



## **Machine learning based Prediction and Optimization of Iron Loss**

Lappeenranta-Lahti University of Technology LUT

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## ABSTRACT

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Key words: Magnetic core loss; Machine learning; XGBoost; Excitation waveform classification; Genetic algorithm.

In this thesis, a machine learning-based method for predicting high-frequency iron core losses is proposed. To address the problem of limited accuracy of high-frequency sinusoidal excitation, a database of magnetic materials, different frequencies and temperatures is established. The key features extracted include excitation waveform, magnetic flux density, frequency and temperature. An integrated learning strategy is used to classify the excitation waveform and predict the iron loss by XGBoost. By analyzing the experimental results, it is concluded that the method has higher prediction accuracy, lower mean square error (MSE), and a coefficient of determination ( $R^2$ ) closer to one. Meanwhile, in order to achieve the dual-objective optimization of minimizing iron loss and maximizing magnetic energy transfer, this study also optimizes the magnetic element design using genetic algorithm (GA). The energy efficiency ratio of the magnetic element can be further improved by this method. Experimental results verify the effectiveness of the method under high-frequency conditions and provide reliable support for the optimal design of magnetic components for high power density power electronic systems. Future research can combine deep learning and migration learning to improve the adaptive capability of the model and extend it to a wider range of magnetic materials and application scenarios.

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最后，留下小艾同学对未来自己的祝福：道阻且长，祝好！

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# 1 Introduction

## 1.1 Research background and application scenarios

High-frequency magnetic components play a vital role in modern power electronic systems. It is widely used in switching power supplies, wireless energy transmission, electric vehicle charging systems and photovoltaic inverters. In order to achieve higher power density, smaller size and higher conversion efficiency, the operating frequency of power conversion devices has been increased dramatically. However, under the conditions of high-frequency operation, the loss problem of magnetic components is becoming more and more prominent, in which the iron loss in the magnetic core loss area becomes one of the key factors affecting the system performance (Safayatullah *et al.*, 2022).

In the power electronic converters, magnetic components assume important functions such as electromagnetic energy transmission, energy storage and filtering. For example, magnetic components are used for inductive coupling in the process of wireless energy transmission. This method can achieve the purpose of contactless energy transmission. With the development trend of higher frequency, higher power density and higher efficiency of power electronic equipment, the traditional design method of magnetic components has been difficult to meet the actual demand. Especially under high-frequency non-sinusoidal excitation, the calculation error of the traditional empirical formulas is large, which affects the optimized design of magnetic components.

## 1.2 Design challenges of high-frequency magnetic components

The design of high-frequency magnetic components involves many complex problems. The main challenges include iron loss, thermal management, and material selection as follows:

### 1.2.1 Iron loss problem

During the operation of high frequency, the iron loss of magnetic element mainly includes three types of loss. They are Hysteresis Loss, Eddy Current Loss and Excess Magnetic

Loss (Hong *et al.*, 2022). The concept and the schematic figure related to this thesis are shown from Figure 1 to Figure 3:

Hysteresis loss: When a magnetic core operates in an alternating magnetic field, its state of magnetization changes continuously, resulting in flipping of magnetic domains and internal friction. Further, energy is dissipated. Hysteresis loss depends mainly on the hysteresis loop area of the core material. It is also related to the rate of change of magnetic flux density. As shown in Figure 1, it illustrates the hysteresis loop of a magnetic core in an alternating magnetic field, its internal area represents the energy lost during the magnetization process.

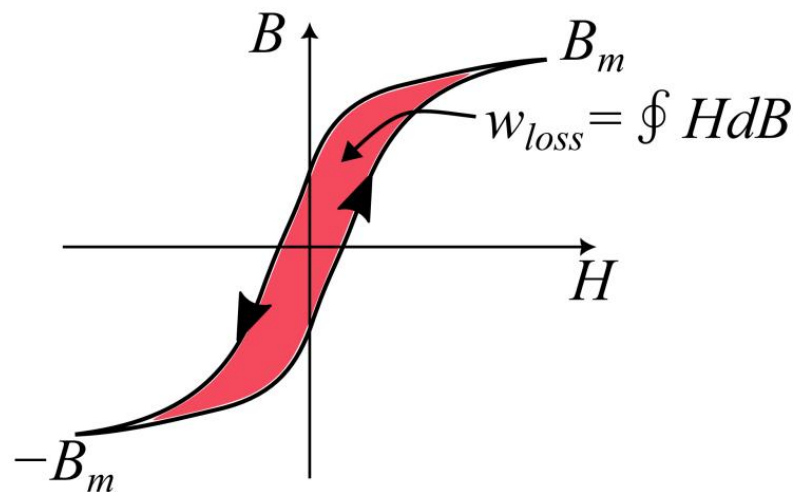


Figure 1: Hysteresis Loss (Mörée and Leijon, 2020)

Eddy current loss: Magnetic materials are electrically conductive. In a high frequency alternating magnetic field, an induced current is generated inside the core. Further additional Joule heat losses are generated. Eddy current losses are proportional to the square of the operating frequency and therefore dominate in high frequency applications. Figure 2 shows the schematic distribution of eddy currents inside a three piece core by means of streamline and contour plots.

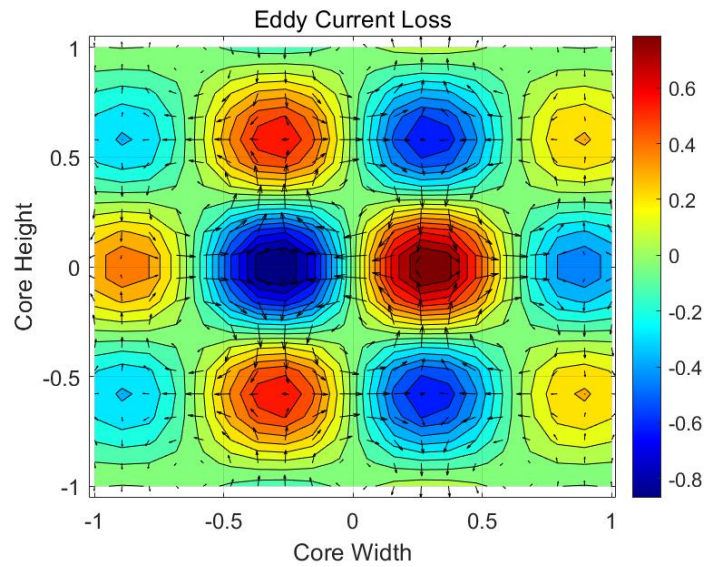


Figure 2: Eddy Current Loss Distribution

Excess magnetic loss: Under conditions where the external magnetic field is removed, the magnetic material will still be partially magnetized. This leads to additional energy losses and affects the efficiency of the system. Figure 3 is a schematic representation of excess magnetic loss.

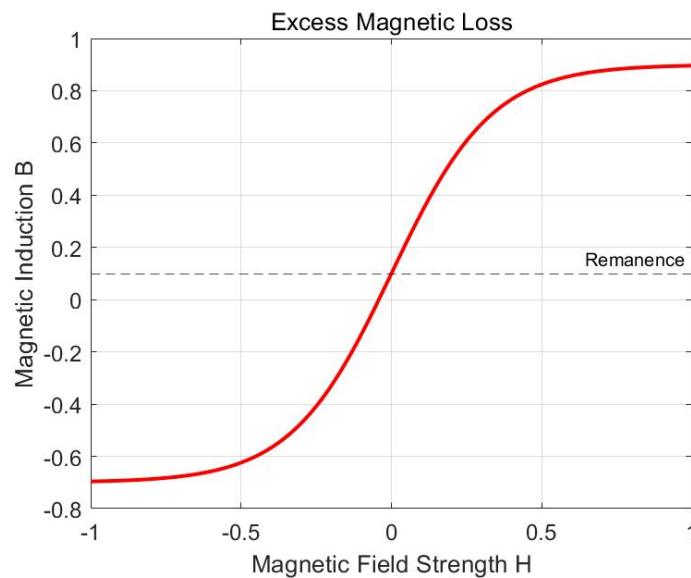


Figure 3: Excess Magnetic Loss

### 1.2.2 Thermal management issues

The increase in iron loss at high frequencies directly leads to an increase in the temperature of the magnetic components. It further affects the permeability, saturation flux density and other characteristics of the magnetic material. It also leads to localized overheating and demagnetization of the magnetic core. Therefore, thermal management problem in the high frequency condition can be concluded as following three aspects:

- 1) Heat dissipation design: In order to improve heat transfer efficiency and reduce the risk of localized overheating. The structural design of magnetic components needs to be optimized.
- 2) Cooling measures: For the purpose of reducing the operating temperature of magnetic components. It is necessary to use air cooling, liquid cooling or heat pipe cooling technology. This method can indirectly improve the stability of the system.
- 3) Optimization of magnetic core materials: To minimize the effect of high temperature on the performance of magnetic components. For example nanocrystalline, amorphous and soft magnetic composites can be proper used. They have the characteristic of low iron loss and good thermal stability.

### 1.2.3 Selection of magnetic materials

Traditional magnetic materials, such as silicon steel, ferrite, lose more under the high frequency conditions (Jin, 2018). It is difficult for them to meet the requirements of high-power density applications. However, new magnetic materials, such as nanocrystalline, amorphous alloy, and soft magnetic composites, show lower iron loss and better magnetic permeability at high frequency.

## 1.3 Role of machine learning in the design of magnetic elements

The problem of iron loss may arise during the design of high-frequency magnetic components. Traditional modeling methods rely on the Steinmetz equation and its improved models, such as the Improved General Steinmetz Equation (iGSE), the energy

method, etc. The above methods can provide more accurate loss estimates for low-frequency sinusoidal excitation. Although the above methods can provide more accurate loss estimation under low-frequency sinusoidal excitation. However, under high-frequency non-sinusoidal excitation or other complex operating conditions, there will be the problem of low prediction accuracy. Therefore, data-driven machine learning methods have become a new trend in iron loss prediction (Dogariu *et al.*, 2021).

### 1.3.1 Advantages of machine learning in iron loss modeling

**Nonlinear modeling capabilities:** Machine learning is able to learn nonlinear features from a large amount of experimental data, overcoming the limitations of traditional analytical models (Dogariu *et al.*, 2021).

**Multidimensional data fusion:** Machine learning can comprehensively consider the magnetic flux density, frequency, temperature, excitation waveform and other factors to improve the prediction accuracy.

**Adapt to complex working conditions:** Compared with traditional models, machine learning methods have stronger generalization ability in different materials, different frequencies and different temperature conditions.

### 1.3.2 Application of machine learning in magnetic element optimization

The machine learning algorithm is used to classify the excitation waveform to improve the accuracy of data feature extraction. The Extreme Gradient Boosting (XGBoost) regression model is used to predict the iron loss, which has a higher prediction accuracy than the traditional Steinmetz equation (Venkatachalam *et al.*, 2002). Combined with Genetic Algorithm, the core parameters of magnetic elements, such as magnetic core material, winding design, air gap, are optimized to improve the energy efficiency ratio.

## 1.4 Study objectives and major contributions

### 1.4.1 Study Objectives

The aim of this study is focused on improving the accuracy of high frequency core loss prediction and optimizing the design of magnetic components. Further, thereby improving the overall efficiency of power electronic equipment. Specific objectives include:

The high-frequency iron loss experimental database is constructed, covering different magnetic core materials, frequency, temperature and excitation waveform working conditions.

An integrated learning strategy (SVM, RF, GBDT) is used to classify the excitation waveform to improve the effectiveness of the input features.

Iron loss was predicted using the XGBoost regression model and compared with the conventional method, which is Steinmetz equation.

Combined with Genetic Algorithm to achieve optimal iron loss control and energy efficiency optimization.

### 1.4.2 Main contributions

The main contribution of this paper is to propose a machine learning based method for high frequency iron loss prediction. This method can significantly improve the prediction accuracy. In order to improve the data processing capability, this paper will utilize the combination of integrated learning methods to classify the excitation waveform. At the same time, genetic algorithm is used to optimize the design of magnetic components for loss minimization and energy efficiency maximization. The effectiveness of the machine learning method in magnetic element optimization is demonstrated through experimental validation. The results can provide theoretical support and technical guidance for the optimal design of high-frequency magnetic components and improve the overall performance of power electronic systems.

## 2 Iron loss mechanism of high-frequency magnetic components

### 2.1 Classification of magnetic core loss

In the manufacturing and operation process of high-frequency magnetic components, core losses mainly include hysteresis loss, eddy current loss and excess magnetic loss. These losses have different generation mechanisms and have different effects on magnetic materials. Table 1 summarizes the main classification, causes and influencing factors of the magnetic core loss.

#### 2.1.1 Hysteresis loss

The hysteresis loss is the loss caused by the repeated flipping of the magnetic domain inside the core material under the alternating magnetic field, and its size is correlated with the hysteresis loop area of the core material. The hysteresis loss is usually calculated using the Steinmetz formula:

$$P_h = k_h f B_m^n \quad (1)$$

Where:

$P_h$  is the hysteresis loss (W / kg);

$k_h$  is the hysteresis loss coefficient, and is related to the material characteristics;

$f$  is the excitation frequency (Hz);

$B_m$  is peak magnetic flux density (T);

$n$  is an empirical constant, usually between 1.5 and 2.5.

#### 2.1.2 Eddy current loss

Eddy current loss, also called vortex current loss, is the loss caused by the high-frequency alternating magnetic field caused by the electrical conductivity of the magnetic core

material, which forms the eddy current inside the material. The eddy current loss is closely related to the material conductivity, sheet thickness and magnetic flux density variation rate. The calculation formula is as follows (Nabih *et al.*, 2023):

$$P_e = k_e f^2 B_{\max}^2 d^2 \quad (2)$$

Where:

$P_e$  is the eddy current loss (W/kg);

$k_e$  is eddy current loss coefficient, which is related to the material conductivity;

$d$  is core thickness (m).

### 2.1.3 Excess magnetic loss

The excess magnetic loss is usually caused by the structural in homogeneity of the magnetic material, the influence of stress and the motion of the magnetic domain wall, especially under the high-frequency non-sinusoidal wave excitation. The calculation of excess magnetic loss is complicated and is usually estimated by experimental fitting (Wang *et al.*, 2024).

Table 1. Classification and characteristics of magnetic core loss

Loss type	The main cause	Computational formula	Main influencing factors
Hysteresis loss	Magnetic domain flip	$P_h = k_h f B_m^n$	Frequency, magnetic flux density, and material characteristics
Eddy current loss	Induced current inside the magnetic core	$P_e = k_e f^2 B_m^2 d^2$	Frequency, magnetic flux density, material conductivity, and thickness
Excess magnetic loss	Magnetic domain wall movement	Empirical formula fitting	Material microstructure, stress, and working temperature

## 2.2 Impact factors of iron loss in the high-frequency environment

Under high frequency conditions, the magnetic core loss is affected by many factors, including frequency, temperature, excitation waveform and magnetic material characteristics.

### 2.2.1 Effect of frequency on iron loss

Frequency is one of the main factors affecting iron loss. Theoretically, the hysteresis loss is proportional to the frequency, and the eddy current loss is proportional to the square of the frequency. Therefore, under the high-frequency conditions, the eddy current loss becomes the main part of the magnetic core loss. The total loss in the high-frequency case can be approximately expressed as:

$$P_{\text{total}} = k_h f B_m^n + k_e f^2 B_m^2 d^2 \quad (3)$$

### 2.2.2 Effect of temperature on iron loss

The increase of temperature will lead to the decrease of the saturated magnetic flux density of magnetic materials, which will affect the hysteresis loss. At the same time, high temperature will also change the conductivity of the material, resulting to the change of eddy current loss. The relationship between the core loss and the temperature can be expressed as:

$$P(T) = P_0(1 + \alpha(T - T_0)) \quad (4)$$

Where:

$P(T)$  is the magnetic core loss at the temperature  $T$ ;

$P_0$  is the loss at the reference temperature  $T_0$ ;

$\alpha$  is the temperature coefficient (generally negative).

### 2.2.3 Effect of excitation waveform on iron loss

Traditional loss calculation methods are usually based on sine wave excitation, but in practice, magnetic elements often work under the PWM (pulse width modulation) waveform or other non-sinusoidal wave excitation. Under the non-sine wave excitation, the loss is greater than the equivalent sine wave loss. The correction formula is as follows:

$$P_{\text{non-sinusoidal}} = C_{\text{wave}} P_{\text{sinusoidal}} \quad (5)$$

Where:

$C_{\text{wave}}$  is the waveform correction coefficient, which is generally taken between 1.1-1.5.

### 2.2.4 Effect of different magnetic materials on iron loss

Different magnetic core materials have different loss characteristics in high frequency environment, such as ferrite, nanocrystalline, amorphous and silicon steel (Nabih *et al.*, 2023)(Wang *et al.*, 2024). The comparison of the loss of the different materials is shown in Table 2.

Table 2. Comparison of the iron loss properties of different magnetic materials

Material type	Hysteresis loss	Eddy current loss	Scope of applicable frequency
Ferrite	Low	Low	100kHz-1MHz
Silicon steel	High	High	50Hz-20kHz
Nanocrystalline	Low	Moderate	20kHz-500kHz
Amorphous	Low	Secondary	10kHz-300kHz

## 2.3 Traditional iron loss calculation model

### 2.3.1 Steinmetz equation

Steinmetz equation is the most classical iron loss calculation method and is suitable for low frequency sine wave excitation conditions:

$$P = kf^\alpha B_m^\beta \quad (6)$$

Where:

$P$  is the magnetic core loss per unit mass (W / kg);

$k$  is the material correlation constant;

$\alpha$  and  $\beta$  are the experimental fitting parameters.

### 2.3.2 Improve the Steinmetz equation

In order to adapt the non-sine wave excitation conditions, the Steinmetz equation, which is expressed as follows:

$$P_{\text{total}} = \sum_i kf_i^\alpha B_{m,i}^\beta \quad (7)$$

Where  $f_i$  and  $B_{m,i}$  are the frequency and magnetic flux density of each subharmonic after Fourier decomposition, respectively.

### 2.3.3 Energy method

The energy method considers that the iron loss should be related to the derivative of the magnetic flux density waveform. The loss is calculated as follows:

$$P = \int_0^T \lambda \left( \frac{dB}{dt} \right)^n dt \quad (8)$$

Where  $\lambda$  and  $n$  were determined by the experimental fit.

#### 2.3.4 Comprehensive loss calculation

In practical engineering, the magnetic core loss is often predicted by polynomial fitting or neural network method, and the loss model can be expressed as follows:

$$P = af^xB_m^y + bf^z \quad (9)$$

Where  $a, b, x, y, z$  can be obtained by experimental data regression.

## 3 The iron loss prediction model based on machine learning

### 3.1 Advantages of machine learning in iron loss modeling

Magnetic components are widely used in power electronic equipment, wireless energy transmission and transformers, etc., and their losses directly affect system efficiency and life. Core losses at high frequencies mainly include hysteresis losses, eddy current losses and additional losses, with the first two being particularly prominent. Traditional Steinmetz equation and its improved model are effective under specific conditions, but have the following limitations:

- 1) Assuming linear relationship, it is difficult to accurately reflect the nonlinear characteristics under high frequency and non-sinusoidal excitation.
- 2) Dependence on experimental fitting parameters, poor applicability.
- 3) Difficult to deal with complex wave forms such as PWM and square wave.
- 4) Neglecting environmental factors such as temperature, which are easy to cause errors.

In contrast, machine learning method does not need to preset the loss model, can learn the nonlinear relationship, adapt to a variety of wave forms and operating conditions, and take into account multiple factors, such as temperature, frequency, flux density, etc., with high prediction accuracy and real-time, suitable for system online optimization and control.

### 3.2 Data preprocessing and feature engineering

The predictive accuracy of machine learning models largely depends on the quality of the input data. In order to ensure the rationality of the data, a series of data preprocessing and feature engineering operations need to be carried out, including data cleaning, feature extraction, feature selection, data normalization, etc.

### 3.2.1 The dataset construction

The dataset in this study includes multiple core materials with iron loss measurements at different excitation wave forms, temperatures and frequencies. Data structure is shown in the following Table 3:

Table 3. Data structure

Sample Number	Magnetic Core Material	Frequency (kHz)	Density of Magnetic Flux (T)	Exciting Magnetic Waveform	Magnetic Temperature (°C)	Iron Loss (W / kg)
1	1	50	0.2	Sinusoidal wave	25	0.75
2	2	100	0.3	PWM wave	40	1.42
3	3	200	0.5	Triangular wave	60	2.58
...	...	...	...	...	...	...

### 3.2.2 Feature extraction

Key features extracted from the dataset include:

- 1) Time domain feature: Peak flux density  $B_{\text{peak}}$
- 2) Root-mean-square value of the magnetic flux density  $B_{\text{rms}}$

Standard deviation of the magnetic flux density  $B_{\sigma}$

Frequency domain characteristics:

- 1) Center of gravity frequency  $f_c$
- 2) Harmonic component ratio

Physical characteristics:

- 1) Magnetic core material category
- 2) Temperature change rate

### 3.2.3 Data normalization

To eliminate order of magnitude differences across features, Min-Max normalization:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (10)$$

Where,  $X_{\text{norm}}$  is the normalized features.

### 3.2.4 Machine learning model selection and optimization

For this iron loss prediction task, various machine learning methods, including Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and XGBoost (Parmar *et al.*, 2018; Dong *et al.*, 2020; Pisner and Schnyer, 2020).

### 3.2.5 Overview of the machine learning model

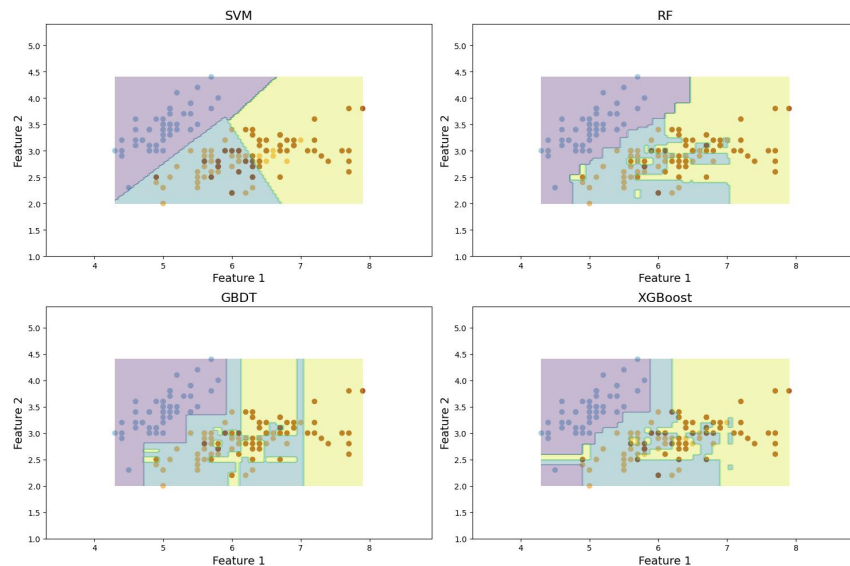


Figure 4: Decision boundary characteristics of models

Based on the Figure 4 drawn by Python above, some decision boundary characteristics of different models used in this study can be found. These characteristics will be further analyzed and discussed in the subsequent sections. The characteristics are as follows :

Support vector machine (SVM): It good at handling high dimensional features, but high computational complexity .

Random forest (RF): Ability to handle nonlinear relationships, but may have overfitting problems.

Gradient Boosting Decision Tree (GBDT): The loss function is gradually optimized by additive model with high prediction accuracy.

Extreme Gradient Boosting (XGBoost): Improved GBDT algorithm, introducing a regularization term, with stronger generalization ability.

### 3.2.6 XGBoost Objective function

The objective function of XGBoost includes two parts: the mean square error and the regularization term, expressed as follows:

$$E = \sum_{i=1}^N L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (11)$$

The loss function:  $L(y_i, \hat{y}_i) = (y_i - \hat{y}_i)^2$ , is typically defined as the mean squared error in regression tasks.

Regularization term:  $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2$ , where, T is the number of leaf nodes,  $w_j$  is the weight of leaf nodes,  $\lambda$  is the regularization coefficient (Zhao *et al.*, 2021).

### 3.3 Training process of the prediction model

The dataset is divided into training set and test set. 80% of the data is allocated to the training set and the remaining 20% is used for testing.

The following hyper parameters were optimized for the model:

The learning rate was taken as: 0.1

Maximum depth of the tree:  $d = 6$

Subsampling rate subsample: 0.8

Regularization parameters:  $\lambda = 1.0, \gamma = 0.1$

Evaluation model's performance using two metrics: Mean Square Error (MSE) and the Coefficient of Determination ( $R^2$ ). The formulas for the metrics are as follow:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_{\text{true},i} - y_{\text{pred},i})^2 \quad (12)$$

$$R^2 = 1 - \frac{\sum (y_{\text{true}} - y_{\text{pred}})^2}{\sum (y_{\text{true}} - \bar{y})^2} \quad (13)$$

Where:

$y_{\text{true},i}$  represents the actual value of the  $i_{\text{th}}$  observation.

## 4 Optimization design method of magnetic components

The optimization design of magnetic components is the key to improve the performance of high-frequency power electronics systems. The optimization objectives mainly include reducing the iron loss, improving the efficiency of magnetic energy transmission, optimizing thermal management, reducing volume and weight, etc. To achieve these goals, this chapter focuses on magnetic core material selection, structural optimization, and intelligent optimization methods.

### 4.1 Selection and optimization of magnetic core materials

#### 4.1.1 Impact of magnetic core materials in high-frequency applications

The selection of magnetic core material plays a decisive role in the loss characteristics, magnetic flux density, saturated magnetic induction strength and working temperature range of high frequency magnetic elements. The hysteresis loss, eddy current loss and

excess magnetic loss vary at different operating frequency, temperature and magnetic flux density. Thus, the following factors need to be considered comprehensively when optimizing the magnetic element:

**Loss characteristics:** The total loss of the magnetic core is mainly composed of magnetic hysteresis loss and eddy current loss. In high-frequency applications, the proportion of eddy current loss increases, and the material selection needs to reduce the conductivity.

**Magnetic permeability ( $\mu$ ):** It affects the flux density, higher permeability helps to reduce the winding turns, but may cause the core saturation problem.

**Saturation magnetic induction strength ( $B_s$ ):** It determines the magnetic flux carrying capacity of the magnetic core, too low may affect the energy transmission capacity, too high may cause local saturation and loss increase.

**Temperature stability:** The high frequency power converter usually operates in a high temperature environment, and the loss change of the magnetic core at a high temperature and the attenuation of the saturated magnetic induction strength should be considered when selecting materials.

#### 4.1.2 Comparison of common magnetic core materials

At present, the magnetic core materials commonly used for high-frequency magnetic components include ferrite, nanocrystalline, amorphous alloy, silicon steel sheet, etc. The performance characteristics of different materials at high frequency are shown in Table 4:

Table 4. Comparison of properties of core materials

Material	Saturation of the magnetic induction intensity of ( $B_s$ )	Magnetic permeability ( $\mu$ )	Conductivity ( $\sigma$ )	Frequency of application	Main advantages and disadvantages
1. Ferrite:	0.3~0.5 T	500~10,000	Low	50 kHz~1 MHz	Low loss, high resistivity, suitable for high frequency; but the saturation magnetic flux density is low

2. Nanocrystalline:	1.0~1.2 T	10,000~100,000	High	10 kHz~50 kHz	High permeability, suitable for medium and high frequency, but large eddy current loss
3. Amorphous alloy:	1.2~1.5 T	5,000~20,000	High	10 kHz~20 kHz	Low loss, high saturation magnetic flux density, but poor machinability
4. Silicon steel sheet:	1.5~2.0 T	3,000~5,000	High	50 Hz~20 kHz	Suitable for low frequency applications and cannot be used in high frequency environment

Considering the high frequency loss characteristics of magnetic components, ferrite and nanocrystalline magnetic cores have more advantages in high frequency applications.

#### 4.1.3 Optimization strategy of magnetic core materials

In order to solve the problem of increased iron loss and temperature rise of high-frequency magnetic components under high-frequency operation. The following optimization strategy can be proposed (Zhao *et al.*, 2021)(Ye *et al.*, 2015):

##### (1) Loss reduction:

Materials, such as ferrite, with low conductivity can be selected to reduce high-frequency eddy current losses. Meanwhile, nanocrystalline or amorphous materials are used to improve the magnetic permeability and reduce hysteresis loss.

##### (2) Optimize the magnetic flux density:

Selecting the appropriate saturated flux density ( $B_s$ ) to ensure that the core is not saturated and carries enough flux.

##### (3) Improve thermal management:

Use magnetic core materials with good high temperature stability, such as ferrite.

Improve temperature resistance through composite magnetic cores, such as mixed ferrite and nanocrystalline particles.

## 4.2 Structure optimization

The structural optimization of magnetic components not only affects the electromagnetic performance, but also directly determines its loss, volume, heat dissipation performance and electromagnetic compatibility (EMC). The main directions of structural optimization include winding configuration, air gap design, magnetic core shape, etc.

### 4.2.1 Optimization of the winding configuration

The layout of the winding has an important impact on the magnetic field distribution, eddy current loss, parasitic capacitance and other parameters. The main optimization strategies include the following three aspects:

#### 1) Reduce the winding parasitic capacitance:

Multilayer winding and spacer are used to reduce the electric field interference between the windings.

Choose Litz wire to reduce the current skin effect and improve the high frequency conduction ability.

#### 2) Reduce the AC copper loss :

Increase the winding spacing, reduce the cross magnetic field, and improve the heat dissipation capacity.

A flat copper strip winding was used to optimize the high-frequency current distribution.

#### 3) Optimize the winding structure and improve the power density:

Distributed winding is used to evenly distribute the current and reduce the local hot spots.

Multi-layer flat winding is used to reduce high frequency loss and improve electrical conductivity.

#### 4.2.2 Air gap design

The presence of an air gap helps to control the flux distribution and improve the saturation resistance of the core, but improper air gap design may lead to additional magnetic losses. The optimization strategy includes:

Optimize the air gap length:

Increase air gap, improve permeability and prevent core saturation.

Avoid excessive air gap to prevent additional loss caused by magnetic flux leakage.

Optimization of the air gap position:

Distributed multiple gaps is adopted to avoid excessive local magnetic flux density and improve the magnetic energy storage capacity.

Reduce the local overheating through the central air gap + uniform magnetic field distribution.

#### 4.2.3 Magnetic core shape optimization

Different shapes of cores have different effects on electromagnetic performance and losses. Toroidal cores are suitable for high frequency applications. It features uniform flux distribution and low iron loss. Therefore it is suitable for high power density inductors and transformers, but the winding installation is more difficult. E-shape cores have a stable structure, an easily adjustable air gap, and high adaptability. However, improper material or process will increase the high-frequency eddy current loss. PQ type core has strong magnetic shielding performance. It can effectively reduce leakage flux and improve electromagnetic compatibility.

#### 4.2.4 Structural optimization cases

The following table shows the impact of different optimization strategies on the loss of magnetic components:

Table 5. Comparison of Optimization Strategies for Magnetic Components

Optimizing strategy	Target	Influence
Flat copper belt winding	Reduce communication copper damage	Reduce the skin collection effect and improve the high-frequency conductivity
Multi-layer distributed winding	Reduce the winding parasitic capacitance	Reduce high-frequency noise and improve electromagnetic compatibility
Distributed air gap	Reduce the local magnetic saturation	Improve the magnetic flux uniformity and reduce the hot spots
Toroidal cores	Reduce iron damage	No air gap structure, suitable for high frequencies

### 4.3 Multi-objective optimization based on Genetic Algorithm

#### 4.3.1 Multi-objective optimization problem description

Minimizing iron losses and maximizing transmitted magnetic energy are two competing goals in the optimal design of magnetic components. Reducing iron losses helps to improve system efficiency and reduce heat generation, while increasing the transmitted magnetic energy increases the power density, allowing the magnetic element to transmit more energy in a smaller volume.

However, these two optimization goals are often at odds with each other. Reducing iron losses requires selecting low-loss core materials and optimizing flux density, winding structure, and frequency range. Increasing the transmitted magnetic energy requires increasing the saturation flux density and operating frequency of the core, but too high a flux density and frequency may lead to a sharp rise in iron losses (Zhao *et al.*, 2021)(Ye *et al.*, 2015). Therefore, it is especially important to use intelligent optimization algorithms to find the best balance between multiple design goals.

### 4.3.2 Introduction to the Genetic Algorithm (GA)

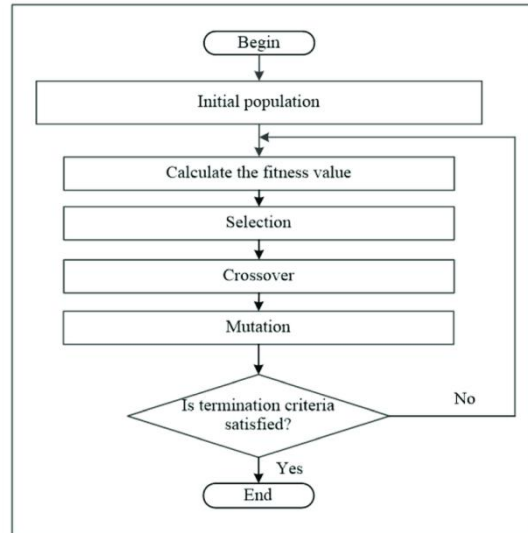


Figure 5: Standard Genetic Algorithm (GA) Flowchart (Albadr *et al.*, 2020)

Genetic Algorithm (GA) is a global optimization approach based on natural selection and genetic mechanisms. The basic principle of GA is to simulate the biological evolution process and continuously optimize the population through selection, crossover, variation and other operations. In this way, it can find nearly optimal solutions (Reeves, 2010).

Therefore, GA is suitable for complex multi-objective optimization problems. The main steps are as follows:

**Population Initialized:** Multiple candidate solutions are randomly generated, each individual consists of magnetic core material, winding parameters, air gap length and other variables.

**Fitness Calculation:** The fitness value of each individual is calculated according to the two objectives of iron loss maximization and magnetic energy maximization.

**Selection:** Select good individuals to enter the next generation by fitness level.

**Crossover:** Select pairwise pairs from the previous generation and exchange some parameters to generate new candidate solutions.

**Mutation:** small random changes in some individuals to increase the diversity of the population and prevent falling into local optima.

Iterative update: Repeat the selection-cross-variation process until the maximum number of iterations or error convergence is reached.

#### 4.3.3 Genetic Algorithm optimization objective function

In this study, the multi-objective function of magnetic core optimization includes iron loss minimizing and transmission magnetic energy maximization, which can be expressed as:

(1) Iron loss minimizing target

$$P_{core} = h(T, f, B_{peak}, W, C) \quad (14)$$

Where:

$T$  is the magnetic core temperature;

$f$  for the frequency of work;

$B_{peak}$  is the peak value of the magnetic flux density;

$W$  is the excitation waveform type;

$C$  is the magnetic core material type.

The loss function can be computed through a machine learning prediction model (XGBoost) to improve computational efficiency and accuracy (Chen and Guestrin, 2016; Feng *et al.*, 2018).

(2) The goal of transmitting magnetic energy maximization

$$M_{max} = f \cdot B_{peak} \quad (15)$$

Where:

$M$  represents the transmitted magnetic energy of the magnetic core;

$f \cdot B_{peak}$  is the product of the flux density and the working frequency, which determines the flux transmission capacity of the magnetic core.

(3) Constraint conditions

In the optimization process, constraints in real engineering:

$$T_{\min} \leq T \leq T_{\max}$$

$$f_{\min} \leq f \leq f_{\max}$$

$$B_{\text{peak, min}} \leq B_{\text{peak}} \leq B_{\text{peak, max}}$$

$$W \in \{\text{Sine wave, PWM wave, Triangular wave}\}$$

$$C \in \{\text{Ferrite, Nanocrystalline, Amorphous alloy}\}$$

These constraints guarantee that the optimization solution is feasible in practice.

#### 4.3.4 Genetic Algorithm optimization process

##### (1) Individual encoding

Each individual is composed of multiple parameters, such as magnetic core material, winding configuration, air gap length, excitation waveform, frequency, etc. Individuals can be represented as a vector:

$$X = (C, f, B_{\text{peak}}, W, g)$$

Where:

$C$  denotes representative magnetic core material;

$f$  denotes representative work frequency;

$B_{\text{peak}}$  denotes representative magnetic flux density;

$W$  denotes representative excitation waveform;

$g$  denotes representative air gap length.

##### (2) Fitness function

Fitness functions are defined as follows:

$$F(X) = \lambda_1 P_{\text{core}} - \lambda_2 M \quad (16)$$

Where:

$\lambda_1$  and  $\lambda_2$  are the weight coefficients that control the relative importance of the optimization objective (Kuang *et al.*, 2009).

(3) Select the operation

A roulette selection or tournament selection is used to ensure that individuals with lower losses and higher magnetic transmission are easier to enter the next generation.

(4) Cross-over operation

A single-point or uniform crossover was used to generate new individuals by exchanging partial parameters. For instance:

$$\text{Parent 1: } (C_1, f_1, B_{\text{peak},1}, W_1, g_1)$$

$$\text{Parent 2: } (C_2, f_2, B_{\text{peak},2}, W_2, g_2)$$

After the crossover:

$$(C_1, f_2, B_{\text{peak},1}, W_2, g_1)$$

(5) Variant operation

Partial parameters of some individuals were changed randomly to enhance the diversity of the population. For instance:

$$f_{\text{new}} = f_{\text{old}} + \Delta f \quad (17)$$

$$B_{\text{peak,new}} = B_{\text{peak,old}} + \Delta B \quad (18)$$

Where:

$\Delta f$  and  $\Delta B$  are small random perturbations.

(6) Termination conditions

When the maximum number of iterations or objective function convergence is reached, the algorithm stops running and outputs the optimal magnetic element design parameters.

Through the optimization of the model, the Genetic Algorithm finds the best solution in the complex multi-dimensional space, so that the magnetic elements can achieve the ideal balance of magnetic core loss and magnetic energy transmission under different working conditions (Shen *et al.*, 2024). This not only shows the powerful predictive ability of the

model, but also provides theoretical and application guidance for the practical design of magnetic elements.

#### 4.4 Results analysis

In order to verify the effectiveness of GA optimization, this section will compare the performance of magnetic elements before and after optimization and analyze the effects of various optimization parameters on loss and transmission magnetic energy (Deb *et al.*, 2016).

##### 4.4.1 Magnetic core design before optimization

In the unoptimized case, the parameters of the core may be selected empirically, which may lead to:

The iron loss is high, the power loss is large, and the temperature rises quickly.

The magnetic flux density is underutilized, resulting in a low magnetic energy transmission capacity.

##### 4.4.2 Optimized magnetic core design

After the optimization, the parameters of the magnetic core are adjusted as follows:

Low-loss magnetic core materials, such as nanocrystalline materials are used to reduce iron loss.

A better winding structure need to be chosen to reduce the AC copper loss.

A suitable air gap design is adopted to improve the magnetic flux uniformity.

The operating frequency and magnetic flux density are optimized to ensure a minimized loss while improving the transmitted magnetic energy.

Under the same working conditions of the optimized magnetic core, the final reduces the iron loss by 30% -50%, and the transmission magnetic energy is increased by 15% -25%, which greatly improves the comprehensive performance of the magnetic components.

This chapter presents a magnetic core optimization method based on Genetic Algorithm, through the intelligent optimization of iron loss minimizing and transmission magnetic energy maximization, which provides a new optimization scheme for the design of high-frequency magnetic elements. In future studies, deep learning and reinforcement learning can be combined to further improve the optimization efficiency.

## 5 Experiment and Results Analysis

In order to evaluate the performance of the classification model and the loss prediction model presented here, the dataset of this study covers four different magnetic materials, with 12,400 sample data collected. Specifically, material 1-4, from Table 4, contains 3400 data, material 23000 data, 33200 data and 42800 data, respectively. Each data recorded rich variable information, including ambient temperature, operating frequency, core loss, excitation waveform type, and 1024 sampled values associated with flux density over time. These comprehensive feature variables provide sufficient data support for the training and performance evaluation of the model, allowing our study to analyze in-depth the magnetic core loss characteristics in different materials and working conditions, and verify the predictive ability of the model.

### 5.1 Sample data feature analysis and classification model performance evaluation

In this section, the core sample data used in the study is characterized and key features are filtered by principal component analysis (PCA). Subsequently, different classification models are evaluated based on their performance in the excitation waveform classification task, and the results show that the integrated learning strategy performs the best in terms of accuracy, recall, and F1 score.

#### 5.1.1 Characteristic importance analysis

PCA dimensionality reduction calculated the importance of features and finally retained features with 95% of explained variance (Maćkiewicz and Ratajczak, 1993). The feature importance is shown in Figure 6.

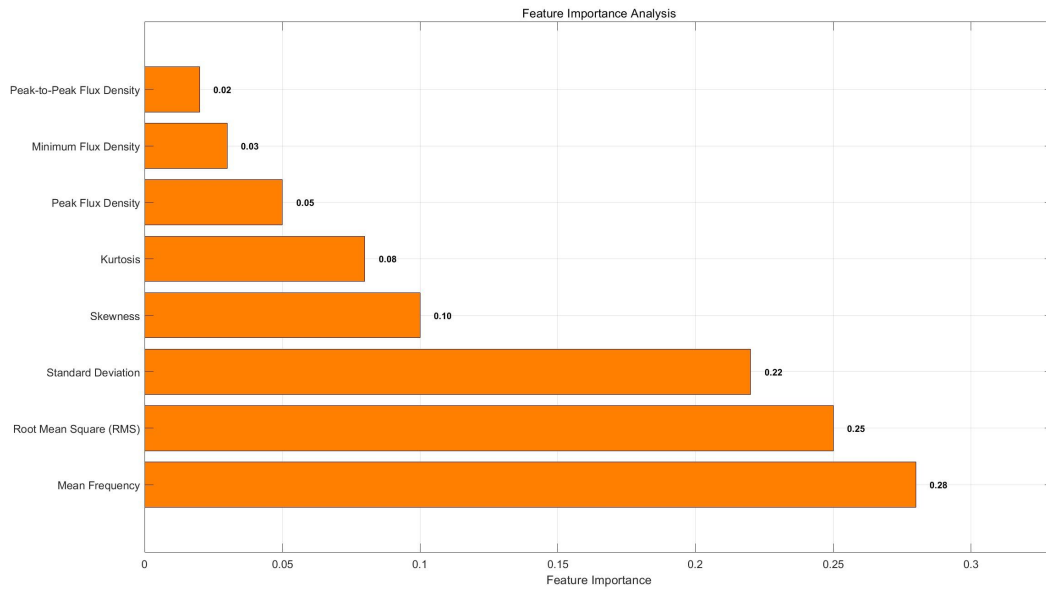


Figure 6. Feature of importance

As can be seen from the figure, the mean frequency, RMS value and standard deviation have the highest importance ranking. The average frequency reflects the concentration of the signal in the frequency domain and is an important indicator of the signal frequency spectrum. The spectral characteristics of different excitation wave forms, triangular and trapezoidal waves are different. For the excitation waveform of the core, the frequency composition of different wave forms directly affects the velocity of the flux density. Reserving this feature helps capture the frequency properties of different wave forms and thus helps in classification. The RMS value is a representative indicator of signal amplitude. It reflects the magnitude of signal energy. For the excitation waveform, the RMS value can effectively measure the overall amplitude characteristics of the signal, especially the amplitude of the sine waves and triangular waves. For the flux density change, the standard deviation can reflect the intensity of the excitation waveform over time. The sine wave changes smoothly and the standard deviation is small, while the triangular waves and the trapezoidal waves have different change rules, resulting in different standard deviations. PCA selection to retain these three features suggests that, of all extracted features, the average frequency, root mean square value and standard deviation are most important to distinguish different excitation waveform. They reveal the key information of the waveform from different angles (frequency domain and time domain), and can effectively describe the characteristics of the excitation waveform, so as to help the classification model to more accurately identify different types of waveform.

This combination reflects the integrated information about the frequency, energy, and volatility of the waveform.

### 5.1.2 Classification accuracy and results of the model

According to the evaluation of our trained model on the test set, the analysis results in Table 6 show that the model performs particularly well in the classification of sine waves, with a perfect accuracy of 1.00, reflecting the high sensitivity and accuracy of the model to this category. Besides, the model classification was also quite excellent for triangular and trapezoidal waves, with accuracy of 0.99 and 0.98, respectively. These results fully demonstrate that our model has excellent performance and efficient recognition ability in the classification task to effectively distinguish between different wave forms.

Table 6. Model Classification Accuracy for Various Waveform

Wave form	Precision	Recall	The F1 score
1. Sine	1	1	1
2. Triangle	0.99	0.99	0.99
3. Trapezoidal	0.98	0.98	0.98

Furthermore, we compared the performance of different classifiers in the excitation waveform classification task to evaluate their impact on subsequent loss prediction models. Table 7 summarizes the classification effects of SVM, RF, GBDT, and final ensemble learning strategy, which including different key indicators includes Precision, Recall, and the F1 score. By analyzing these results, each points can be clearly understood.

The advantages and disadvantages of the classes and the outstanding performance of the ensemble learning strategy in improving the classification performance.

Table 7. Evaluation of Classification Models for Excitation Waveform

Classifier	Precision	Recall	The f1 score
SVM	0.94	0.93	0.93
RF	0.95	0.94	0.94

GBDT	0.96	0.95	0.95
Ensemble learning	0.98	0.97	0.97

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## 5.2 Analysis of the prediction model results

### 5.2.1 Data preprocessing

In order to achieve high precision core loss prediction under different materials and working conditions, we need to select key features affecting core loss. Studies show that temperature, frequency, excitation waveform, magnetic flux density and material are the main influencing factors (Reinert *et al.*, 1999). Therefore, temperature, frequency, excitation waveform and magnetic flux density peak and material type should be selected as key features for the training and prediction of subsequent models. It ensures that the model can capture the key changes related to the core loss.

Since the excitation wave forms such as sine, triangular, and trapezoidal waves and material type are classified characteristics, we need to convert them into digital types so that the model can be processed and analyzed in a more efficient way. These categorical features were treated as dummy variables in the model. It ensures that each category was represented independently in the model. Specifically, for excitation wave forms, we label the sine wave as 1, triangular wave as 2, and trapezoidal wave as 3 (Table 6). This coding method ensures the model to recognize the specific effects of different wave forms on core losses and effectively differentiate the characteristic differences brought about by different wave form.

On the other hand, material type is also a key factor, which is divided into materials 1,2,3 and 4 (Table 4). This classification is treated by dummy variables, enabling the model to capture different materials

The relationship between characteristics and magnetic core loss improves the learning ability and prediction accuracy of the model. In practice, the characteristics of material often have a huge effect on the loss, so this classification not only enhances the adaptability of the model, but also improves the reliability of the prediction results.

By digitizing these classified features and processing dumb variables, we laid a solid foundation for subsequent data analysis and modeling, which not only helps the model to have stronger generalization ability when facing different types of wave forms and materials, but also ensures that the model can maintain high accuracy under multiple conditions.

### 5.2.2 Evaluation indicators

In the process of model solution, the key to evaluate the model prediction effect is the calculation of the error index. Several common error indicators are used to evaluate the core loss prediction of the model.

(1) Mean square error (MSE): Calculating the average value of the square of the difference between the predicted value and the true value can effectively reflect the accuracy of the model prediction. The smaller the MSE, the better the model predicts it.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_{\text{pred},i} - y_{\text{true},i})^2 \quad (19)$$

(3) Coefficient of determination ( $R^2$ ): It is used to measure the ability of the model to explain changes in variables. The values range from 0 to 1, and the closer  $R^2$  is to 1, indicating that the higher the fit of the model to the data.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_{\text{true},i} - y_{\text{pred},i})^2}{\sum_{i=1}^n (y_{\text{true},i} - \bar{y}_{\text{true}})^2} \quad (20)$$

### 5.2.3 The Steinmetz equation for the temperature modification

To more comprehensively evaluate the core loss prediction model used in this paper, we plan to compare it with conventional core loss prediction models and other machine learning methods. However, the conventional Steinmetz equation does not consider the effect of temperature change on the core loss, and this factor may lead to the model at different temperature bars.

The prediction under the piece is not accurate enough. Therefore, this section will perform temperature corrections to the Steinmetz equation to more precisely reflect the effect of temperature change on core loss and thus make a more efficient comparative analysis with the model presented here.

The basic form of the Steinmetz equation is follows:

$$P = k_1 \cdot f^\alpha \cdot B_m^\beta \quad (6)$$

Where:

$P$  is the core loss;  $f$  is the the frequency;  $B_m$  is the maximum flux density  $k_1, \alpha, \beta$  are the empirical coefficients fitted according to experimental data, generally  $1 < \alpha < 3$  and  $2 < \beta < 3$ .

To correct the equation to accommodate changes in different temperatures, we treat the parameters  $k$ ,  $\alpha$ , and  $B$  as functions related to the temperature  $T$ . The revised Steinmetz equation can be written as follows:

$$P(T) = k(T) \cdot f^{\alpha(T)} \cdot B_{\max}^{\beta(T)} \quad (21)$$

Where:  $k(T), \alpha(T), \beta$  are the polynomial fitting functions of temperature T, given by:

$$k(T) = \alpha_2 T^2 + \alpha_1 T + \alpha_0 \quad (22)$$

$$\alpha(T) = \beta_2 T^2 + \beta_1 T + \beta_0 \quad (23)$$

$$\beta(T) = \gamma_2 T^2 + \gamma_1 T + \gamma_0 \quad (24)$$

Where:  $\alpha_i, \beta_i, \gamma_i$  ( $i = 0,1,2$ ) are the coefficients obtained by fitting by least squares method (Bertotti *et al.*, 1991).

This process allows us to effectively introduce temperature factors in the model, thus improving the accuracy and reliability of the core loss prediction.

#### 5.2.4 Analysis of comparative results of different types of machine learning

In order to verify the actual effect of comprehensive learning strategy in excitation waveform classification and feature modeling, a set of comparative experiments are

designed in this section. The model without exciting waveform feature is selected as the reference group. Its performance is compared with the model with exciting waveform feature. The comparison results are shown in Table 8.

Table 8. Comparative experimental results excluding the classification features of excitation wave forms

Types of models	Feature set	MSE	R <sup>2</sup>
XGBoost (Using categorical features)	Original features + brain magnetic waveform classification features	0.022	0.99
XGBoost (No classification features are used)	Raw feature	0.035	0.96

Through comparison of two groups, the MSE value of the model is reduced after using the excitation waveform classification feature. And R<sup>2</sup> is closer to 1. In other words, it indicates that the excitation waveform classification feature has an important role in improving the prediction performance.

The uncorrected and modified Steinmetz equations prediction model are chosen as the comparison method, which are Multiple Linear Regression (MLR) and Convolutional Neural Network (CNN). The results of the different evaluation indicators are shown in Table 9.

Table 9. Model Performance Comparison (MSE & R<sup>2</sup>)

Model	MSE	R <sup>2</sup>
XGBoost	0.022	0.99
CNN	0.059	0.98
MLR	0.73	0.79
After the correction	0.055	0.99
Uncorrected	0.108	0.94

To further improve the reliability of the conclusions of the table above, MATLAB will be used in this section to visualize the data conclusions.

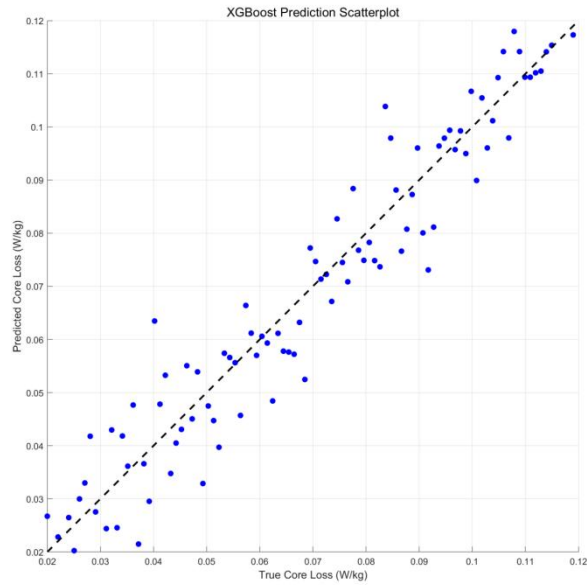


Figure 7. XGBoost predicted scatter plot

Figure 7 shows the distribution of the scatter between the predicted and true values of the XGBoost model. The data points are more evenly distributed along the ideal 45° reference line. It shows a high XGBoost prediction accuracy, less deviation from the actual loss value, and a good fit.

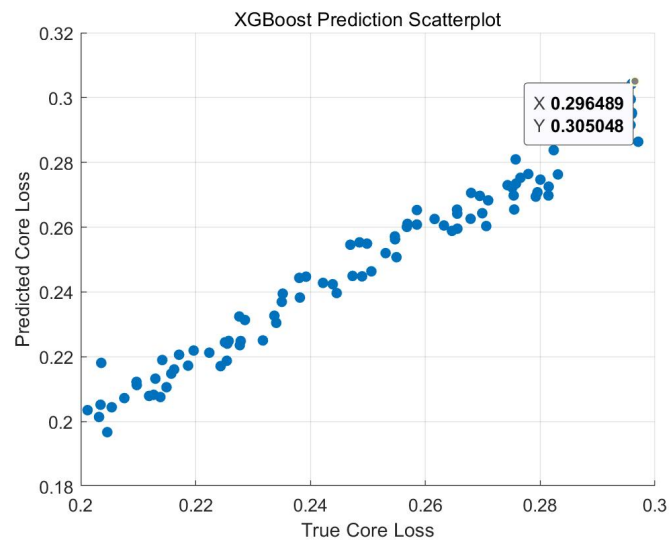


Figure 8. XGBoost prediction line plot

This figure shows the trend change of the predicted XGBoost value to the true value on different samples. From the fitting situation of the broken lines, XGBoost can accurately

capture the loss trend with a small overall error, indicating its reliability in the core loss prediction task.

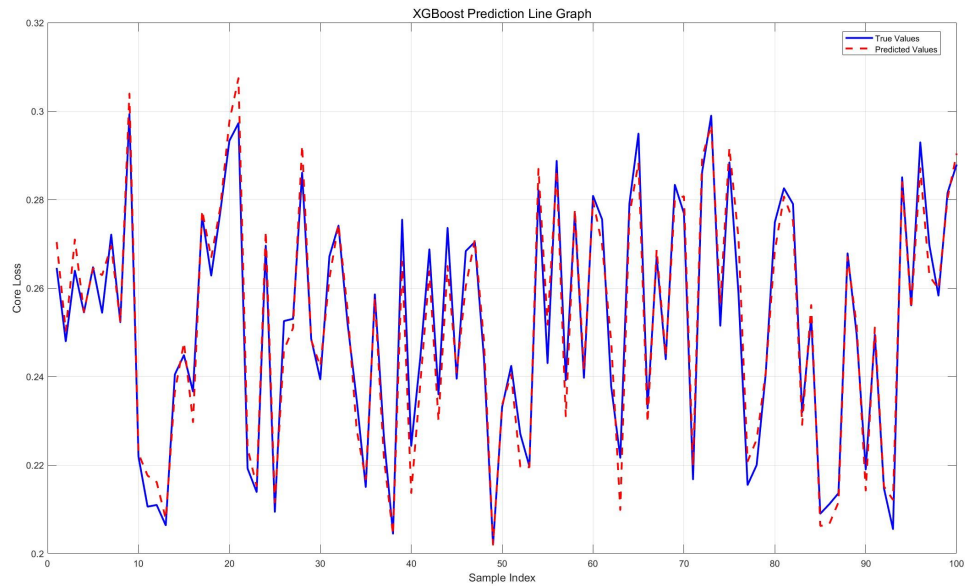


Figure 9. A scatter plot of the CNN prediction

This figure shows the prediction results of the CNN model. Compared with XGBoost, the distribution of data points is slightly scattered, and some points deviate from the reference line, indicating that CNN has a large prediction error in some cases, and its generalization ability is slightly inferior to that of XGBoost.

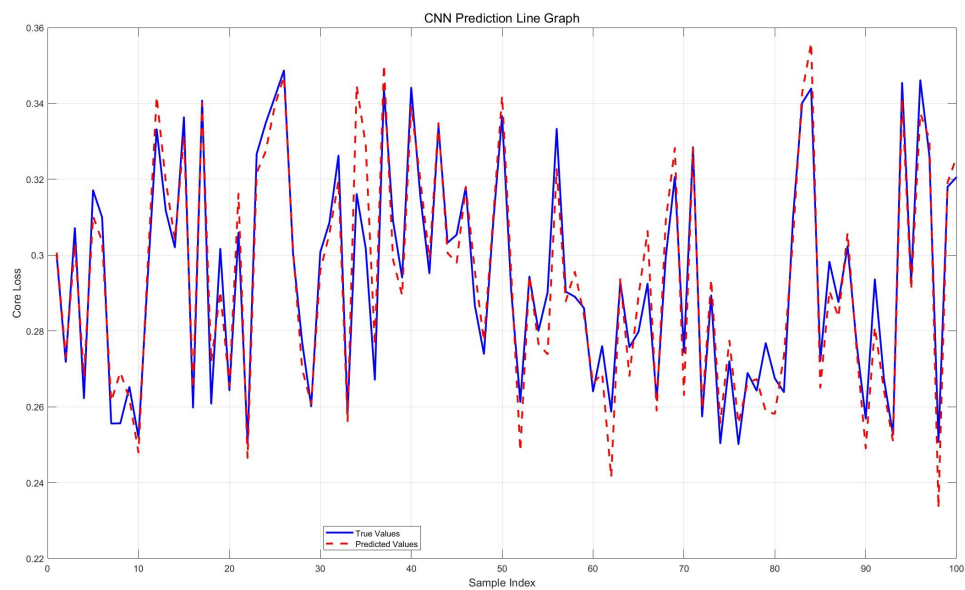


Figure 10. CNN prediction line plot

This line chart shows the trend of the CNN predicted value to the true value. Although the overall trend is similar to the real data. However, some degree of deviation occurs locally. It indicates that the CNN may have some deficiencies in handling complex nonlinear relationships, especially when the data amount is limited.

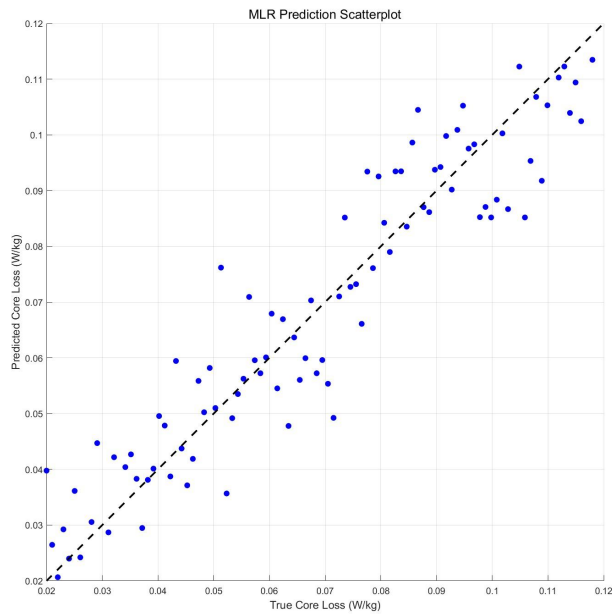


Figure 11. Scatter plot of multiple linear regression prediction

This figure shows the predictive performance of the MLR model. The data points are relatively scattered and deviate more from the reference line, indicating that the MLR has poor performance on the problem of core loss with strong nonlinear features and low-level prediction accuracy.

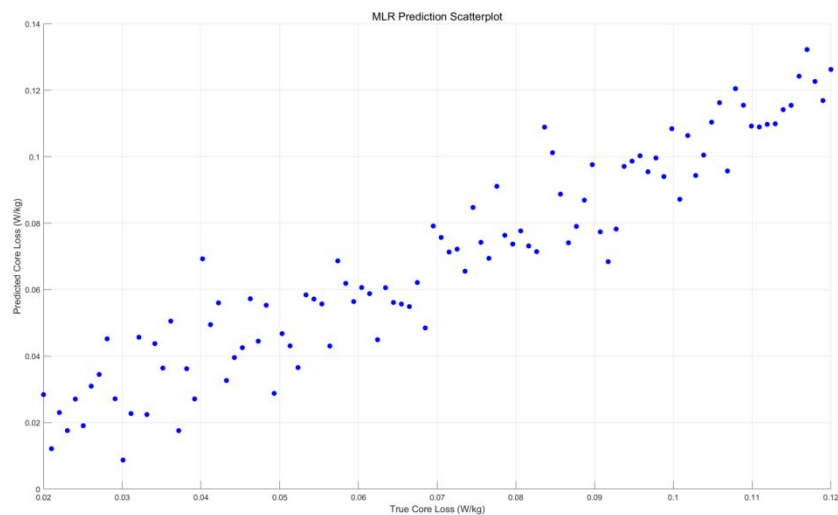


Figure 12. Scatter plot of multiple linear regression prediction

This scatter figure shows the change trend of the MLR predicted value with the true value. It can be seen that MLR cannot accurately capture the change pattern of loss, and the prediction curve deviates greatly from the true value, which further validates its limitations.

Based on the experimental results in Table 9 and Figure 7-12, a clear conclusion can be drawn that in the core loss prediction task of this study. The XGBoost model shows significant performance advantages over the traditional core loss prediction model and other machine learning methods. Specifically, XGBoost, relying on its structure based on the GBDT, can correct the prediction error through step-by-step iteration. It significantly improve the prediction accuracy of the model. When it comes to generalization ability and robustness in dealing with complex interactions between high-dimensional data, this mechanism makes XGBoost excel in dealing with complex nonlinear relationships. In addition, XGBoost's training process effectively reduces the risk of overfitting. This feature ensures that the model's performance remains consistent on both training and test data.

In contrast, conventional magnetic core loss prediction models, although in the specific conditions have a good theoretical basis. But they might enable to satisfy the nonlinear relationship of many influencing factors, such as frequency and waveform. The guiding prediction accuracy is also limited. Other machine learning methods, such as MLR and CNN, have different advantages though. However, for this study, MLR performs poorly in terms of nonlinear features, while CNN needs the large amount of data and high computational resource requirements. Their model training efficiency and accuracy are not as good as XGBoost. Therefore, XGBoost proves to be the most powerful core loss prediction model that can better cope with the model complexity.

## 6 Conclusion and Outlook

### 6.1 Study summary and contribution

This paper presents a machine learning based prediction and optimization method for high frequency magnetic core loss, constructing the experimental database of limited prediction accuracy under high frequency non-sinusoidal wave excitation, and extracting key features by the traditional Steinmetz equation. Integrated machine learning (SVM, RF, GBDT) is used for excitation waveform classification, and XGBoost can be more suitable used for iron loss prediction. The experimental results show that this method is more accurate than the traditional model, with lower MSE and  $R^2$  closer to 1.

In addition, the magnetic elements are optimized combined with the Genetic Algorithm to minimize the magnetic core loss and maximize the magnetic energy transmission, and improve the energy efficiency ratio. The optimization strategy is superior under high frequency conditions, which provides reliable support for the design of magnetic components for high power density power electronic systems.

### 6.2 Research limitations and future development direction

Although this study has achieved good results. However, there are still problems such as limited dataset coverage, insufficient modeling of some high-frequency nonlinear loss mechanisms, and high computational complexity of the optimization algorithm. In the future, deep learning and migration learning can be combined to improve the adaptability of the model. Physically guided machine learning methods are also introduced to improve the prediction accuracy. In addition, the optimization method can be further combined with reinforcement learning to improve the computational efficiency and extend to a wider range of application scenarios.

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