimplifications of physically interlinked variables as limited by the allowable dimensions in classic curve/surface fitting. Moreover, thanks to the ease of training, the NNALM can adapt to the increased fitting demand to shift from material-based to component-based datasheets for magnetics, improving accuracy by factoring in the geometry-related, component-specific, large-signal effects (e.g., gap losses). The NNALM file, which is only a few kilobytes in size, can be generated by the manufacturers and distributed to the end users for individual standardized magnetics.

REFERENCES


Navid Rasekh (S’20) received the B.Sc. degree from the Kermanshah University of Technology, Kermanshah, Iran, in 2015 and the M.Sc. degree from the AmirKabir University of Technology, Tehran, Iran, in 2018, both in Electrical Engineering. Currently, he is pursuing a Ph.D. at the Electrical Energy Management Group, University of Bristol, Bristol, U.K. His main research interests include designing and controlling high-power/high-frequency converters, modelling and measuring magnetic component losses, wireless power transfer (WPT), and finite element analysis (FEA).
Jun Wang (S’17–M’19) received the B.S. degree from Sichuan University, China, the M.Sc degree from University of Nottingham, U.K., both in Electrical Engineering, in 2014, and the Ph.D. degree in Power Electronics from University of Bristol, U.K., in 2019. He is currently a Lecturer and member of the Electrical Energy Management Group (EEMG), University of Bristol. His research interests include PWM power converters, wide-bandgap semiconductors, multilevel converter topologies, modelling of high-frequency losses, system-level design optimization and electric vehicles.

Xibo Yuan (Senior Member, IEEE) received the B.S. degree from the China University of Mining and Technology, Xuzhou, China, and the Ph.D. degree from Tsinghua University, Beijing, China, in 2005 and 2010, respectively, both in Electrical Engineering. He became a Professor in 2017 at the University of Bristol and holds the Royal Academy of Engineering/Safran Chair in Advanced Aircraft Power Generation Systems. He is the Director of the U.K. National Centre for Power Electronics. He is also a Distinguished Lecturer of IEEE Power Electronics Society. He is a Fellow of IET and received The Isao Takahashi Power Electronics Award in 2018.

His research interests include power electronics and motor drives, wind power generation, multilevel converters, application of wide-bandgap devices, electric vehicles and more electric aircraft technologies.