

Article

Low-Loss Design of Magnetic Material and Operating Conditions via a Physics–Data Dual-Driven Core Loss Model

Lejing Lin ^{1,*}, Guiping Zhang ¹, Hongyu Li ² and Yuchen Liu ¹¹ School of Mathematics and Statistics, Wuhan University of Technology, Wuhan, 430070, China² School of Automation, Wuhan University of Technology, Wuhan, 430070, China

* Correspondence: lynd@whut.edu.cn

Abstract

Accurate core loss evaluation is essential in the design of magnetic components. Core loss is critically influenced by excitation waveform, temperature, and magnetic material; therefore, we develop a waveform equivalence coefficient, a temperature polynomial, and an electrical conductivity term to revise the Steinmetz Equation and propose a physics–data dual-driven core loss model across materials and operating conditions. The waveform equivalence coefficient achieved 100% waveform classification, and temperature polynomial modification reduced the mean square error by an order of magnitude. Using three-way analysis of variance (ANOVA), we measured the individual and synergistic impacts of the three key factors on core loss. The waveform exerts the greatest individual influence while waveform and material, as a combination, exerts the greatest synergistic influence. Given the discovery that Material 1 demonstrates a property transition point under triangular waveform, the dual-objective optimization result indicates that using Material 1 under operating conditions of 90 °C, 501,180 Hz frequency, 0.0047 T peak flux density, and a triangular excitation waveform enables the magnetic component to achieve minimum core loss with maximum transmitted magnetic energy.

Keywords: core loss optimization; high-frequency non-sinusoidal excitation; waveform analysis; temperature modification of the Steinmetz Equation; magnetic materials

MSC: 78A25, 90C90, 65Z05

1. Introduction

1.1. Problem Background

With national economic development and social progress, power conversion technologies based on power electronics—including Direct Current (DC) voltage regulation and bidirectional conversion between DC and Alternating Current (AC) [1–3]—have developed rapidly, especially in fields such as new energy and information and communication technology. These power conversion technologies are extensively adopted in many aspects of communication power supplies, computing power supplies, data center power supplies, new energy power conversion, rail transportation, electric vehicles [4,5], electrical drives, smart grids, and green lighting. Driven by the evolution of third-generation wide-bandgap semiconductor devices, high frequency, high power density, and high reliability have become key development directions for power converter products. Magnetic components (e.g., transformers and inductors) are indispensable elements in power

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converters, serving critical functions like magnetic energy transfer, storage, and filtering. They significantly impact the converter's volume, weight, power loss, and cost. A vital indicator of a transformer is its core flux, as transformer overexcitation leads to complex problems, including increased magnetizing current, excessive harmonic generation, overheating, increased reactive power demand, and maloperation of differential relays [6].

To achieve high efficiency and high power density, magnetic components must not only meet basic electrical parameter requirements but also exhibit low power loss. Therefore, a detailed investigation and analysis of their loss characteristics are essential. The losses in magnetic components consist of winding losses and core losses. Winding losses in copper conductors can be accurately determined using finite element analysis (FEA) of electromagnetic fields. Core loss, however, refers to the power dissipation within the magnetic material under high-frequency alternating flux. This loss mechanism is complex due to the intricate microstructure of high-frequency magnetic materials (e.g., ferrites, alloy powder cores, amorphous, nanocrystalline, etc.). Furthermore, core loss depends on multiple factors, including operating frequency, flux density, excitation waveform, temperature, and the core material itself, exhibiting complex nonlinear and interdependent behaviors. Existing core loss models often fall short in meeting the demands of practical applications.

Currently, core loss models are primarily categorized into two types: loss separation models and empirical calculation models. The separation model calculates the total core loss by summing its three constituent parts: hysteresis loss, eddy current loss, and excess loss [7]. In contrast, empirical models estimate core loss using formulas derived from experimental data or theoretical reasoning. Among these, the Steinmetz Equation (SE) [8] is one of the most renowned empirical models. The original SE primarily targets core loss calculation under sinusoidal excitation, and its parameters require adjustment for different core materials and operating conditions (i.e., the specific working environment of the material, including temperature, frequency, and excitation waveform). To enhance its accuracy, researchers have developed various improvements, leading to modified models such as the Modified Steinmetz Equation (MSE) [9,10], the Generalized Steinmetz Equation (GSE) [11], and the Improved Generalized Steinmetz Equation (iGSE) [12].

However, these SE-based models exhibit limited accuracy for specific waveforms and frequency ranges. Furthermore, they require a substantial amount of experimental data covering the entire parameter space. In recent years, particularly in the area of high-frequency power electronics devices, there has been an increasing demand for highly accurate simulation techniques to precisely analyze core loss and magnetic properties. Recent advancements in data-driven (e.g., [13,14]) and model–data dual-driven (e.g., [15]) approaches offer promising solutions to this challenge. The variables, advantages, and disadvantages of these models and methods are summarized in Table 1. These methods and architectures each have their own rationality and advantages, showing significant improvements in accuracy compared to the more theoretical SE models. Among them, the model-and-data-driven approach exhibits exceptionally high accuracy and stability. However, it is noteworthy that, for the independent variable of “material”, common practice involves training models tailored to specific materials [13,15]. Building on this, [14] further attempted to train models using joint datasets of multiple materials but did not achieve better results than single-material models.

Table 1. Data-driven core loss estimation methods.

References	Method	Variables	Advantages	Limitation
[13]	LSTM	magnetic flux density, frequency, temperature, waveform, material	The average error was less than 7%	Models are separately trained for each single material.
[14]	Fast-Fourier Transform (FFT) + Feedforward Neural Network (FNN)	frequency, magnitude, temperature, material	Lower average error than LSTM + FNN	The error of the multi-material model is higher than the single-material model.
[15]	Finite Element (FE) - ML Framework (Gradient boosting (GB), Extreme Gradient Boosting (XGB), Random Forest (RF), K-nearest neighbors (KNN), and multilayer perceptron (MLP))	Material composition (electric and magnetic parameter), frequency, flux density	A combination of mathematical Finite Element method and ML-based models, achieving an accuracy of approximately 91.78%, a 17% increase compared to the Steinmetz Equation-based model.	The model is specifically designed for Mn-Zn ferrite type of materials.

Consequently, this study aims to develop a high-accuracy core loss prediction model capable of adapting to various materials and operating conditions, founded on a dual-driven approach that integrates physical principles with data analysis. Such a model is anticipated to significantly enhance both the accuracy and efficiency of the magnetic component design process.

1.2. Research Framework

The research framework of this paper comprises two primary components: the construction of a generalized core loss model and the optimization of core loss and transmitted magnetic energy. In Section 2, based on the existing model and experimental data, we revise the Steinmetz Equation through the incorporation of an excitation waveform coefficient, a temperature modification, and a material-related term. These modifications yield a physics–data dual-driven model endowed with robust prediction capability and high accuracy across diverse material types and operating conditions, including temperature, frequency, peak flux density, and excitation waveform.

Following the establishment of a precise and generalized core loss prediction model, we proceed to optimize the magnetic component. The objective is to select the optimal material and operating conditions that minimize core loss while simultaneously maximizing the transmitted magnetic energy. Section 3 first employs a combined quantitative and qualitative approach, grounded in physical properties and experimental data, to assess the individual and synergistic impacts of material and operational conditions (namely, excitation waveform and temperature) on core loss. Subsequently, a dual-objective optimization is performed to identify the optimal material composition and set of operating conditions that enable the magnetic component to achieve minimal core loss concurrently with maximum transmitted magnetic energy.

2. The Construction of a Generalized Core Loss Model

Within the realm of core loss research, numerous traditional models (as outlined in “Section 1.1”) exist, each demonstrating utility under specific conditions. However, they are generally challenged by limited accuracy or a narrow scope of applicability. A critical gap persists in the industry: the lack of a core loss model that is both universally applicable

and capable of delivering high-precision predictions. This gap directly hinders the accurate assessment of losses in magnetic component design, consequently impeding the precise evaluation of overall power converter efficiency. In light of this situation, there is a strong impetus within the industry to develop more convenient and accurate data-driven models. The goal is to create a predictive core loss model capable of transcending different material types and operating conditions. Such a model would significantly enhance the precision and efficiency of magnetic component design, thereby laying a solid foundation for the continued advancement of power electronics technology.

This section will leverage experimental data to construct a core loss prediction model based on an analysis of materials and operating conditions (e.g., excitation waveform and temperature). We will perform data analysis and modeling, subsequently evaluating the model's prediction accuracy, generalization capability, and its potential implications for industrial applications.

2.1. Data Acquisition and Model Assumptions

The dataset used in this study is Question C of the 21st China Post-Graduate Mathematical Contest in Modeling (2024), publicly provided by the contest organizers [16]. The dataset includes four training subsets for different magnetic core materials (Materials 1–4). Each record contains environmental parameters (temperatures: 25 °C, 50 °C, 70 °C, and 90 °C; frequencies: 49,990–501,180 Hz; and excitation waveforms: sinusoidal, triangular, and trapezoidal); the measured core loss in watts per cubic meter (W/m^3); and 1024 uniformly sampled magnetic flux density points per cycle in tesla (T). The total numbers of experimental observations for Materials 1–4 are 3400, 3000, 3200, and 2800, respectively. The training set and test set are divided in an 8:2 ratio. The programming software used in this paper is Python, version 3.9.

The proposed model is established based on the following key assumptions:

- (1) The core loss is predominantly influenced by the factors explicitly considered in this work (i.e., temperature, frequency, excitation waveform, material type, and peak flux density), with no significant impact from other unspecified environmental or operational conditions.
- (2) The physical properties of the magnetic core material, such as its microstructure and composition, are homogeneous throughout the component.
- (3) The intrinsic magnetic characteristic parameters of the core material are assumed to remain constant across the varying frequencies and flux densities considered in this study.

The symbols, their definitions, and corresponding units used throughout this paper are summarized in Table 2.

Table 2. Nomenclature.

No.	Symbol	Unit	Definition
1	P	W/m^3	Core loss
2	B(t)	T	Excitation flux density
3	B_m	T	Peak excitation flux density
4	$B_i^+, i = 0, 1, \dots, N-1$	T	Absolute value of the excitation flux density
5	f	Hz	Frequency
6	τ	°C	Temperature
7	λ		Excitation waveform equivalence coefficient
8	σ	S/m	Electrical conductivity
9	S	m^2	Effective cross-sectional area of the magnetic core

2.2. Excitation Waveform Identification Factor

The excitation waveform stands as a critical factor influencing the magnetic core performance, with its shape profoundly impacting the core loss characteristics. The distinctive contour of an excitation waveform directly governs the dynamic behavior of the internal magnetic flux. Different waveform profiles alter the rate of change of magnetic flux density over time, leading to significant variations in loss behavior. Therefore, the accurate identification of the excitation waveform is paramount for a deeper understanding of core loss mechanisms and for the optimization of the magnetic core design.

The excitation waveform is primarily manifested in the distribution of magnetic flux density as a function of time. Different excitation waveforms result in distinct patterns of flux density growth, decay, or oscillation. This section leverages magnetic flux density data from experiments. We first analyze the distribution characteristics of the flux density and the shape attributes of different waveforms to extract feature variables that reflect these distributions and shapes. Subsequently, these feature variables are utilized to construct a classification model for identifying three types of excitation waveforms. The rationality and effectiveness of the classification model are then analyzed.

Since the excitation flux density can be both positive and negative, integrating over a full period leads to cancellation. Focusing solely on the positive half-cycle values of the flux density is more conducive to feature extraction.

2.2.1. Shape Characteristics of the Excitation Waveform

First, we analyzed excitation flux density functions of experimental data from Material 1, from which we abstracted the characteristic shapes of the three waveforms; see Figure 1.

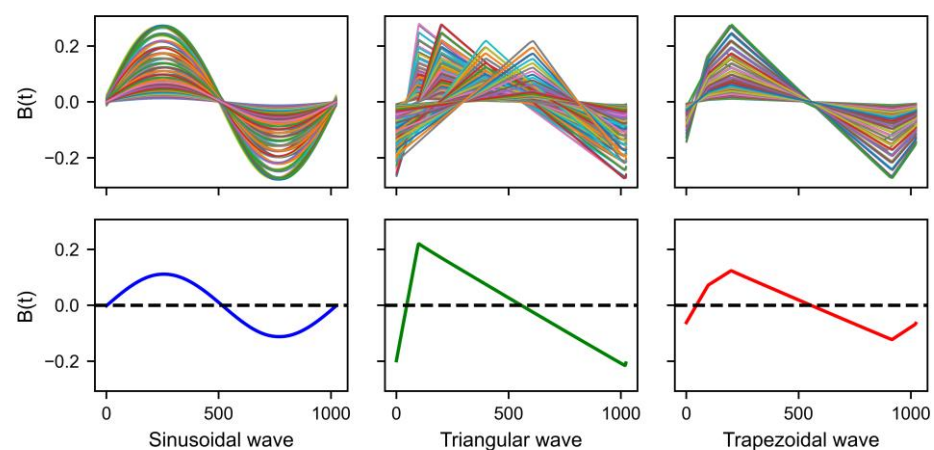


Figure 1. Excitation flux density functions of three waveform types (Material 1), in the first row of subplots, each colored line represents a sample, while the second row of subplots, from left to right, abstracts the general shape of sinusoidal, triangular, and trapezoidal wave, respectively.

For conciseness, coordinate systems are established at appropriate positions. Let B_m denote the peak value and T denote the period. The expressions for the three types of excitation flux density functions within the positive half-cycle are derived as follows:

(1) Sinusoidal Wave

$$B(t) = B_m \sin(\omega t), 0 \leq t \leq \frac{T}{2} \quad (1)$$

where $\omega = \frac{2\pi}{T}$ is the angular velocity, and $(\frac{T}{4}, B_m)$ is the inflection point of the sinusoidal wave, where the peak value B_m is achieved at $t = \frac{T}{4}$.

(2) Triangular Wave

$$B(t) = \begin{cases} \frac{B_m}{T_1} t, 0 \leq t \leq T_1 \\ -\frac{2B_m}{T-2T_1} (t - \frac{T}{2}), T_1 < t \leq \frac{T}{2} \end{cases} \quad (2)$$

where (T_1, B_m) is the inflection point of the triangular wave, where the peak value B_m is achieved at $t = T_1$.

(3) Trapezoidal Wave

$$B(t) = \begin{cases} \frac{B_1}{T_1} t, 0 \leq t \leq T_1 \\ \frac{B_m - B_1}{T_2 - T_1} (t - T_2) + B_m, T_1 < t \leq T_2 \\ -\frac{2B_m}{T-2T_2} (t - \frac{T}{2}), T_2 < t \leq \frac{T}{2} \end{cases} \quad (3)$$

where (T_1, B_1) and (T_2, B_m) are the two successive inflection points of the trapezoidal wave, and the peak value B_m is achieved at $t = T_2$.

All three waveforms exhibit a pattern of initial increase followed by a decrease within the positive half-cycle. However, the rate of change of magnetic flux density with respect to time, $\frac{dB}{dt}$, displays distinct characteristics, leading to their unique shape features:

- (1) Sinusoidal wave has only one inflection point $(\frac{T}{4}, B_m)$, where the curve is smooth and differentiable. The slope of the sinusoidal wave changes uniformly throughout the cycle without abrupt changes.
- (2) Triangular wave has only one inflection point (T_1, B_m) , which is a non-differentiable cusp. At this point, the slope undergoes an abrupt sign change (from positive to negative).
- (3) Trapezoidal wave has two inflection points, (T_1, B_1) and (T_2, B_m) , both of which are non-differentiable cusps. The slope changes abruptly at both points. At (T_1, B_1) , the sign of the slope does not change, but the absolute value of slope drops, while, at (T_2, B_m) , the sign of the slope changes from positive to negative, marking the transition point where the flux density switches from increases to a decrease.

2.2.2. Physical Definition and Geometrical Interpretation of the Waveform Factor

To quantify the shape of the magnetic flux density function $B(t)$, geometric analysis reveals that, for three waveforms with the same period and peak value, the area under the $B(t)$ curve and above the time axis within the positive half-cycle can reflect the characteristic shape of the waveform. This metric can be further refined as the average of this enclosed area over the half-period $\frac{T}{2}$, which is geometrically equivalent to the height of the rectangle with the same base length, as demonstrated by the green line in Figure 2. The magnitude relationship of this average value follows: sinusoidal wave > trapezoidal wave > triangular wave (see Figure 2).

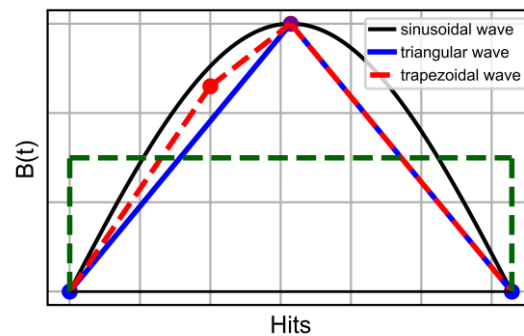


Figure 2. Shapes of the excitation flux density function $B(t)$.

In physics, the geometric interpretation of positive magnetic flux density average, B_{av} [17], aligns precisely with the area average derived from the above analysis. The definition of positive magnetic flux density average B_{av} is provided below and subsequently generalized for the trapezoidal waveform. Let B_m be the peak value of the periodic excitation flux density function and T the period length.

For sinusoidal excitation (corresponding to a sinusoidal wave), the positive magnetic flux density average is calculated as

$$B_{av_sin} = \frac{2}{T} \int_0^{T/2} B_m \sin(\omega t) dt = \frac{2B_m}{\pi} \quad (4)$$

For square-wave excitation (corresponding to a triangular wave), the positive magnetic flux density average is calculated as

$$B_{av_tri} = \frac{2}{T} \left[\int_0^{T_1} \frac{B_m}{T_1} t dt + \int_{T_1}^{T/2} -\frac{2B_m}{T-2T_1} \left(t - \frac{T}{2}\right) dt \right] = \frac{B_m}{2} \quad (5)$$

We generalize the positive magnetic flux density average to the trapezoidal wave:

$$B_{av_tra} = \frac{2}{T} \left\{ \int_0^{T_1} \frac{B_1}{T_1} t dt + \int_{T_1}^{T_2} \left[\frac{B_m - B_1}{T_2 - T_1} (t - T_2) + B_m \right] dt + \int_{T_2}^{T/2} -\frac{2B_m}{T-2T_2} \left(t - \frac{T}{2}\right) dt \right\} \quad (6)$$

The waveform equivalence coefficient λ is defined, using the sinusoidal wave as the benchmark, to measure the ratio of the positive magnetic flux density average of a given excitation waveform to that of a sinusoidal wave with the same peak value and period length:

$$\lambda_{wave} = \frac{B_{av_wave}}{B_{av_sin}} \quad (7)$$

where B_{av_wave} is the positive magnetic flux density average under the given excitation.

Theoretical analysis yields the waveform factors for the three excitation waveforms:

$$\begin{cases} \lambda_{sin} = \frac{B_{av_sin}}{B_{av_sin}} = 1 \\ \lambda_{tri} = \frac{B_{av_tri}}{B_{av_sin}} = \frac{\pi}{4} \\ \lambda_{tra} = \frac{B_{av_tra}}{B_{av_sin}} \in \left[\frac{\pi}{4}, 1\right] \end{cases} \quad (8)$$

where λ_{sin} , λ_{tri} and λ_{tra} represent the equivalent coefficients for the sinusoidal, triangular, and trapezoidal waves, respectively, relative to the sinusoidal benchmark.

In order to define sample waveform equivalence coefficient, we first provide the definition of the sample positive magnetic flux density average B_{av} :

$$B_{av} = \frac{2}{N} \sum_{i=0}^{N-1} B_i^+ \quad (9)$$

where $B_i^+, i=0,1,\dots,N-1$ are the sample values where the flux density is positive, N is the number of equally spaced sampling points in the positive half-cycle, and in this dataset, $N=1024$.

Subsequently, the sample waveform equivalence coefficient λ is defined based on Equation (7):

$$\lambda_{wave} = \frac{B_{av_wave}}{B_{av_sin}} = \frac{\pi \sum_{i=0}^{N-1} B_i^+}{N B_m} \quad (10)$$

where B_{av_sin} is the positive magnetic flux density average of the sinusoidal wave with the same peak value and period length as the sample. From Equation (4), we have $B_{av_sin} = \frac{2B_m}{\pi} = \frac{2\max\{B_i\}}{\pi}$, where $B_m = \max\{|B_i|\}$ is the estimated peak value of the periodic excitation flux density function.

The sample waveform equivalence coefficient is computed using Equation (10), and the resulting violin plots for different materials are shown in Figure 3. It can be observed that the value ranges of the waveform equivalence coefficients for different waveforms do not overlap, demonstrating the feasibility of this metric for practical applications.

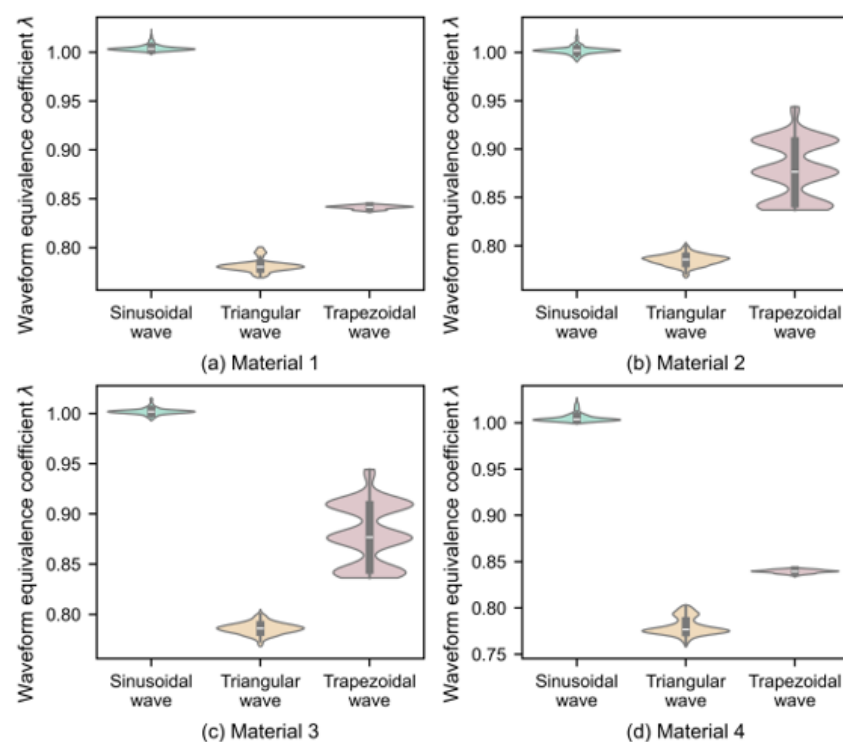


Figure 3. Violin plots of the waveform equivalence coefficient for the four materials.

2.2.3. Waveform Coefficient–Random Forest Classification Model

The waveform equivalence coefficient developed in Section 2.2.2 serves as the physics-driven component, while the Random Forest model acts as the data-driven

component, working in concert to achieve excitation waveform classification. The configuration of the Random Forest model is summarized in Table 3.

Table 3. Random Forest model configuration.

Model Parameter	Value
number of decision trees	100
cross validation	5-fold

The sample waveform coefficients of the three waveform types calculated by Equation (10) are expected to be close to their theoretical counterparts given by Equation (8). Leveraging this single metric—the waveform equivalence coefficient—we construct a physics–data dual-driven Random Forest classification model to identify waveforms from the experimental data. This hybrid approach offers several key advantages:

- (1) **Model Rationale:** As observed in the violin plots of waveform coefficient for the four materials (Figure 3), the value ranges for different waveforms show no overlap. This clear separation underpins the model’s excellent classification performance.
- (2) **Model Effectiveness:** The confusion matrices for waveform classification across the four materials (Figure 4) demonstrate that the model achieved a 100% accuracy rate on the test set for all materials. This perfect performance is robustly supported by the theoretical properties of the waveform coefficient.

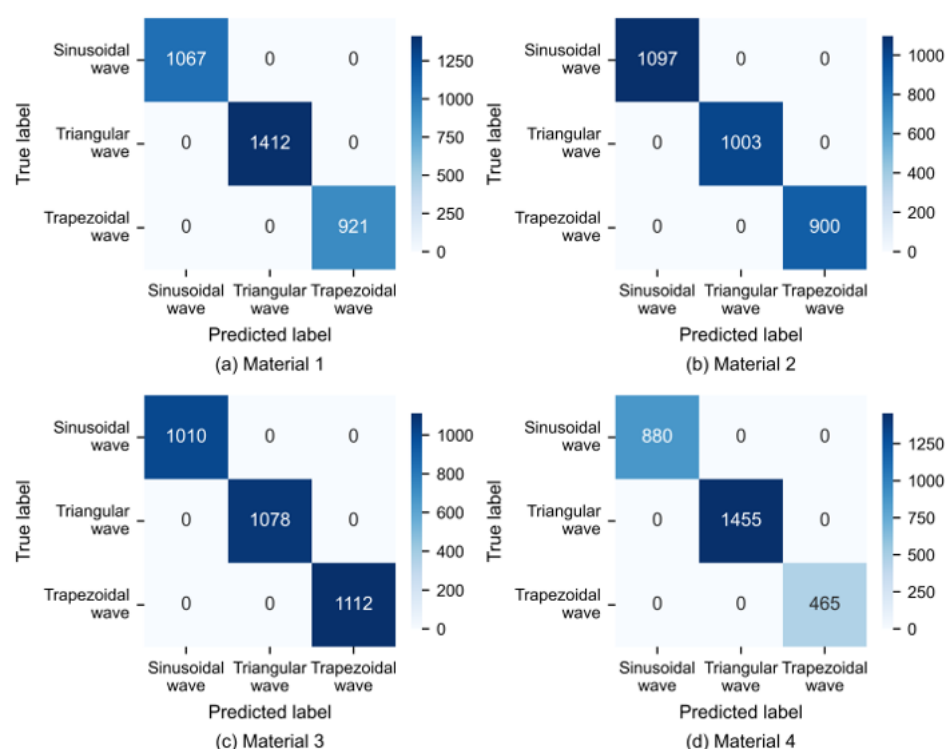


Figure 4. Waveform classification confusion matrices for the four materials.

The perfect classification accuracy shown in Figure 4 may raise concerns about possible data leakage or overfitting. However, this result is analytically guaranteed by the design of the waveform equivalence coefficient λ_{wave} defined in Equation (7). The coefficient maps each waveform to a scalar value, and its theoretical ranges for the three waveform types are strictly non-overlapping, as derived in Equation (8). Consequently, any input waveform can be assigned deterministically to its correct category without ambiguity. This mathematical separability ensures 100% accuracy on any properly

preprocessed dataset, reflecting the robustness of the feature engineering rather than a methodological flaw. The result was consistently observed on both training and independent test data, confirming the generalizability of the proposed coefficient.

- (3) **Model Simplicity:** To validate the sufficiency of the waveform coefficient, other distribution features of the positive flux density $B^+(t)$ —namely its mean, standard deviation, and peak value—were included alongside the waveform coefficient as training features for the Random Forest. The feature importance was then measured. The results, shown in Figure 5, reveal that the importance of the waveform coefficient far exceeds that of all other metrics, with a value virtually identical to 1. This finding confirms that the waveform coefficient alone is sufficient for accurate excitation waveform classification based on shape characteristics.

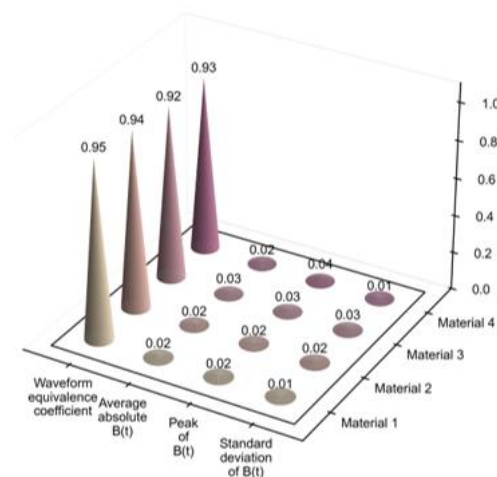


Figure 5. Comparison of classification feature importance.

2.3. Temperature Modification of the Steinmetz Equation

Beyond the excitation waveform, temperature is another critical operating condition that significantly impacts core loss. However, the traditional Steinmetz Equation (SE) (Equation (11)), as a core loss model, is notably limited by its specific application conditions. For instance, the equation was primarily designed for sinusoidal waveforms and exhibits substantial errors when applied to different core materials and varying operating temperatures, introducing inconveniences and complexities in practical engineering applications. While previous modifications have addressed core loss under non-sinusoidal waveforms [9–12], this section focuses on incorporating the influence of temperature. We modify the SE using two distinct temperature-dependent terms: a polynomial form [18] and a power function form. The prediction accuracy of these two modified models is then compared against the baseline performance of the original SE. The optimal model is selected based on relevant evaluation metrics.

(1) Steinmetz Equation (SE)

In the late 19th Century, Steinmetz proposed an empirical model for calculating core loss under sinusoidal excitation [8]. He postulated that core loss is related to the frequency and the peak magnetic flux density, expressed as

$$P_1 = k_1 \cdot f^{\alpha_1} \cdot B_m^{\beta_1} \quad (11)$$

where P_1 is the core loss, f is the frequency, B_m is the peak flux density, and k_1, α_1, β_1 are the parameters to be estimated.

(2) Temperature polynomial-modified Steinmetz Equation

Following [18], we introduce a second-order temperature polynomial to modify the SE:

$$P_2 = k_2 \cdot f^{\alpha_2} \cdot B_m^{\beta_2} \cdot \mu_2(\tau) \quad (12)$$

where P_2 is the core loss, $\tau \in [0, T_{\max}]$ is the temperature, $\mu_2(\tau) = a\tau^2 + b\tau + c$ is the second-order temperature polynomial, and $a, b, c, k_2, \alpha_2, \beta_2$ are the parameters to be estimated.

(3) Temperature power-modified Steinmetz Equation

Given that core loss exhibits a nonlinear but non-exponential relationship with temperature, a temperature power function is also employed to modify the SE model:

$$P_3 = k_3 \cdot f^{\alpha_3} \cdot B_m^{\beta_3} \cdot \mu_3(\tau) \quad (13)$$

where P_3 is the core loss, $\tau \in [0, T_{\max}]$ is the temperature, $\mu_3(\tau) = \tau^d$ is the temperature power function, and $d, k_3, \alpha_3, \beta_3$ are the parameters to be estimated.

Using the processed experimental data with temperature, frequency, and peak flux density as independent variables and core loss as the dependent variable, the three core loss models are fitted via the least squares method. The resulting equations for the fitted SE, temperature polynomial SE, and temperature power function SE models are given in Equations (14)–(16), respectively (fitted coefficients are rounded to three decimal places).

$$P_1 = 1.500f^{1.430} \cdot B_m^{2.471} \quad (14)$$

$$P_2 = 0.001f^{1.467} \cdot B_m^{2.451} \cdot (0.093\tau^2 - 16.609\tau + 1338.472) \quad (15)$$

$$P_3 = 4.738f^{1.463} \cdot B_m^{2.449} \cdot \tau^{-0.402} \quad (16)$$

The fitted SE, temperature polynomial SE, and temperature power function SE models are used to predict the core loss under various operating conditions. A comparison of the prediction performance between the modified and the original SE models is shown in Figure 6. A significant improvement in prediction accuracy is observed after introducing the temperature coefficients.

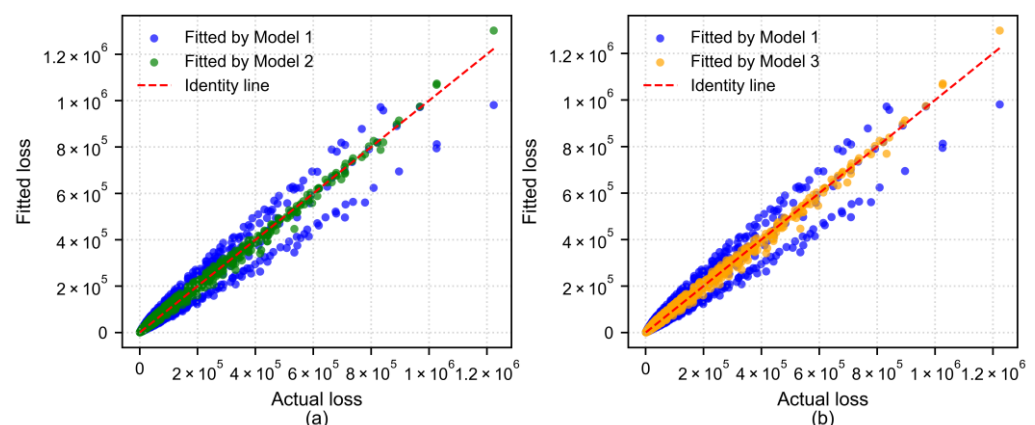


Figure 6. Comparison between the temperature-modified SE and the original SE: (a) temperature polynomial-modified SE vs. the original SE; (b) temperature power-modified SE vs. the original SE.

The model fitting performance is summarized in Table 4. The temperature-modified SE models show substantial improvements in both the R-squared (R^2) and Mean Squared Error (MSE) compared to the original model, with the MSE reduced by an order of

magnitude. Between the two temperature modification methods, the polynomial form yields superior results to the power function form.

Table 4. Evaluation metrics for the three models.

Model	R-Squared (R^2)	Mean Squared Error (MSE)
SE	0.9448	1.64×10^9
Temperature polynomial-modified SE	0.9955	1.35×10^8
Temperature power-modified SE	0.9953	1.39×10^8

The prediction performance, including predicted values and relative errors, is detailed in Table 5. The average relative error when using the original SE model is as high as 35.66%. The power function-modified model reduces this error to 22.38%, which is 13.28% lower than the baseline. The polynomial-modified SE model achieves an average relative error of 14.61%, which is only 41% of the error from the baseline model. These results demonstrate that the temperature-modified SE models significantly outperform the original SE model, and the polynomial modification more accurately captures the influence of temperature on core loss compared to the power function modification.

Table 5. Comparison of predicted values and relative errors (REs) for different models.

Sample No.	Core Loss W/m ³	SE		Temperature Polynomial-Modified SE		Temperature Power-Modified SE	
		Predicted Value	RE (%)	Predicted Value	RE (%)	Predicted Value	RE (%)
555	99,013.82	124,416.93	25.66	104,732.61	5.78	107,461.34	8.53
556	134,923.46	163,710.62	21.34	137,498.73	1.91	141,043.41	4.54
557	182,082.03	216,260.51	18.77	181,219.30	0.47	185,840.64	2.06
558	234,476.06	273,690.18	16.72	228,897.61	2.38	234,681.00	0.09
559	322,173.76	367,920.28	14.20	306,960.48	4.72	314,625.36	2.34
560	689.63	1150.83	66.88	1012.35	46.80	1043.26	51.28
561	914.19	1521.19	66.40	1335.07	46.04	1375.46	50.46
562	1634.40	2779.14	70.04	2427.06	48.50	2499.01	52.90
563	2250.01	3627.68	61.23	3161.16	40.50	3254.04	44.62
564	3001.07	4774.27	59.09	4150.91	38.31	4271.73	42.34
565	4015.75	6364.67	58.49	5520.59	37.47	5679.67	41.43
Average Relative Error(%)		35.66		14.61		22.38	

The value in bold means the smaller relative errors for each sample or on average.

2.4. A Core Loss Prediction Model Across Material and Operating Conditions

In Sections 2.1 and 2.2, we developed the waveform coefficient and the temperature modification term to quantify the impact of different operating conditions. Building upon this foundation, this section incorporates the influence of the core material to establish a core loss prediction model that is applicable across diverse materials and operating conditions.

(1) Waveform-coefficient Steinmetz Equation (WcSE)

The Waveform-coefficient Steinmetz Model (WcSE) [19] defines the waveform coefficient λ as the ratio of the area enclosed by the flux density curve and the axes over one magnetization cycle under a given excitation to that under a sinusoidal excitation. Its expression is as follows:

$$P = \lambda \cdot k \cdot f^\alpha \cdot B_m^\beta \quad (17)$$

where k, α, β are the parameters to be estimated. λ is the ratio of the positive magnetic flux density average of a given excitation (waveform), after removing any DC bias, to that of a sinusoidal waveform with the same peak-to-peak value. Here, we adopt the waveform equivalence coefficient constructed in Equation (7) of Section 2.1, i.e.,

$$\lambda_{\text{wave}} = \frac{B_{\text{av_wave}}}{B_{\text{av_sin}}} \quad . \quad \text{Its sample estimate is given by Equation (10), i.e.,}$$

$$\lambda_{\text{wave}} = \frac{B_{\text{av_wave}}}{B_{\text{av_sin}}} = \frac{\pi}{N} \frac{\sum_{i=0}^{N-1} B_i^+}{B_m}, \quad \text{where } B_i^+, i=0,1,\dots,N-1 \text{ are the sample values where the flux density is positive, } N \text{ is the number of equally spaced sampling points in the positive half-cycle, and } B_m = \max\{B_i\} \text{ is the estimated peak value of the periodic excitation flux density function.}$$

(2) Temperature polynomial-modified Steinmetz Equation

Based on the discussions in Section 2.2, the temperature polynomial-modified Steinmetz Equation is selected, as shown below:

$$P = \mu(\tau) \cdot k \cdot f^\alpha \cdot B_m^\beta \quad (18)$$

where τ is temperature, $\mu(\tau) = a\tau^2 + b\tau + c$ is the second-order temperature polynomial term, and $a, b, c, k, \alpha, \beta$ are the parameters to be estimated.

(3) Separation model considering the core material

Bertotti incorporated material influence factors into the core loss, proposing the core loss separation model [7]. In the model, core loss consists of three components: hysteresis loss, eddy current loss, and excess loss, calculated by Equations (19)–(22):

$$P_{\text{core}} = P_h + P_{\text{cl}} + P_e \quad (19)$$

$$P_h = k_h \cdot f \cdot B_m^\beta \quad (20)$$

$$P_{\text{cl}} = k_{\text{cl}} \cdot f^2 \cdot B_m^2 \quad (21)$$

$$P_e = 8 \cdot \sqrt{\sigma \cdot S \cdot G \cdot V_0} \cdot f^{1.5} \cdot B_m^{1.5} \quad (22)$$

where k_{cl} is related to the core's cross-sectional area and resistivity, σ is the electrical conductivity, S is the effective cross-sectional area of the magnetic component, G is a constant (0.1356), and k_h, β, V_0 are the parameters to be estimated.

Parameters for the separation model are set as follows. S takes the unit effective cross-sectional area, and the electrical conductivity σ of the core material is set to 10^{-4} S/m . This value is chosen to be applicable to the four materials in our experimental dataset, considering the conductivity ranges of common high-frequency magnetic materials (ferrite, alloy powder cores, amorphous, and nanocrystalline) listed in Table 6.

Table 6. Electrical conductivity of four common core materials.

Material	Ferrite	Alloy powder	Amorphous	Nanocrystalline
Conductivity	$[10^{-10}, 10^{-3}]$	$[10^{-6}, 10^{-3}]$	$[10^{-6}, 10^{-2}]$	$[10^{-5}, 10^{-2}]$

(4) The core loss prediction model across material and operating conditions

Integrating the WcSE model, the temperature polynomial-modified SE model, and the core loss separation model, we construct a core loss prediction model that spans different material types and operating environments. The expression is given in Equation (23):

$$P = \lambda \cdot v \cdot k \cdot f^\alpha \cdot B_m^\beta \cdot \mu(\tau) \quad (23)$$

where $\lambda = \frac{\pi}{N} \sum_{i=0}^{N-1} B_i^+$, $\mu(\tau) = a\tau^2 + b\tau + c$, $v = \sqrt{\sigma \cdot S \cdot G}$, and $k, a, b, c, \alpha, \beta, V_0$ are the parameters to be estimated.

Parameters of the proposed generalized core loss model are estimated using the gradient descent method based on experimental data. The resulting model is

$$P = 0.98\lambda f^{1.42} B_m^{2.19} (0.00015\tau^2 - 0.026\tau + 2.54) \quad (24)$$

where $R^2 = 0.95$ and $RMSE = 85901.51$.

The prediction performance of the proposed model is shown in Figure 7, which compares the predicted values against the true values. It can be observed that the generalized core loss prediction model fits the true values well. The errors are bounded within two parallel lines, indicating that the error does not increase with the actual core loss magnitude.

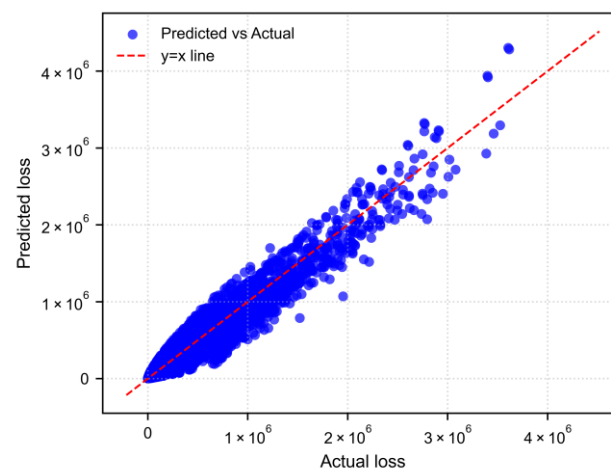


Figure 7. Fitting performance of the generalized core loss prediction model.

The model fitting performance, in terms of R-squared and Root Mean Square Error, is presented in Table 7. The results indicate that the generalized core loss prediction model achieves a high goodness-of-fit and a low error, demonstrating high model accuracy.

Table 7. Evaluation metrics for the generalized core loss prediction model.

R-Squared (R^2)	Root Mean Square Error (RMSE)
0.948	85,901.5

3. Optimization of Magnetic Components

3.1. Quantifying Influence via Three-Factor ANOVA

This section employs a combined quantitative and qualitative approach to measure the degree and manner of the individual and synergistic influences of three factors on core loss. First, a quantitative analysis is conducted using a three-factor analysis of variance

(ANOVA) to separately measure the extent of the individual and interactive effects of temperature, excitation waveform, and core material on core loss. Subsequently, given the complex nonlinear and interdependent nature of these influences, a qualitative analysis is performed using the control variable method to elucidate the specific ways in which these factors individually and jointly affect core loss. The insights gained from this analysis regarding individual and synergistic effects also provide a theoretical basis for minimizing core loss.

ANOVA works by dividing the sum of squares for each factor by its degrees of freedom to obtain a mean square. An F-statistic is then constructed from the ratio of these mean squares, and hypothesis testing is conducted to determine the significance of the main effects of individual factors and their interactions. Prior to performing the ANOVA, the variables—temperature, waveform, and material—were treated as categorical. The results of the three-factor ANOVA are presented in Table 8.

Table 8. Individual and joint influences of temperature, excitation waveform, and core material.

Source of Variation	Sum of Squares	Degrees of Freedom	F-Statistic	p-Value
Temperature	5.38×10^{11}	3	1.37	0.249
Waveform	9.10×10^{12}	2	34.88	*
Material	2.54×10^{12}	3	6.48	*
Temperature and Waveform	1.37×10^{12}	6	1.75	0.105
Temperature and Material	9.55×10^{11}	9	0.81	0.604
Waveform and Material	1.22×10^{13}	6	15.64	*

* indicates statistical significance.

3.1.1. Individual Effects

Degree of Influence: Waveform >> Material > Temperature

The ANOVA results (Table 8) indicate that the effects of both excitation waveform and material are significant, and waveform has the most substantial influence on core loss among individual factors. This finding aligns with theoretical expectations, as different waveform profiles alter the rate of change of magnetic flux density over time, leading to significant differences in loss characteristics. Subsequently, we analyze the effect of each individual factor in descending order of their influence on core loss.

(1) Waveform: Sinusoidal wave is the minimum

The impact of the waveform varies between material groups:

- (i) For Materials 1 and 4: Sinusoidal wave < Trapezoidal wave < Triangular wave
- (ii) For Materials 2 and 3: Sinusoidal wave < Trapezoidal wave $\approx$ Triangular wave

Figure 8 uses Materials 1 and 2 as examples to illustrate the differing ways in which the waveform influences the core loss for the two material categories.

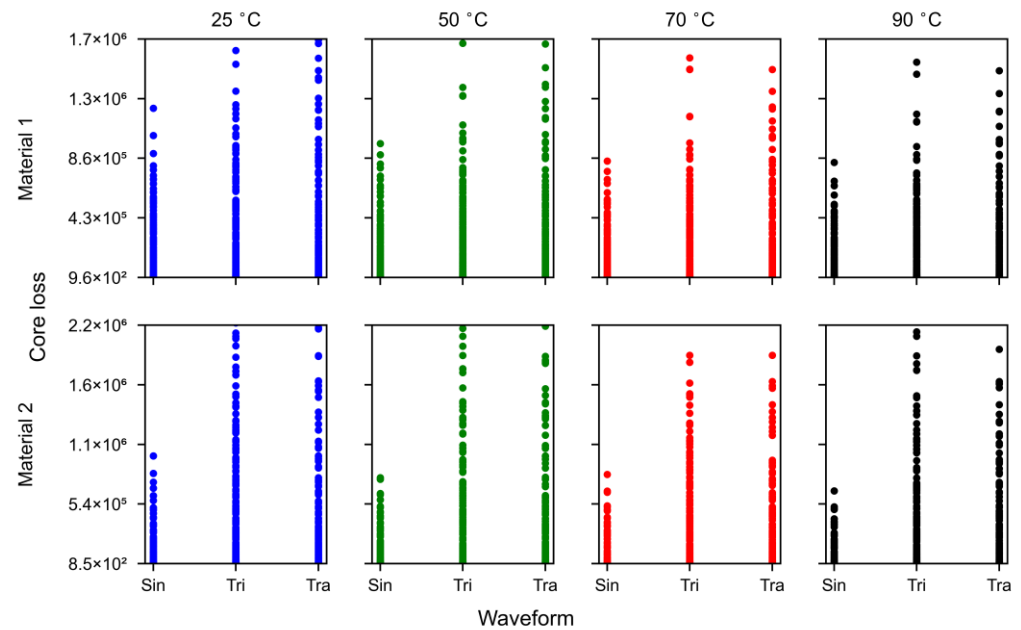


Figure 8. Variations of core loss with waveforms (Materials 1 and 2, different temperatures).

As shown in Figure 8, regardless of the material or temperature, the sinusoidal wave consistently yields the lowest core loss, generally contained within $1.0 \times 10^6 \text{ W/m}^3$. For Materials 1 and 4, building upon the baseline range of sinusoidal wave loss, the losses for the trapezoidal wave exhibit a dense, upward shift, while those for the triangular wave show a sparse, upward shift. Consequently, the range width and peak value of the core loss for the triangular wave are significantly greater than those for the trapezoidal wave. For Materials 2 and 3, the increase in core loss for both triangular and trapezoidal waves, compared to the sinusoidal wave, is comparable. The range width and peak value of the core loss for these two waveforms are similar.

Based on these distinct patterns of waveform influence on core loss, we can categorize the waveforms into two types. This categorization is consistent with the characteristics observed in the sampling distribution of excitation waveforms for different materials. Samples of Material 1 and Material 4 exhibit relatively small phase differences (Figure 9), whereas samples of Material 2 and Material 3 display a variety of phase differences (Figure 10).

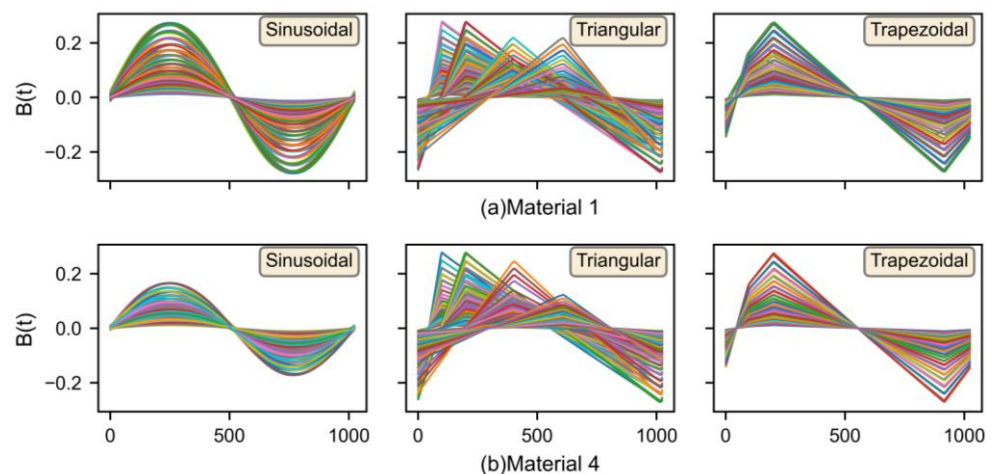


Figure 9. Excitation flux density functions of Materials 1 and 4 under different working conditions, each colored line represents a sample, with consistent phases.

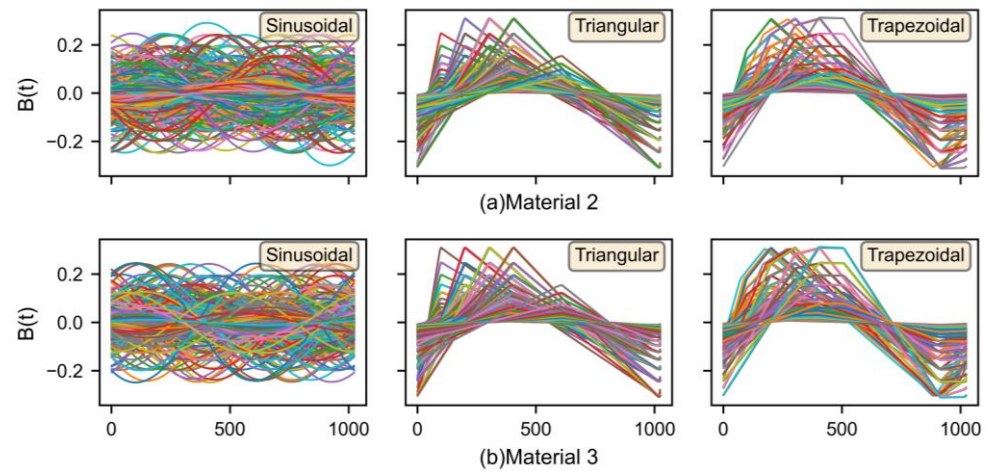


Figure 10. Excitation flux density functions of Materials 2 and 3 under different working conditions, each colored line represents a sample, with various phases.

This comparison reveals that the two categories of core materials possess distinct properties, which is consistent with the finding that their core losses are influenced by the excitation waveform in two distinct modes.

(2) Material: Material 4 exhibits the minimum loss

- (i) Sinusoidal Waveform: Material 4 < Material 2 < Material 3 $\approx$ Material 1
- (ii) Trapezoidal Waveform: Material 4 < Material 1 < Material 2 < Material 3
- (iii) Triangular Waveform: Material 1 demonstrates a property transition point (analyzed in Section 3.1.2 concerning the waveform and material synergy).

Figure 11 depicts the variation of core loss with materials under different waveforms and temperatures.

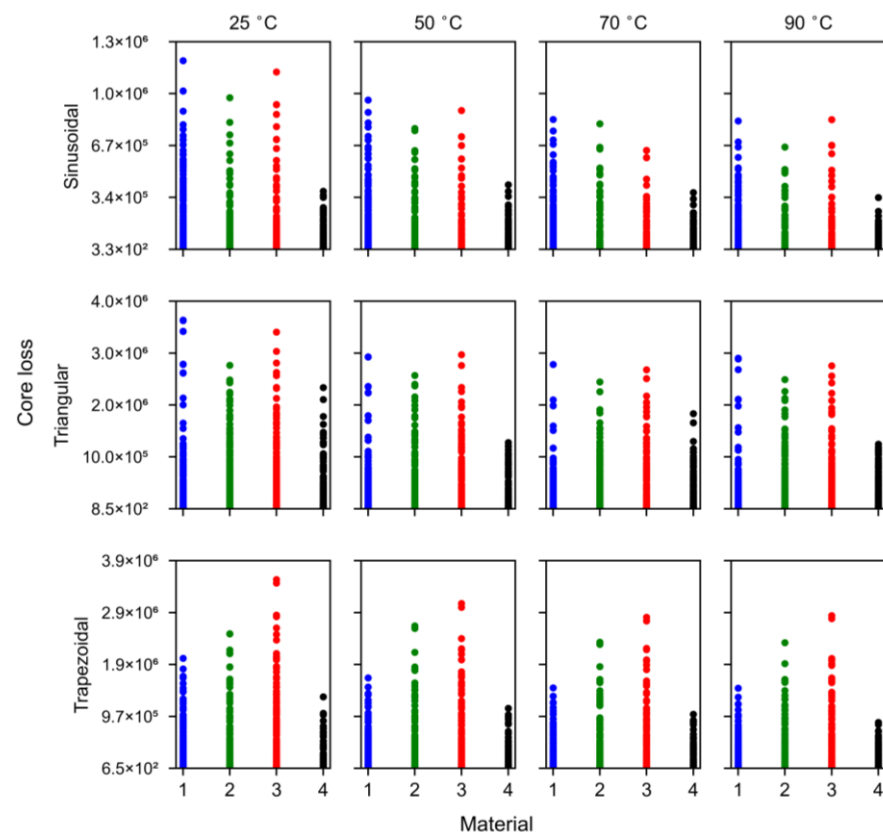


Figure 11. Variation of core loss with materials (different waveforms and temperatures).

(3) Temperature: higher temperature, lower core loss

For different materials and waveforms, core loss generally exhibits a decreasing trend as the temperature rises, as shown in Figure 12 (using Material 1 as an example).

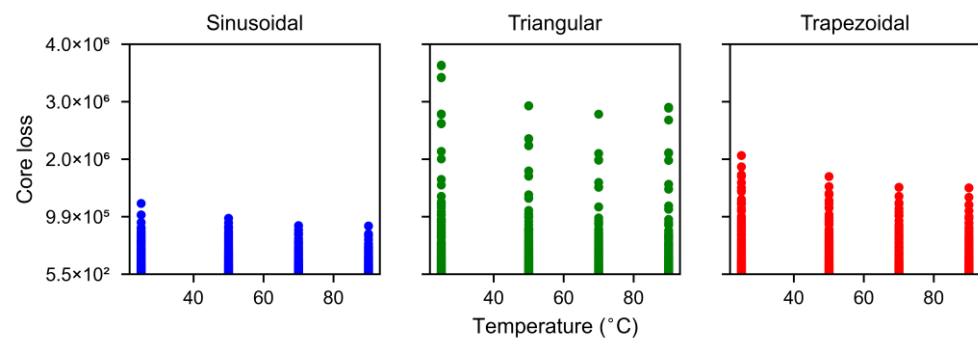


Figure 12. Variations of core loss with temperatures (Material 1, different waveforms).

3.1.2. Synergistic Effects

Degree of influence: Waveform and Material $\gg$ Temperature and Waveform $>$ Temperature and Material

As indicated by the ANOVA results (Table 8), the synergistic effect between waveform and material is the most significant, followed by waveform and temperature, while the temperature and material interaction is relatively weak. The synergistic effect between waveform and material is statistically significant, warranting further investigation.

Material 1 under triangular waveforms (unstable outliers being controlled) exhibits the minimum core loss. In Section 3.1.1, we noted that the triangular waveform represents an operational turning point where the properties of Material 1 change. Under triangular excitation waveforms, if unstable factors affecting core loss are considered, the ranking of core loss is: Material 4 $<$ Material 2 $<$ Material 3 $\approx$ Material 1, which is consistent with the conclusion under sinusoidal waveforms. However, if the infrequently occurring high-loss outliers are disregarded, the core loss ranking becomes: Material 1 $<$ Material 4 $<$ Material 2 $<$ Material 3, resembling the pattern observed under trapezoidal waveforms, where Material 1 can even achieve lower core loss than Material 4.

Therefore, the triangular waveform serves as a critical operational threshold where material properties undergo a change. Among the materials, Material 1 is the most significantly affected, with its properties being substantially altered by the waveform interference. Consequently, if the unstable factors can be controlled, Material 1 can achieve the minimum core loss under triangular waveforms.

The waveform–material synergistic effect on core loss is illustrated in Figure 11.

3.1.3. Three-Factor Combination for Minimum Core Loss

Based on the preceding analysis, the following combinations of factors can minimize the core loss:

Combination 1: Material 4, Sinusoidal Wave, 90 °C;

Combination 2: Material 1, Triangular Wave, 90 °C, and unstable outliers being controlled.

These results serve as the basis for the optimization process detailed in Section 3.2.

3.2. Dual-Objective Optimization for Minimum Core Loss with Maximum Transmitted Magnetic Energy

In the design and optimization of magnetic components, we face a dual-objective optimization problem aimed at minimizing core loss while maximizing transmitted magnetic energy. From Section 2.3, we have established a generalized prediction model for core loss P (Equation (24)) that accounts for material type (represented by electrical conductivity σ) and operating conditions (temperature τ , frequency f , peak flux density B_m , and excitation waveform equivalence coefficient λ). This model serves as the objective function to be minimized.

The objective function to be maximized is the transmitted magnetic energy. Given the complexity of this concept, we approximate its magnitude E using the product of frequency f and peak flux density B_m , expressed as

$$E = f \cdot B_m \quad (25)$$

For the operating conditions (temperature τ , frequency f , peak flux density B_m , and excitation waveform equivalence coefficient λ), constraints are defined within a narrow interval that encompasses the data ranges of both the training and test sets.

A dual-objective optimization was first carried out with respect to the operating conditions. Following this, the optimal core material was selected based on the findings from Section 3.1.1 (2), which identifies the material yielding the minimum loss under the specific optimal waveform.

The dual-objective optimization problem for the operating conditions can be formulated as

$$\begin{aligned} \min P &= 0.98\lambda f^{1.42} B_m^{2.19} (0.00015\tau^2 - 0.026\tau + 2.54) \\ \max E &= f \cdot B_m \\ \text{s.t. } &\begin{cases} \tau \in \{25, 50, 70, 90\} \\ f \in [49990, 501180] \\ B_m \in [0, 0.3] \\ \lambda \in [\frac{\pi}{4}, 1] \end{cases} \end{aligned}$$

Solving this problem via the particle swarm optimization algorithm yields the following optimal operating conditions:

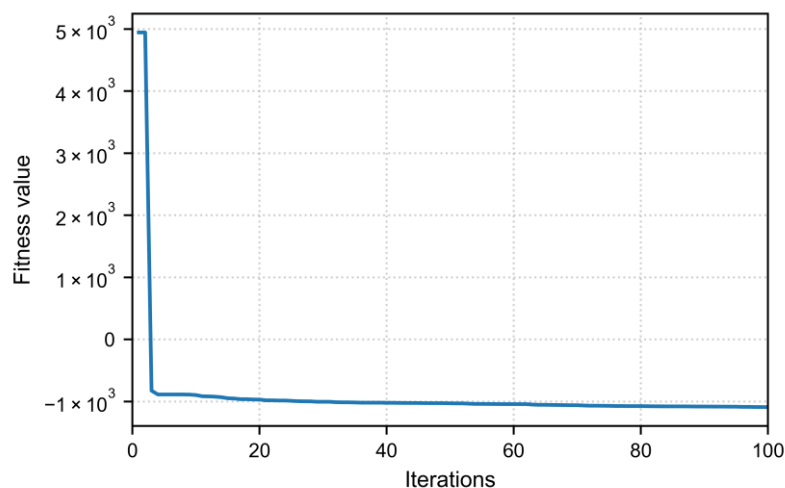
$$\begin{cases} \tau = 90 \\ f = 501180 \\ B_m = 0.0047 \\ \lambda = 0.79 \end{cases}$$

The magnetic component simultaneously achieves minimum core loss and maximum transmitted magnetic energy under the following optimal operating conditions: a temperature of 90 °C, a frequency of 501180 Hz, a peak flux density of 0.0047 T, and a triangular excitation waveform. Guided by the analysis of the waveform–material synergistic effect in Section 3.1.2, Material 1 achieves the minimum core loss under a triangular waveform, provided that operational conditions leading to high-loss outliers are avoided. Consequently, Material 1 is selected as the optimal core material for the final design, with the explicit constraint of avoiding operational conditions attributed to high-loss outliers. The complete set of optimal material and operating conditions is summarized in Table 9.

Table 9. Optimal conditions for the magnetic component.

Conditions	Temperature	Frequency	Peak Flux Density	Waveform	Material
Optimal value	90 °C	501,180 Hz	0.0047 T	Triangular	Material 1

The iterative convergence process of the particle swarm optimization algorithm is illustrated in Figure 13.

**Figure 13.** Convergence process of the particle swarm optimization algorithm.

4. Conclusions

While traditional core loss models overlook variations in materials and operating conditions and purely data-driven models lack physical interpretability, this study proposes a physics–data dual-driven core loss prediction model applicable across material and operating conditions.

The established model successfully revises the classical Steinmetz Equation through the introduction of key physical parameters, including a waveform equivalence coefficient, a temperature polynomial, and electrical conductivity. This significantly enhances the prediction accuracy of core loss under diverse magnetic materials, wide temperature ranges, various frequencies, and complex excitation waveforms, achieving precise prediction across material and operating conditions. Compared to the unmodified model, the Mean Square Error of the revised model is reduced by an order of magnitude.

A three-factor analysis of variance (ANOVA) quantitatively revealed the individual and synergistic influences of waveform, material, and temperature on core loss. The study found that excitation waveform is the most significant individual factor affecting core loss, while the synergistic effect between waveform and material constitutes the most critical interactive combination. These findings highlight key priorities for the optimization design of magnetic components.

Leveraging the generalized model and the uncovered influence mechanisms, the magnetic component was successfully co-optimized for the dual objectives of minimizing core loss and maximizing transmitted magnetic energy. The final optimal design specifies Material 1 as the core material operating under conditions of 90 °C, 501–180 Hz frequency, 0.0047 T peak flux density, and a triangular excitation waveform. This provides a concrete and feasible solution for the high-efficiency, low-loss design of such components.

In summary, this research not only delivers a highly accurate and universally applicable core loss prediction model but also deepens the understanding of core loss mechanisms under various conditions through the integration of physics and data. It

thereby establishes a solid theoretical and methodological foundation for the intelligent design and optimization of next-generation high-performance power electronics magnetic components.

5. Future Directions

- (1) Limited conductivity data availability: Incorporating precisely measured electrical conductivity values for different materials in future experiments could further enhance the model's fitting and predicting accuracy, enabling a clearer representation of material-specific effects.
- (2) Outlier management for Material 1: Although the combination of Material 1 with a triangular waveform was found optimal in minimizing core loss, its practical application requires controlling occasional high-loss outliers. Future research could focus on identifying specific operating boundaries to mitigate these outliers in real-world conditions.

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