

Data-Driven Core Loss Prediction Model Research and Magnetic Component Optimization Design

Zhecheng Yin ^{1,*}, Linpei Shou ², Yushan Ye ³

¹School of Physics, Hangzhou Normal University, Hangzhou, China, 311121

²School of Public Health, Hangzhou Normal University, Hangzhou, China, 311121

³School of Mathematics, Hangzhou Normal University, Hangzhou, China, 311121

* Corresponding Author Email: yinzhecheng0106@163.com

Abstract. Accurate core loss prediction is essential for the design of high-performance magnetic components for power electronics. In this study, a modified Steinmetz's equation incorporating a temperature factor is introduced to improve the accuracy of core loss prediction. By analyzing the independent and synergistic effects of various factors on core loss using multiple linear regression, partial correlation analysis, and Bayesian factor analysis, this study applies a genetic algorithm to find the conditions for minimizing core loss and constructed a model based on the Random Forest algorithm for predicting the core loss of different materials. In addition, considering that core loss is not the only thing that affects the performance of magnetic elements, this study considers both core loss and transmitted magnetic energy and uses particle swarm optimization (PSO) to determine the optimal conditions for magnetic elements. It is shown that the modified model and optimization method can more accurately predict and optimize the performance of magnetic elements, providing a comprehensive solution for power conversion systems.

Keywords: Core loss prediction, Magnetic component optimization, Data-driven, Steinmetz's equation, Model construction.

1. Introduction

Magnetic components are the bottleneck to improved power conversion which in turn is a bottleneck in future computing, vehicle and advanced scientific applications, as well as in bulk energy generation, transmission, and storage [1-2]. Therefore, in order to design higher frequency and power density power conversion systems, it is necessary to accurately predict and reduce the core loss and optimize the performance of magnetic components [3].

In the existing research, the most widely used method of calculating the existing core loss prediction is the Steinmetz's equations. Despite promising results using Steinmetz's equations, those are not enough to calculate the core losses accuracy according to the need for the power electronic community [4], so many scholars have optimized on its basis. Chao Feng et al. have introduced a frequency correction for peak magnetic flux density for silicon steel wafers [5]. J. Drappier et al. have explored the implications of nonlinear anisotropic behavior models on the simulation of magnetic losses in a toroidal core made of a conventional grain-oriented electrical steel (GOES) within a finite element method (FEM) simulation environment [6]. Wenfei Yu et al. have proposed a high-frequency core loss prediction method based on finite element and numerical computation method (NCM) [7]. Chao Mei et al. have investigated the effect of excitation waveform and DC bias field on core loss for soft magnetic composites (SMCs) [8]. Most of the teams, exemplified by the scholars mentioned above, have used different algorithms for a particular material and introduced different parameters to correct the prediction of core loss [9-10], but the effect of material type, synergies between factors, etc. are not quantitatively considered. On the other hand, in order to improve the performance of magnetic components, Huairun Chen et al. have proposed an optimization method to increase the power density and efficiency of integrated magnets by reducing core losses [11], Deqiu Yang et al. have proposed a simple differential method for measuring core loss under sinusoidal excitation [12]. However, these existing studies on performance optimization of magnetic components have basically only considered the prediction and reduction of core losses, without taking into account the fact that

optimizing core losses may lead to other performance degradations [13]. So optimization models based on core loss prediction, while also considering other performance indicators, need further in-depth research.

Based on existing real databases, for the same material, this study firstly modifies the conventional Steinmetz's equations and introduces the temperature factor to construct a more accurate core loss prediction model, and comparative tests were conducted. Then, this study further considers different core materials and investigates the independent effects of temperature, excitation waveform and core material on core loss and the synergistic effects among them by multiple linear regression, partial correlation analysis and pairwise correlation Bayesian factor analysis, and applied genetic algorithms to find out the conditions that minimize the core loss. Finally, on the basis of the core loss prediction, this study further considers the transmitted magnetic energy index and explores the conditions for the optimal overall performance of magnetic components with the help of particle swarm algorithm.

2. Methodology

2.1. Description of the Dataset

In order to construct the core loss prediction model more realistically and to check its accuracy, this paper chooses the public dataset of magnetic components provided by the China Post-graduate Mathematical Contest in Modeling available at <https://cpipc.acge.org.cn/cw/hp/4>.

The dataset consists of temperature, frequency, core loss, excitation waveforms, and flux densities at 1024 different phases for magnetic elements made of four different materials, with one set of physical quantities corresponding to one sample. There are 3400 samples for material I, 3000 samples for material II, 3200 samples for material III, and 2800 samples for material IV, totaling 12,400 samples with 1028 data features for each sample, constituting a dataset with high dimensionality and a large number of samples. The core loss and other related physical quantities of these different material magnetic components provided in the dataset are utilized to construct a core loss prediction model.

2.2. Modification of the Steinmetz's equation

2.2.1. Data-driven predictive modeling of the conventional Steinmetz's equation

The main influencing factors of core loss are operating frequency, magnetic flux density, excitation waveform, operating temperature, core material, etc., while applying the empirical calculation model can be more conveniently calculated to obtain the core loss, for sinusoidal waveforms, this paper directly applies the conventional Steinmetz's equation for the calculation, the formula is as follows:

$$P = k_1 \cdot f^{\alpha_1} \cdot B_m^{\beta_1} \quad (1)$$

It is known that in a sinusoidal wave, the core loss per unit volume (core loss density) P depends on the power function of the frequency f and the peak flux density B_m , but the three coefficients, k_1 , α_1 , β_1 , may be changed for different core materials and operating environments. In order to verify the prediction accuracy of the conventional Steinmetz's equation without considering the effect of environmental factors on the three coefficients, the parameters in the Steinmetz's equation need to be obtained by fitting from experimental data.

Taking material I as an example, this paper chooses a nonlinear least squares method for fitting. This paper firstly finds 1067 sets of data from the dataset with sinusoidal waveforms, and for each set of data constructs vectors $[B_m, f]$. A data matrix is obtained using 1067 sets of data, and it is necessary to find a set of vectors set $[k_1, \alpha_1, \beta_1]$ to minimize the value of the following objective function:

$$\min_{k_1, \alpha_1, \beta_1} \sum_{i=1}^n \left(P_i - k_1 \cdot f_i^{\alpha_1} \cdot B_{m,i}^{\beta_1} \right)^2 \quad (2)$$

where P_i is the actual loss value of the i th sample, f_i and $B_{m,i}$ are the frequency and peak flux density of the i th sample, and n is the total number of samples, and the values of these three parameters can be found by regression analysis of these three variables.

This paper obtains the three coefficients corresponding to each of the four materials by this method as shown in Table.1.

Table 1. Conventional Steinmetz's equation fitting coefficients

Material type	k_1	α_1	β_1
Material I	1.4997	1.4296	2.4713
Material II	0.5615	1.5128	2.3211
Material III	0.9705	1.4907	2.3854
Material IV	0.3997	1.5781	2.4526

Taking the data of material I as an example, the three coefficient values were obtained as follows: $k_1=1.4997$, $\alpha_1=1.4296$, $\beta_1=2.4713$, so the Steinmetz's equation for material I can be obtained as:

$$P = 1.4997 \cdot f^{1.4296} \cdot B_m^{2.4713} \quad (3)$$

2.2.2. Modified equation modeling

After reviewing the literature, this paper finds that temperature also has a significant effect on core losses, but the temperature parameter is not introduced in the conventional Steinmetz's equation[14-15]. Therefore, this paper constructs the modified equation as follows by including the temperature correlation function as part of the multiplier factor with together:

$$P = k_1 \cdot f^{\alpha_1} \cdot B_m^{\beta_1} \cdot T^\gamma \quad (4)$$

Still taking the data of Material I as an example, the three values of the coefficients from the fitting are as follows: $k_1=4.7383$, $\alpha_1=1.4635$, $\beta_1=2.4485$, $\gamma=-0.4018$.

Thus for material I, the modified equation can be obtained as:

$$P = 4.7383 \cdot f^{1.4635} \cdot B_m^{2.4485} \cdot T^{-0.4018} \quad (5)$$

Substituting 1067 sets of temperature, frequency, peak flux density, and core loss into the conventional and modified Steinmetz's equations, respectively, this paper applies matlab to plot the point set plots as shown in Figure 1 below, comparing the fitted data and the actual data predicted by the two equations.

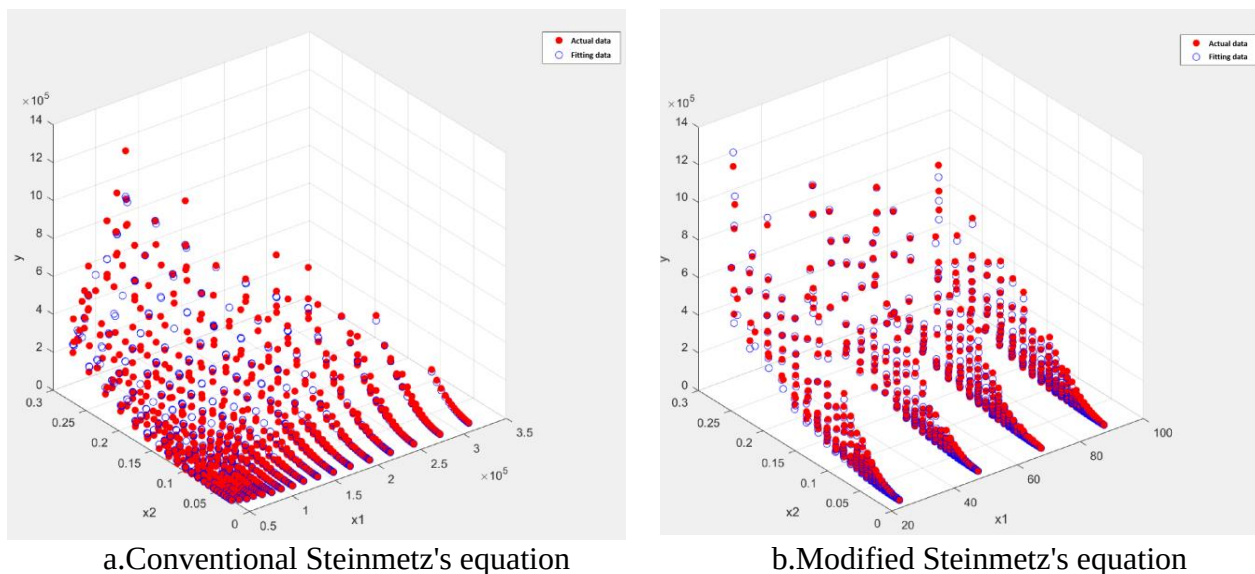


Figure 1. Fitting image points

In order to make the comparison more obvious, a two-dimensional comparison plot containing only the predicted and actual values is plotted as in Figure 2 below, where it can be qualitatively obtained that the deviation of the core loss values predicted by the modified Steinmetz's equation from the actual values is smaller than that of the conventional equation.

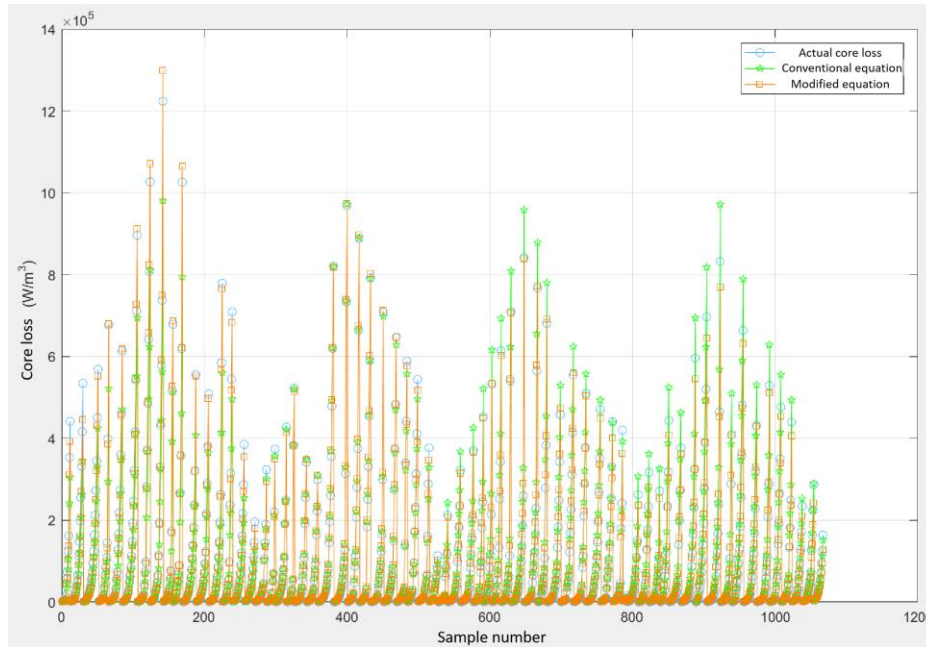


Figure 2. Plot of predicted versus actual values for conventional and modified equations

2.3. Analysis of core loss factors and optimal solutions

In the previous section, the modified Steinmetz's equation equations constructed in this study can only predict the core loss for the same material and waveform. In this section, the study will further investigate the effects of material, excitation waveform, and other factors on core loss to construct a prediction and optimization model with wider applicability.

2.3.1. Independent factor analysis based on multiple linear regression models

For temperature, excitation waveform, material type, and the core loss corresponding to each parameter, this study develops the following multiple linear regression model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon, \quad (6)$$

where y denotes the core loss, x_i denotes the dummy variables of temperature, different excitation waveforms and core materials, respectively, β denotes the regression coefficients corresponding to each item, and ε denotes the error term. The final running results are obtained as follows:

Table 2. Goodness of fit, data independence test results of multiple linear regression analysis

R	R ²	Adjusted R ²	Durbin-Watson
0.653	0.427	0.388	1.532

The above results show that the model fits well and the Durbin-Watson test falls between 0-4, indicating that the datas are consistent with independence.

In this study, by analyzing the significance, confidence interval and correlation of the multiple linear regression results, it is found that the excitation waveform is relatively significant and its coefficient is greater than 0, which is a positive effect relationship, while for the temperature and the core material, it is a negative effect relationship, which is just in line with our intuitive perceptions, that is to say: in the state of higher temperatures, the core loss decreases slightly but the effect is not very significant; for the For sine waves, the core loss is also relatively small. Therefore, considering only the independent factors, this paper gains:

$$y = 101986.561 - 483.281x_1 + 81139.822x_2 - 16115.608x_3. \quad (7)$$

To further investigate the independent effects of each factor, this paper uses Pearson correlation coefficient and partial correlation analysis to measure the linear relationship between the two variables. Meanwhile, this study also utilizes pairwise correlation Bayesian factor inference for analysis, comparing the support for the null hypothesis and alternative hypothesis using Bayesian factors. Based on the above analysis, this study finds that among various factors, the excitation waveform has the greatest impact, followed by the magnetic core material.

2.3.2. Synergy analysis based on linear regression modeling

In addition to the independent effects of individual factors, this study also analyzes the synergistic effects between pairwise factors. The interaction term can be used in mathematics to represent the synergy between two factors, i.e., how one independent variable moderates the effect of another independent variable. Therefore, for the analysis of the synergistic effect of the three factors, temperature, excitation waveform and core material, two by two in this question, this paper can build a regression model with an interaction term as follows:

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \beta_4(x_1x_2) + \beta_5(x_1x_3) + \beta_6(x_2x_3) + \varepsilon, \quad (8)$$

The meaning of each parameter is the same as the independent analysis in the previous text, and the product of the two parameters represents the interaction term between the two factors.

After conducting goodness of fit, data independence, significance, confidence interval, and correlation analysis, it can be seen from the data that adding synergistic factors also has a certain impact on magnetic core losses, and it can be seen that under the dual effects of temperature and excitation waveform, temperature and magnetic core material, etc., there is a negative correlation effect, while under the dual effects of excitation waveform and magnetic core material, there is a positive correlation effect. Specifically, there are:

$$y = 30691.420 + 1095.876x_1 + 114097.372x_2 - 22555.719x_3 - 743.791(x_1x_2) - 36.630(x_1x_3) + 4296.064(x_2x_3). \quad (9)$$

Taking material and excitation waveforms as examples, this paper conducts visualization processing to support the above conclusion, as shown in Figure 3:

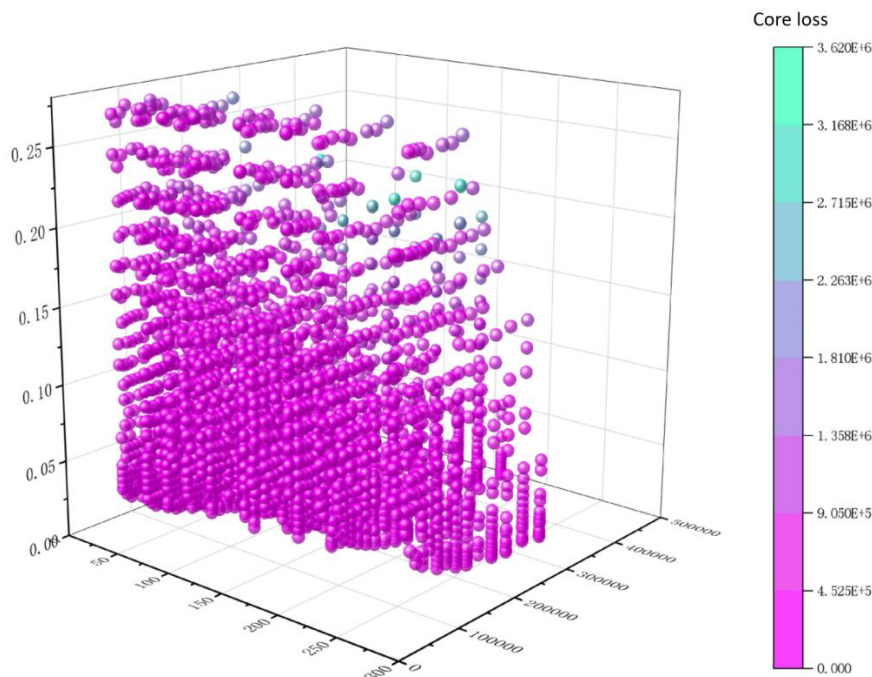


Figure 3. Visualization image of the synergistic effect between excitation waveform and material

Alternatively, if the relationship between certain factors is not considered to be linear, for example, the effect of temperature on losses may be nonlinear, this paper can also consider introducing a nonlinear term, for example, the model with a quadratic term can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 (x_1 x_2) + \beta_5 (x_1 x_3) + \beta_6 (x_2 x_3) + \beta_7 x_1^2 + \beta_8 x_2^2 + \beta_9 x_3^2 + \varepsilon, \quad (10)$$

This allows us to capture the nonlinear relationship between temperature, excitation waveform and core material, which is a generalization of the linear model.

2.3.3. Solving for optimal core loss

In the above analysis this paper has obtained that the interaction of different factors affects the core loss. In order to optimize the core design and minimize the loss, this paper considers genetic algorithm in order to get the optimal solution.

In a genetic algorithm, each individual represents a possible solution. Our goal is to optimize the effect of temperature x_1 , excitation waveform x_2 , and core material x_3 on core loss. This paper encodes each individual as a set of parameters (x_1, x_2, x_3) , initializes a population, and generates a set of random solutions. Assuming a population size of 100, each individual is a randomized combination. Since this paper wants to minimize the core loss, the fitness function should be based on the value of the core loss. For different combinations, the corresponding core loss is calculated. The better individual is then selected based on the fitness, using the classical selection method, and crossover operation is used to generate a new generation of individuals. The new individuals will inherit some of the properties from their parents, but will be able to explore new solutions. To avoid the algorithm from falling into a local optimum, a mutation operation is required, i.e., randomly changing some genes of the individuals. For the discrete variables excitation waveform and core material, they can be randomly replaced with another possible value. When the termination condition is satisfied, the individual with the highest fitness is selected as the optimal solution.

2.4. Optimization of magnetic components based on core loss prediction

In this section, this study will further apply machine learning algorithms to refine the core loss prediction model. At the same time, this study considers that the purpose of reducing core loss is to improve the performance of magnetic components, so this paper also needs to comprehensively consider other performance metrics.

2.4.1. Multifactor core loss prediction model with application of random forests

The core loss is related to the temperature (1), material (2), excitation waveform (3), frequency (4), and peak flux density (5), so this study uses a random forest model to fit on this basis, where the importance of each factor is shown in Figure 4.

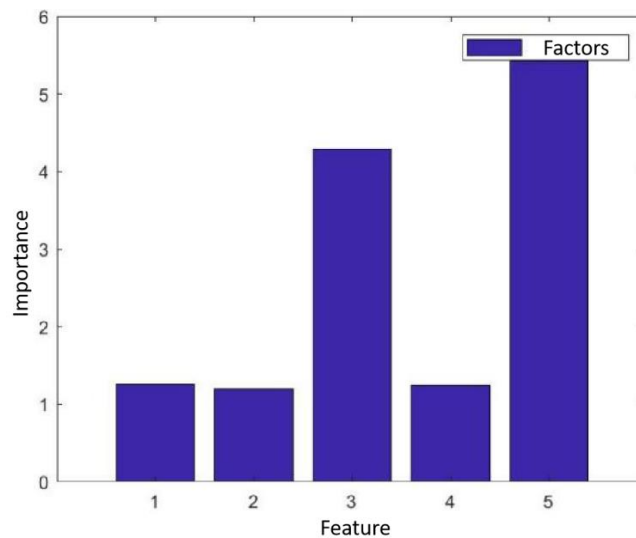


Figure 4. Plot of predicted versus actual values for conventional and modified equations

To further measure the model prediction performance, this paper utilizes the mean square of the difference between the predicted and actual values (MSE), which is used to assess the accuracy and effectiveness of the Random Forest model in predicting continuous values, and the MSE value obtained is 4877931180.5022, which indicates a good prediction performance.

2.4.2. Dual-objective optimization model

Considering that in addition to the core loss, other factors such as the transmitted magnetic energy also affect the performance of the magnetic element, this study seeks to find conditions that allow the magnetic components to achieve the smallest possible core losses while transmitting the maximum possible magnetic energy.

Here, this paper can try to turn a dual objective into a single objective, i.e., put the two variables in the same functional expression and assign different weights. If this paper makes the new objective function z , this paper has:

$$z = \alpha y - \beta(f \cdot B_{max}) \quad (11)$$

Where α, β are the respective weights, y denotes the core loss of the magnetic element, f represents the frequency, and B_{max} is the peak magnetic flux density, then this paper just needs to find the minimum value of the function z . If this paper makes $\beta = 1 - \alpha$, the objective function is transformed into:

$$z = \alpha y + (\alpha - 1)\beta(f \cdot B_{max}) \quad (12)$$

This allows us to further utilize the optimization method for the analysis of the objective function, and through calculations this paper concludes that $\alpha=0.6815$, $\beta=0.3185$.

2.4.3. Optimization analysis of magnetic components based on PSO

This paper chooses to use the particle swarm optimization (PSO) algorithm to solve the problem. For the whole process, this paper proceeds in the following steps:

I. Particle representation and initialization: firstly, a group of particles are randomly generated in the solution space, the position of each particle represents a potential solution, and the velocity is initially a random value of zero or small, and then the parameters of the algorithm are set up to compute the objective function value corresponding to the initial position of each particle.

II. Setting the data structure: each particle maintains an individual historical optimal position, i.e., the Pareto optimal solution found by that particle (pBest); the whole group shares a global historical optimal solution set, storing the non-dominated solutions found by all particles (gBest).

III. Iterative search: for each iteration, perform the following steps:

(i) Update velocity and position: the velocity update formula is usually:

$$v_{new} = w \cdot v_{old} + c_1 \cdot r_1 \cdot (pBest - x_{old}) + c_2 \cdot r_2 \cdot (gBest - x_{old}) \quad (13)$$

Where w is the inertia weight, c_1 and c_2 are the learning factor, r_1 and r_2 are random numbers, and the position update formula is:

$$x_{new} = x_{old} + v_{new} \quad (14)$$

(ii) Evaluate new positions: calculate the objective function value for each new position.

(iii) Update pBest: update pBest if the solution at the new position dominates the pBest of that particle.

(iv) Update gBest: compare the solution at the new position with the solutions in the gBest set and update the Pareto front, i.e., add non-dominated solutions and remove dominated solutions.

IV. Pareto frontier maintenance: ensure that the solutions in the gBest set are non-dominated and maintain the diversity of the set.

V. Termination conditions: check whether the algorithm satisfies the termination conditions, such as the maximum number of iterations is reached, the quality of the solution meets a predefined criterion, or the improvement of the solution is below a threshold.

VI. Output result: output the gBest set, i.e. the set of Pareto-optimal solutions found by the algorithm.

3. Results and discussion

3.1. Modification of the Steinmetz's equation

In the previous Methodology section, this study derives the modified Steinmetz equation and plots the prediction accuracy of the conventional versus modified equations. In order to quantitatively compare the prediction effects of the two equations, still taking the data of Material I as an example, this study uses Matlab to calculate the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean relative error (MRE), and coefficient of determination (R^2) under the two equations respectively, and a summary of the comparison of the error values is shown in Table.3.

Table 3. Summary of error values for conventional and modified Steinmetz's equations

Equation	Traditonal: $P = 1.4997 \cdot f^{1.4296} \cdot B_m^{2.4713}$	Modified: $P = 4.7383 \cdot f^{1.4635} \cdot B_m^{2.4485} \cdot T^{-0.4018}$
MSE	1638190471.6410	138596508.8086
RMSE	40474.5657	11772.7018
MAE	20615.5353	6850.9815
MRE	0.3566	0.2238
R^2	0.9448	0.9953

It is easy to find that the modified Steinmetz's equation has lower MSE, RMSE, MAE, MRE, and its MSE is about 8.46% of that of the conventional equation, which is reduced by more than 90%, also its R^2 is also better than the conventional equation, i.e., the modified Steinmetz's equation constructed by this paper predicts the core loss with less error and better results.

So this paper can obtain the generalized modified Steinmetz's equation as:

$$P = k_1 \cdot f^{\alpha_1} \cdot B_m^{\beta_1} \cdot T^\gamma \quad (15)$$

3.2. Core loss optimization conditions applicable across materials

On the basis of the existing data set and using the genetic algorithm detailed in the previous Methodology section, this study obtains that the optimal solution that minimizes the core loss is (90°C, 1, 4), i.e., using material IV, corresponding to a temperature of 90°C, and an excitation waveform that is a sine wave.

In this study, this paper considers the independent and synergistic effects of multiple factors on core loss and applies genetic algorithms to analyze and obtain the optimal solution for minimizing core loss. The optimization model can be analyzed across different materials and waveforms, compensating for the limitation to the same material in current research.

3.3. Optimization conditions for Dual-objective magnetic components

By using the particle swarm optimization algorithm based on the core loss prediction model and the dual-objective optimization model detailed in the previous Methodology section, this paper obtain the final results as shown in Table.4:

Table 4. Values of the five impact factors under optimal conditions

Impact factor	Optimal value
Material type	Material II
Temperature	69.08°C
Frequency	53170.00Hz
Excitation waveform	Sine wave
Peak magnetic flux density	0.0245T

Compared to most of the studies on the performance of magnetic components where only core losses are considered, this study uses particle swarm optimization (PSO) algorithm to find conditions that optimize the performance of a magnetic element, considering both core losses and transmitted magnetic energy. The results show that the model can effectively balance these two objectives, resulting in a set of optimal conditions that maximize the transmitted magnetic energy while minimizing the core loss. The values of the influencing factors for the optimum conditions are determined, thus providing a comprehensive understanding of the impact of each factor on the performance of the magnetic element.

4. Conclusions

This study first introduces the temperature parameter to correct the Steinmetz equation, then analyzes the independent and synergistic effects of various factors on the core loss, constructs a model that can predict the core loss across materials using the random forest algorithm, and finally solves the conditions of optimal performance of magnetic components using the PSO algorithm by considering the core loss and the transmitted magnetic energy at the same time. Based on the dataset with huge sample size, by using multiple machine learning and optimization algorithms, this study is able to consider more influencing factors and construct a more accurate prediction and optimization model. However, there are also some shortcomings in this study, such as the random forest algorithm may lead to overfitting of the model on the training data, and the genetic algorithm has less iterative termination in this study, which leads to the accuracy is not idealized enough. In the future, this study will continue to consider more core loss factors, as well as magnetic component performance impact indicators, and incorporate more algorithms to construct more accurate prediction and optimization models.

References

- [1] Hanson A. Opportunities in magnetic materials for high-frequency power conversion [J]. MRS Communications, 2022, 12 (5): 521-530.
- [2] Ragusa C, Solimene L, Musumeci S, et al. Energy loss and constitutive equation of soft magnetic materials for broadband applications in power electronics [C]//2023 IEEE International Magnetic Conference-Short Papers (INTERMAG Short Papers). IEEE, 2023: 1-2.
- [3] Arruti A, Anzola J, Pérez-Cebolla F J, et al. The composite improved generalized steinmetz equation (ciGSE): An accurate model combining the composite waveform hypothesis with classical approaches [J]. IEEE Transactions on Power Electronics, 2023.
- [4] Rodriguez-Sotelo D, Rodriguez-Licea M A, Araujo-Vargas I, et al. Power losses models for magnetic cores: A review [J]. Micromachines, 2022, 13 (3): 418.
- [5] Feng C, Zhang Y, Chi Q. Design of a novel rotary transformer with accurate prediction of nanocrystalline alloy core loss using improved Steinmetz formulation[J]. IEEE Transactions on Industry Applications, 2024.
- [6] Drappier J, Guyomarch F, Cherif R, et al. Anisotropic Models of Nonlinear Magnetic Behavior Laws for Finite Element Modeling of Iron Losses in a Toroidal Core [J]. IEEE Transactions on Magnetics, 2024.
- [7] Yu W, Hua W, Zhang Z. High-frequency core loss analysis of high-speed flux-switching permanent magnet machines [J]. Electronics, 2021, 10 (9): 1076.
- [8] Mei C, Wan K, Zhang B, et al. Research on loss characteristic of soft magnetic composites under nonsinusoidal excitations with DC bias field[J]. AIP Advances, 2024, 14 (6).
- [9] Cheng Qiyun, Sun Caixin, Zhang Xiaoxing, et al. Short-Term load forecasting model and method for power system based on complementation of neural network and fuzzy logic [J]. Transactions of China Electrotechnical Society, 2004, 19 (10): 53-58.
- [10] Tiismus H, Kallaste A, Vaimann T, et al. Eddy Current Loss Reduction Prospects in Laser Additively Manufactured Soft Magnetic Cores [C]//2022 International Conference on Electrical Machines (ICEM). IEEE, 2022: 1511-1516.

- [11] Chen H, Wang Y, Luan R, et al. Optimization of a Novel Integrated Magnetic For LLC Resonant Converter [C]//2022 IEEE International Power Electronics and Application Conference and Exposition (PEAC). IEEE, 2022: 951-954.
- [12] Yang D, Wang B, Zhang J. A DC Differential Method for Core Loss Measurement under Sinusoidal Excitation [C]//2023 11th International Conference on Power Electronics and ECCE Asia (ICPE 2023-ECCE Asia). IEEE, 2023: 2059-2064.
- [13] Li Y, Mu S, Zhang C, et al. Core loss measurement and comparative analysis for soft magnetic materials under complex non-sinusoidal excitations [J]. AIP Advances, 2023, 13 (2).
- [14] Kirkby N J, Ranjram M K. Temperature control for automated high frequency core loss testing [C]//2024 IEEE Workshop on Control and Modeling for Power Electronics (COMPEL). IEEE, 2024: 1-8.
- [15] Li J, Deleu E, Lee W, et al. Investigating the Mutual Impact of Waveform, Temperature, and Dc-Bias on Magnetic Core Loss using Neural Network Models [C]//2024 IEEE Applied Power Electronics Conference and Exposition (APEC). IEEE, 2024: 391-395.