Convolutional Neural Network(CNN) based Planar Inductor Evaluation and Optimization

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***Abstract*— Magnetic component as one of the most lossy and bulky components in power electronic converters has been researched on optimization through calculation, experimental and FEM simulation. However, the traditional methods are normally time-consuming or inaccurate. A novel method that combined FEM simulation and convolutional neural network (CNN) is discussed in this paper, which can predict the inductance and core loss efficiently and accurately. Experimental result shows the accuracy of CNN prediction. Based on the CNN inductor inductance and loss prediction, a novel optimization method is presented which can comprehensively and quickly provide the optimization result considering power loss and power density.**

***Keywords*—inductor design, finite element analysis, convolutional neural network**

I. Introduction

Nowadays, due to the development of power semiconductors, such as silicon carbide and gallium nitride-based switching devices, the switching frequency of power converter can be increased to enhance the power density and efficiency. In these high-efficiency power converters, magnetic devices can contribute to 50% of the weight and volume[1]. Therefore, to continue increasing the power density of the converter, it is critical to research the optimization of inductors, including volume design, loss estimation, and evaluation.

In [2], the authors present a method of inductor's inductance and core loss calculation. And in [3], a calculation method is presented for inductor copper and core losses optimization, considering the temperature rise of the inductor core. However, the calculation optimization method cannot be utilized on different inductor topologies. So in [4], coupled inductors are analyzed and optimized through Matlab. A finite element analysis method is presented in [5]–[7] for inductor core loss simulation. For example, in [6], finite element analysis is implemented for magnetic core loss calculation in complex core structures and under dc bias conditions. In [7], a 3D nonlinear inductor model with a voltage excitation is built to efficiently analyze the eddy current problem using finite element method (FEM). Nonetheless, the 3D inductor FEM models in simulations are normally time-consuming. The experimental inductor loss measurement method is shown in [8]–[10]. There are two ways of measuring the inductor core loss through experiments [11]. The first method is the thermal approach. The total power losses dissipate as heat. The inductor core loss is represented as a function of the temperature rise of the coolant. However, the measurement process is time-consuming, and the experimental setup is complicated. The second method is the electric approach. The product of voltage and current through the inductor is integrated to calculate the inductor loss. However, this method is sensitive to phase discrepancy since reactive energy in the inductor is much higher than inductor loss [8]. The High-frequency inductor design is shown in [12]–[14]. At high frequency (3~30MHz), inductor power losses due to skin effect and proximity effect are hard to calculate and reduce. So new structure has been proposed and tested under high-frequency conditions. For example, in [12] and [14], a new structure of high frequency, low loss inductor has been proposed and shows the potential of achieving low loss under different applications and to produce economically. However, the design and optimization of the inductor are under analytical design guide which may loss accuracy in some circumstances.

The fast-growing artificial intelligence brought a new concept of inductor optimization. To optimize the inductor efficiently and accurately, the artificial neural network is used for fast inductor model and design in [15]. However, the inductor analysis is in the stationary domain. In [16], magnetic core loss is modeled by implementing a machine learning framework but still requires an experimental testing procedure for data acquisition.

Therefore, to predict the inductor inductance and core loss quickly and efficiently, a novel method that combines the accuracy of FEM and fast prediction benefit of convolutional neural network (CNN) is proposed in this paper. Firstly, a 3D planar inductor model has been built in COMSOL, and the database which contains the parameters of the planar inductor is generated with inductance and loss information. Secondly, CNN is implemented for the inductance and core loss prediction of the planar inductor by using Python TensorFlow. The CNN prediction result has been compared with the experimental result. Finally, a novel inductor optimization approach is proposed by using the pre-trained CNN prediction model. The optimization result will be provided considering inductor power loss and area-related power density.

II. PLANAR INDUCTOR DESIGN AND FEM SIMULATION

Planar inductor plays an important role in increasing the system power density in switched tank converter (STC) topologies[17]. And it has been analyzed in [18]–[20]. Since the resonant frequency is high, resonant inductance can be quite small for STC topology. Besides, planar inductor provides flexibility for adjusting inductance by simply modifying the air gap between the top and bottom core. Therefore, planar inductor is chosen as a sample model for the inductance and core loss analysis.

A 3D planar inductor model has been built in COMSOL as shown in Fig. 1. UI core shape is utilized in this design. The material of the inductor core is chosen as P material from Magnetics. In the middle of the core, there is copper that can be changed by adjusting the PCB winding layout, including changing layout layer numbers and the thickness of each layer.

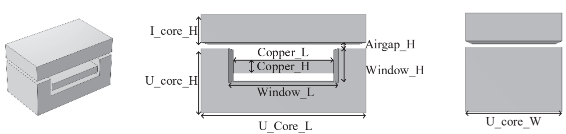


Fig. 1. Planar inductor shape and dimension

Inductance value is simulated and calculated through FEM simulation in frequency domain analysis at 340 kHz. The magnetic field distribution in the inductor core and current distribution through the copper are shown in Fig. 3 and Fig. 3. The effect of eddy current is presented clearly in Fig. 3 which shows the FEM simulation performance in inductance simulation under high-frequency conditions.

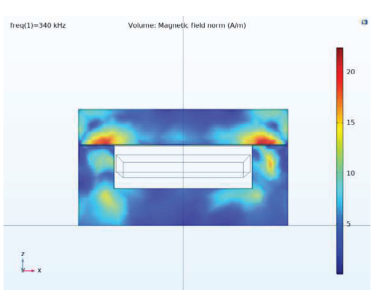


Fig. 2. Magnetic field distribution in planar inductor core

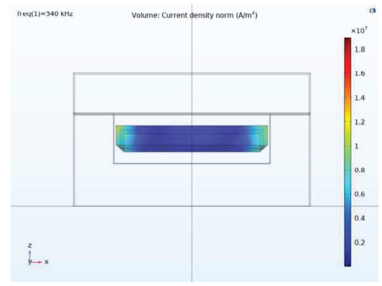
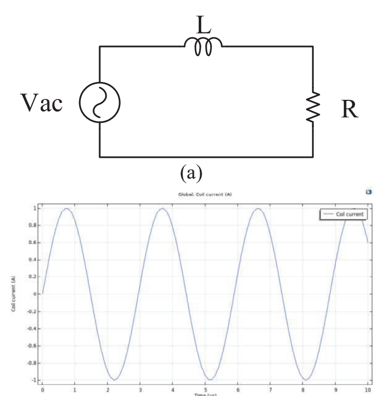


Fig. 3. Current density distribution in planar inductor coil

Planar inductor core loss is calculated in the time domain. In this paper, an RL circuit connected with a 340 kHz AC sinusoidal voltage source is used for simulation of the inductor loss as a sample, as shown in Fig. 4. It needs to be mentioned that the same method to simulate the inductor loss through FEM simulation can be applied to any circuit topologies, such as STC topology. Then, through the "Time to Frequency Losses" study, a forward FFT from time domain to frequency domain is performed to compute the loss of the inductor core. Core loss is calculated by using the Steinmetz equation

$$P_v = kf^aB^b \tag{1}$$

where $k = 3200$ W/m^3, $a = 1.46$, $b = 2.75$ for P material which is used in this paper.



(a)

(b)

Fig. 4. FEM core loss simulation topology (a) Loss calculation topology and (b) Inductor current waveform

To build a database for the analysis of inductance and core loss, planar inductor model with different randomly generated geometry features needs to be simulated in COMSOL. Considering the geometry constrain that the window size cannot exceed the U core size and the coil size cannot exceed the window size, firstly, the U_core_L, U_core_W, U_core_H, I_core_H and $Airgap$ are randomly generated in Matlab. Other geometry parameters are defined as follow:

$$\mathrm{Window_L} = \alpha * \mathrm{U_{core_L}} \tag{2}$$

$$\mathrm{Window_H} = \beta * \mathrm{U_{core_H}} \tag{3}$$

$$\mathrm{Copper_L} = \gamma * \mathrm{Window_L} \tag{4}$$

$$\mathrm{Copper_L} = \delta * \mathrm{Window_L} \tag{5}$$

The range of the inductor geometry parameters is listed in TABLE I.

TABLE I. PLANAR INDUCTOR DIMENSIONAL FEATURE

Features	Range	Unit	Features	Range	Unit
U_core_L	5~25	mm	α	0.1~0.9	p.u.
U_core_W	5~25	mm	β	0.1~0.9	p.u.
U_core_H	5~25	mm	γ	0.1~0.9	p.u.
I_Core_H	3~23	mm	δ	0.1~0.9	p.u.
$Airgap$	20~200	µm			

III. CONVOLUTIONAL NEURAL NETWORK (CNN) ON PLANAR INDUCTOR PREDICTION

FEM simulation can typically provide an authentic prediction for inductance and core loss of planar inductors. However, it is quite time-consuming by using the 3D FEM simulation. Therefore, we are eager to find a solution that can predict the inductance and core loss value without implementing 3D FEM simulation after knowing the dimensional data. In this chapter, convolutional neural network will be used for inductance and core loss prediction. The process of generating the inductor inductance and core loss dataset and CNN training procedure is shown in Fig. 5.

A. CNN model

CNN is a powerful tool for processing data that come in the form of multiple arrays. To utilize natural signals, there are four key ideas: local connections, shared weights, pooling, and the use of many layers[21].

In this paper, the dataset is split into 70% of training data and 30% of testing data. Before the training process, the training and test data must be scaled. Feature scaling is one of the most important steps before building a CNN training model. In this paper, the standard scaler is chosen which assumes the data is uniformly distributed. The distribution center of the new training data is 0 with a standard deviation of 1. The mathematical equation of training data scaling is shown below.

$$x_{train_{scale}} = \frac{x_{train} - \mu_{train}}{\sigma_{train}} \quad (6)$$

where μ_{train} is the mean value of each feature in training data and σ_{train} is the standard deviation of each feature in training data. It needs to be mentioned that the test data is also scaled using the mean and standard deviation of the training data. The scaling equation of test data is shown below.

$$x_{test_{scale}} = \frac{x_{test} - \mu_{train}}{\sigma_{train}} \quad (7)$$

CNN information is shown in Table II. The activation function is set as rectified linear unit (ReLU). The mathematical function of ReLu is shown as:

$$y = \max\{0, x\} \quad (8)$$

The loss function is set as mean square error loss (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (9)$$

In this case, Y_i is FEM simulated inductance or core loss value and $\hat{Y}_i$ is CNN predicted inductance or core loss value.

CNN inductance prediction result has been shown in Fig. 6. The predicted inductance is compared to FEM simulation inductance in Fig. 6 (b). The data points are perfectly located around the reference target $y = x$. The R-squared score is commonly used for predicted result evaluation.

$$R^2 = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - f(x_i))^2} \quad (10)$$

where y_i is the FEM simulation value and $f(x_i)$ is the CNN predicted value in this case. The higher R squared score means the prediction value is closer to the targeted value. The R squared score in the CNN inductance prediction is 98%.

TABLE II. CNN MODEL PARAMETER

Layer (type)	Output shape	Parameter #
Conv1d (Conv1d)	(None, 3, 16)	64
Conv1d_1	(None, 1, 32)	1568
flatten (Flatten)	(None, 32)	0
Dense (Dense)	(None, 30)	990
Dense_1 (Dense)	(None, 1)	31

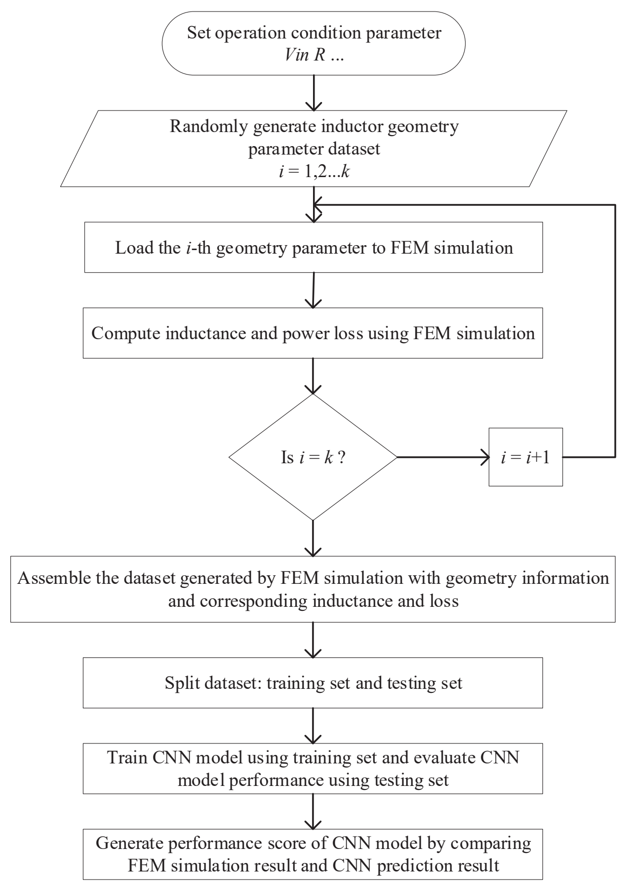
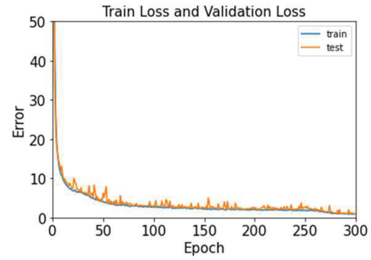
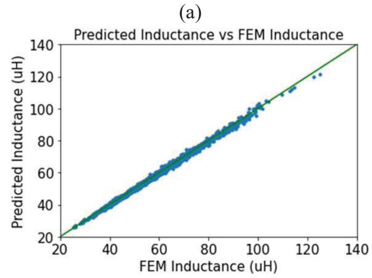


Fig. 5. Flowchart of inductor database built and CNN prediction



(a)



(b)

Fig. 6. CNN inductance prediction result (a) CNN training loss and validation loss (b) CNN predicted inductance and FEM simulation result comparison

Core loss prediction results are shown in Fig. 7. It is also aligned at the reference target $y = x$, where the CNN predicted inductor core loss value is compared with FEM simulation inductor core loss value. R-squared score in the core loss prediction is 94%. One of the reasons the accuracy of core loss prediction is not as high as inductance prediction is the dataset of core loss prediction is smaller than inductance prediction.

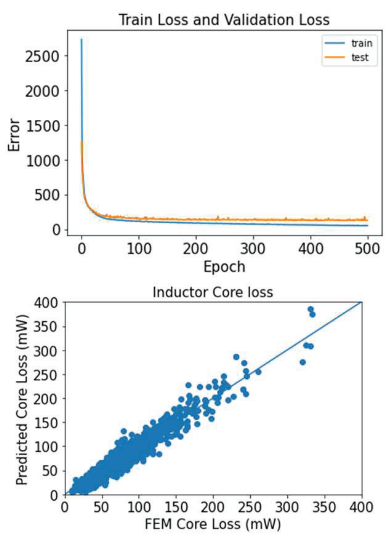


Fig. 7. CNN core loss prediction result (a) CNN training loss and validation loss (b) CNN predicted core loss and FEM simulation result comparison

The calculation time between FEM simulation and CNN prediction is compared in Table III. It can be told from this table that CNN prediction can be thousands of times faster than FEM simulation. The result shows the advantage of CNN prediction which can provide the planar inductance and core loss value prediction much faster than before. The accuracy and fast CNN prediction model provide the foundation for further inductor optimization.

TABLE III. FEM AND CNN TIME COMPARISON

Running Time	Inductance	Core loss
FEM simulation	~180s	~480s
CNN prediction	~0.03s	~0.03s

B. *k-Fold cross-validation*

Cross-validation is a statistical method of evaluating and comparing learning algorithms by dividing data into two segments: one is used to learn or train a model and the other is used to validate the model[22]. The training and validation dataset needs to be cross-over so each data point can be validated data. In this paper, the k-fold cross-validation is chosen as the form of cross-validation.

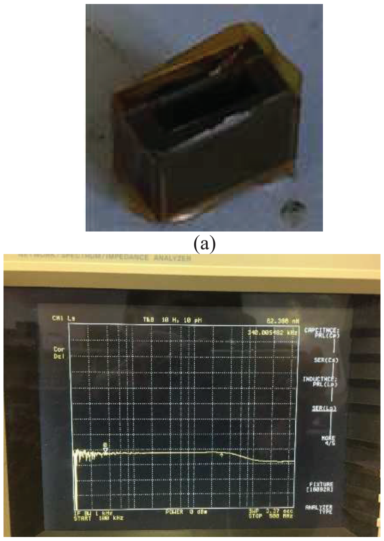
In the k-fold cross-validation, firstly the dataset is shuffled randomly and split into k groups. For each unique group, it is taken as the test group and the remaining k-1 groups are taken as the training data. Then the model is compiled using CNN, fitted the model on training data, and evaluated using testing data. The evaluation score is retained and summarized for total model evaluation.

In this paper, the number of the folder k is chosen as 10, which means each geometry data and its inductance and core loss value is randomly set into one group. The mean R-squared score for inductance prediction is 98% and for core, loss prediction is 94%. The k-Fold cross-validation result proves the accuracy of CNN prediction inductance and core loss value.

IV. EXPERIMENTAL VERIFICATION

An inductor model has been built to verify the accuracy of FEM simulation and CNN prediction inductance and core loss results. In this planar inductor model, U_core_L = 10.85 mm, U_core_W = 6.3 mm, U_core_H = 1.95 mm, $Window\_H$ = 2.24 mm, $Window\_L$ = 7 mm, I_Core_H = 1.83 mm, $Copper\_L$ = 6.492mm, $Copper\_H$ = 0.854 mm which equal to 6 layers of 2 oz per layer PCB copper height, $Airgap$ = 50 μm.

The experiment planar inductor model and test inductance result is shown in Fig. 8. The experimental test result at 340 kHz is 62.4 nH. With the same dimensional data, FEM simulation result is 63.9 nH and CNN prediction result is 64.3 nH. From time consumption perspective, 3D FEM simulation takes more than 3 min, and CNN prediction results can be calculated for less than 1 s. The error of the inductance prediction may also be introduced from the manufacture of core loss material. Therefore, the conclusion can be generated that the new CNN prediction method can predict the inductance efficiently and correctly. The result of core loss experimental verification will be provided in the following research.



(a)

(b)

Fig. 8. Planar inductor inductance measurement (a) planar inductor model (b) inductance measurement result

V. Inductor Optimization Use CNN Model

In [23], an inductor optimization procedure is presented in the paper where the geometry parameter is loaded into the FEM simulator to calculate the efficiency and area-related power density. However, as we discussed before, it requires a long time to generate the FEM simulation result. So, the predefined sets of geometry variables cannot be large enough considering the time complexity, leading to the consequence that the optimal efficiency or power density point can be further improved.

As we mentioned above, CNN can predict the inductance and power loss value quickly and accurately. Therefore, in the optimization design procedure, instead of using FEM simulation, CNN can build a much larger and comprehensive dataset. Under the equal time condition, CNN dataset can be thousands of times larger than FEM dataset. So, the optimal efficiency and power density point are much convincing than before. The flowchart of CNN prediction is shown below in Fig. 9.

In the optimization procedure, the geometry parameters are swept using CNN prediction. The optimization design procedure is proposed below.

1) Determine the required current, voltage, power, and inductance of the planar inductor.

2) Determine the lower and upper boundary of geometry parameters. For example, as shown in TABLE I. , the geometry range of the inductor are determined.

3) Determine the resolution of the swept parameters. For example, 1 mm can be taken as the minimum swept resolution for core and coil geometry and 10 µm can be taken as the minimum swept resolution for planar inductor airgap.

4) Implement CNN prediction of the inductance and core loss at each given geometry data point. Considering that CNN prediction is thousands of times faster than FEM simulation without losing the accuracy, the total optimization time using CNN prediction should also be thousands of times faster than FEM simulation on inductance and core loss.

A more comprehensive optimization experimental test result will be provided in the following research.

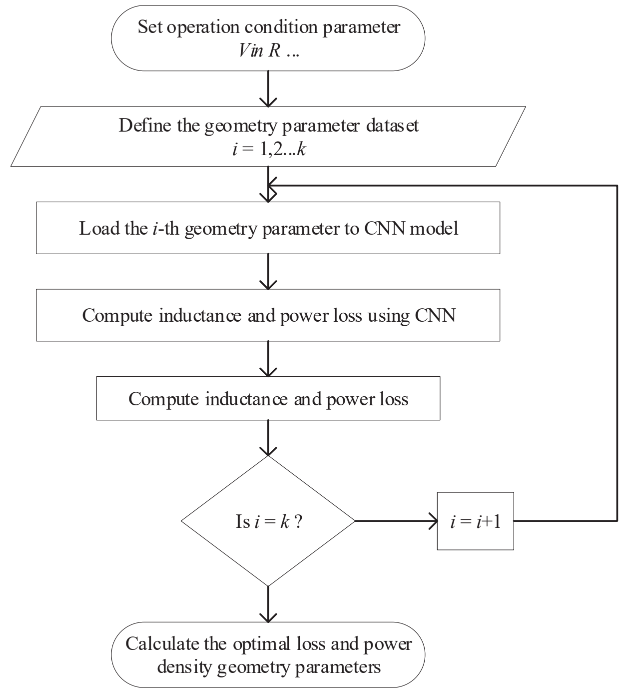


Fig. 9. Flowchart of planar inductor optimization use CNN

VI. Conclusion and Future Work

In this paper, a novel efficient way of calculating inductance has been introduced and verified. A 3D planer inductor model has been built in COMSOL and a database is built based on the model. Through implementing the CNN on the regression of the database, 98% of accuracy on inductance value prediction and 94% of accuracy on core loss value prediction have been achieved. Instead of implementing the time-consuming FEM simulation, CNN prediction can provide the inductance and core loss evaluation quickly and accurately. It needs to be mentioned that although this paper only shows the planer inductor modeling and prediction, this method can be used in any shape of inductors and any circuit topologies. The planar inductor optimization method is invested in the paper. The CNN prediction result is compared with FEM simulation result which shows the accuracy of the optimization result. At the same time, from a time consumption perspective, CNN prediction can be thousands of times faster than FEM simulation.

Future work will focus on three parts. Firstly, a more comprehensive database will be built. Because of time limitations, there are only 6400 inductance data and 1800 core loss data used for CNN prediction. That's also the reason core loss prediction is not as precise as the inductance prediction. With more training data the prediction accuracy will increase. Secondly, an experimental result will be presented for inductor core loss and optimization result verification. Thirdly, different structures of core shape and inductor geometry shape can be analyzed using the same method. The optimized inductor design can be compared between different inductor models.

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