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Core Loss Estimation for Three Phase Transformer Based on GPR and FEA

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Abstract. This study used the Gaussian Process Regression (GPR) method to predict the core losses of the Finite Element Analysis (FEA) based dry-type three-phase transformer. In the estimation and analysis processes, the core area A_c, primary excitation voltage V_p and the primary winding number of turns N_p are used as three input parameters. GPR is a powerful machine learning method for such low-featured data and provides a Bayesian-based regression capable of measuring uncertainty in predictions. The data generated in the ANSYS/MAXWELL environment for core loss estimation is chosen at random using the parametric FEA setup. The Matern 5/2 kernel function is used to train these data using GPR. Thus, the results are pretty satisfactory; Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Squared Error (MSE) performance metric values are calculated as 0.0102, 0.0029, and 0.0534, respectively. Also, the estimated results are very close to the simulation value. As a result, the GPR method can be used as a reliable tool for estimating core losses with high accuracy during the transformer design stage.

Keywords. Core loss estimation, dry-type transformer, FEA, GPR, parametric simulation

1. Introduction

Increasing energy demand worldwide requires more efficient and higher energy production. However, as a solution to the energy issue, the globe is driven to improve overall efficiency by lowering losses because of limited supplies. For this purpose, the efficiency of the electrical energy transmission and distribution equipment gains even more importance. These power system components are transformers that provide efficient energy transmission and distribution and efficient voltage level change without voltage drop [1]. Distribution transformers are divided into oil and dry types according to their design forms. With increasing environmental sensitivity, more environmentally friendly dry-type transformers are preferred in industry, chemical plants, oil or gas facilities, hospitals, and skyscrapers. Therefore, parameter estimation issues become more critical to increasing design speed and efficiency. Significant power losses, such as core, fringing and winding losses, can be encountered if a suitable and correct design is not made [2]. As a result, manufacturers will save time and transaction complexity by precisely calculating the efficiency and power losses of

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transformers without losing their crucial functionalities while the design phase [3]. In this context, Artificial Intelligence (AI) based Artificial Neural Network (ANN) models are applied in transformer design and every field. Considering the accuracy rates obtained in parameter estimation, it is seen that the use of ANN methods provides important contributions in terms of ease of use, accuracy, and design. However, the selection of the estimation method to be used, the accuracy rate of the results obtained, and the determination of the input and output parameters should be considered. In this context, there are various methods in the literature to estimate the core losses during the operation of the system [4, 5].

It is clear from the literature study that AI systems are used to forecast temperature rise, failure, power generation, loss, and transformer design parameters based on datasets studied under certain circumstances. A comprehensive study of AI applications for power system operation, monitoring, and maintenance was carried out by Barja-Martinez, et al. [6]. AI methods and sources of data were identified and categorized for power system applications. The use of AI approaches in each application field was examined, and results such as energy management systems, estimation, and detection of power loss were attained. Kunicki, et al. [7] performed the hot-spot prediction using four different machine learning methods: Binary regression tree (BRT), Gaussian Process regression (GPR), generalized linear model (GLM) and support vector machine (SVM). The researcher got a prediction error of less than 0.71%. In another study by Janjua, et al. [8], the parameters of the transformer were investigated to estimate the useful lifespan of the transformer and a literature review was presented. So, considering variables such as temperature, power loss, amount of loading, hot spot and depletion of transformer' lifespan, estimation was made using the Gaussian process method, unlike other articles. Shadab, et al. [9] made hot spot estimation using the GPR method. In addition, White Box Modelling (SBAWB Modelling) and Sequential Black were used to compare the current classical model in the literature regarding effectiveness and performance in life assessment. Learning Vector Quantization (LVQ) was utilized by Hatziargyriou, et al. [10] to sort out a three-phase 0.25 MVA wound-core transformer's no-load losses. At the conclusion of the trial, the no-load losses' predicted success percentages varied from 78% to 96%. In another study using ANN, Georgilakis, et al. [11] determined the relationship between the iron (core) losses and the design parameters in the transformer core. Mean values of errors were obtained in estimating transformer core losses as 4% and 5.7%, respectively. In another study by Leal, et al. [12], the global errors were 25,9% and 22,8%, respectively, and the obtained errors were fewer than 10%. The investigation was conducted to accurately estimate the distribution losses in this system. The ANN Multilayer Perception (MLP) structure in study by Suppitaksakul and Saelee [13] estimated total losses by reducing time loss and test parameters using data gathered from one hundred three phase transformers, various parameters affecting power losses. A maximum error of 1% was obtained as a test result depending on different temperature conditions and currents. Souza, et al. [14] examined 60 Hz 4 kVA dry-type three-phase transformers under various frequency settings ranging from 40 Hz to 65 Hz using 2 ANN methods: Nero Fuzzy Neuron and MLP. The analysis's findings indicated that, with a 1% error rate, the best results were produced with the prediction results at 60 Hz.

As previously said, time-saving estimation studies for transformers are crucial, particularly during the production process. Passadis and Loizos [15] compared the time-dependent output data based on Magnetic flux density dependent on the power loss curve (B-P curve) and output data obtained by the Support Vector Machine (SVM) algorithm. The outcomes of the estimation process were compared with those derived from the conventional mathematical approach. The biggest errors in the estimation findings, as determined by the SVM and the power loss curve, were found to be 12.66% and 31.056%, respectively. In a different study, Chiu, et al. [16] evaluated via machine learning the relation between the eddy current for a 3000 kVA dry-type transformer and the parameters utilized in transformer size. The Finite Element Analysis (FEA) model and different learning rates were utilized to determine the outputs, which included the copper losses in the clamps and the rises and losses in the winding losses. Accuracy rates were between 0.86% and 0.97%.

Power transformer sizing and modeling in the electrical distribution network are crucial for efficient power distribution. The design features of transformers for optimizing load losses directly depend on the transformer's load profile characteristics. In addition, electricity forecasts play an essential role in the energy market, as accurate forecasts lead to more efficient energy use, resulting in lower costs and a positive environmental impact. At the same time, wrong estimates can cause related financial losses. Incremona and De Nicolao [17] made short - and long-term load estimation using methods such as Fourier analysis, Radial Basis Function (RBF), MLP and Long Short-Term Memory Model (LSTM), ANN, Gaussian Processes, and Shrinkage Methods, including Tikhonov regularisation and smoothing splines. In addition to comparing these methods, that study also added a new dimension in energy load estimation. By taking into account low side voltage, loading factor, standard performance factors, and low side voltage, Grigoraş, et al. [18] used a fuzzy technique to predict the power losses. For variable and fuzzy logic models, precise distribution transformer database with rated power ranging from 0.4 MVA to 1 MVA was utilized. As a result of analysis and tests, an error of 1.05% was obtained in the estimation process. In the other study by Aslan, et al. [19], FEA parametric analysis was used to predict the core losses for a single-phase inverter transformer using the primary current, winding number conversion ratio and operating frequency parameters as input data. An adaptive neuro-fuzzy inference system (ANFIS) was used for this purpose. For training and testing, 500 parametric simulated data sets were utilized. The average calculation error rate for core loss using test data was 5.04%. Core loss estimate was conducted using the LSTM approach in a recent work by Kül, et al. [20]. The LSTM needed input and output values were determined through the use of FEA parametric simulation. The investigation produced an error of 0.15%.

By eliminating the need for labor-intensive and difficult mathematical calculations, the literature review presents research, applications, and success rates that precisely estimate losses while saving time. Unlike other research, this paper chose cross-sectional area (A_c), primary turns number (N_p), and excitation voltage (V_p) as input parameters, and applied the GPR in the estimation process. When previous studies were examined, it was determined that GPR was not used for the core loss estimation. However, generally on small datasets, GPR can model complex datasets with a unique ability and reveal the uncertainties affecting the estimation step [21]. In addition, due to its non-parametric structure, while performing regression, it can provide more successful predictions than other machine learning methods (such as SVM and ANN) even in a minimal dataset [22,23]. Since the data size used in this study is 506×3, the core loss estimation is performed with GPR. As such, the main contribution of this work is the correct estimation of transformer core losses using GPR, which is based on fundamental parameters. To demonstrate this idea, a 3D simulation of a three-phase, 50 kVA dry-type transformer was performed using the Finite Element Method (FEM).

The estimated parametric simulation time-dependent results are employed in the estimation process, and the accuracy of the estimation and simulation outcomes is then compared.

The primary contribution and distinctions of this study from previous ones can be summarized as follows:

- Core loss prediction of the three phase transformer is made using the GPR method and core cross-sectional area (A_c), number of primary turns (N_p), and excitation voltage (V_p) were selected as input parameters for the first time.
- FEA is used to simulate a three-phase, 50 kVA dry-type transformer in 3D. And parametric simulation time-dependent results used for prediction are obtained.
- Core loss values are produced very close to the simulation results using GPR.

This is how the remainder of the paper is structured: Section II provides an explanation of the materials and techniques utilized for parameter estimation. Section III contains the findings and analysis derived from the simulation and GPR parameter prediction. Section IV provides a summary of the conclusion.

2. Methodology

2.1. Fundamental Mathematical Framework for Core Loss & FEA of Dry-Type Transformer

Core losses and load losses are the two categories of transformer losses. Theoretically, there are three distinct components that comprise core losses. These three types of losses include excessive (abnormal), hysteresis, and eddy current. The magnetic flux density, core material type, and frequency all affect core losses. Therefore, during the design phase, it should be considered that the transformer is within the magnetic flux density limits under nominal operating conditions. Moreover, the transformer's fundamental characteristics—power, voltage, and current—have a significant impact on losses [20]. Consequently, the Steinmetz equation [20] below expresses the core losses, where the dependency on flux density and operating frequency is evident.

$$P_v = K f^{a} B_{pk}^{\beta} \tag{1}$$

Here, B_{pk} is the peak flux density and f is the operating frequency. Additionally, the aggregate value of the particular loss constants connected to the transformer's core material type is displayed by the parameter K, also referred to as the principal form of the core loss equation in Eq. (1). More specifically, we find in Eq. (2) the core loss equation, where the parameter K stands for in a distributed manner. Here, the definitions of abnormal loss constant, hysteresis-loss constant and eddy-current loss constant are K_e, K_h, K_c. These parameter values are variables that change according to material properties. Eq. (3) can be used to express the loss formula in detail with all its harmonic components [24].

$$P_v = K_h B_{pk}^{x} f + K_c B_{pk}^{2} f^{2} + K_e B_{pk}^{1.5} f^{1.5} \tag{2}$$

$$P_v = K_h \sum B_n^x f_n + \frac{4\delta^2 K_f^2}{3\gamma_c \rho_e}\left[\sum_{v=1}^{n} B_n^x f_n^2 + \sum_{v=1}^{n} B_n^x f_n^{1.5}\right] \tag{3}$$

Where δ, ρ_e, K_f, and γ_c are called the thickness of core material, the resistivity of core material, the form factor of excitation voltage, and the mass density of core density, respectively. Table 1 shows the core loss coefficients, as shown in Eq. (2), based on the M5 material parameters that the program utilized to do the FEA analysis.

Table 1. M5 material core loss coefficients.

Coeff. (W/kg)	M5
K_h	$603{,}995\ x\ 10^{-5}$
K_c	$3{,}79302\ x\ 10^{-5}$
K_e	$243\ x\ 10^{-6}$

The characteristics of the magnetic-flux principle and the ferromagnetic material determine the transformer's electromagnetic performance. The electromagnetic performance does not have a homogeneous characteristic. Therefore, a homogeneous power loss and magnetic flux density distribution cannot be expected and cannot be readily determined by simple mathematical calculations. Core and winding losses occur when the transformer operates with and without load. In this context, with the help of ANSYS/Maxwell electromagnetic simulation software, time-dependent parametric FEA analysis can be performed, and more realistic results can be obtained with 3-dimensional electromagnetic modelling of core loss, flux density distribution. Figure 1 shows the 3D transformer model.

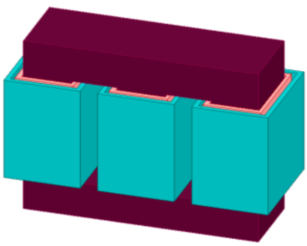


Figure 1. Transformer ANSYS/Maxwell 3D model.

Table 2. Specifications of the transformer.

Specifications	Values
Power	50 kVA
Voltages	380/220 V
Connection	λ/Δ
Windings material	Copper
Lamination thickness	0.3 mm
Specific core losses	1.2 W/kg (for 1.7T and 50 Hz)

Parametric simulations are instrumental in obtaining desired output values by changing one or more circuit parameters. In this study, the number of primary turns (N_p), excitation voltage (V_p), and cross section area (A_c) variables were determined for the no-load situation parametric analysis for the transformer whose essential features are given in table 2. The minimum and maximum values of these parameters are given in table 3. These values for V_p and N_p are determined by considering the nominal operating values. For A_c a total of three different values were used, with the original dimensioning by increasing or decreasing the leg thicknesses at the same rate.

Table 3. The transformer's fea parametric analysis variables.

Parameter	Definition	Min-Max Values
V_p (V)	Excitation voltage	230 - 520
N_p	The primary number of turns	98 - 158
A_c (mm^2)	Cross section area	0,0153-0,0105-0,0084

As a result of parametric simulation studies, time-dependent core loss values to be used as output data were obtained. While creating the data set for GPR analysis, the average values of core loss values were used. Thus, the effect of selected parameters, especially A_c on core losses can be better understood. The obtained loss and magnetic flux distributions are shown in figure 3 and figure 4, respectively. The graphs obtained for a single value seen in figure 3 are added for a fixed number of turns (N_p = 98) and voltage value (V_p = 380).

2.2. Gaussian Process Regression

The Gaussian Process (GP) model is a Bayesian-based, supervised machine learning method. It is a non-parametric approach often preferred for regression and classification applications due to its simplicity and flexibility [25, 26]. Generally speaking, the GP is a stochastic process that gathers random variables indexed by time or space. A multivariate Gaussian distribution determines the distribution of any finite set of these variables. In other words, when two or more input-output samples are selected in a function, the outputs are assumed to follow a multivariate Gaussian distribution. A prior probability distribution is performed on Bayesian inference functions in GP-based AI applications. This prior GP model is updated with the training data, creating GPR where continuous variables are produced [27].

The mathematical expression of the GPR is as follows. As in Eq. 4, GP is a stochastic process ($f(x)$), and its covariance ($k(x, x')$) and mean function ($m(x)$) can be used to express it. Eq. 5 illustrates this function f's response, for instance, at the input x and the output y. In this case, $\in$ represents Gaussian distributed noise (see Eq. 9). The covariance function in GP measures the correlation in two input states (x, x') and is called the kernel. The mean value ($m(x)$) is set to zero to ensure that the GP is kernel dependent only and avoid expensive computations. In this case, GPR becomes a method based on entirely different kernel functions [28]. The kernel function used in our GPR application in this study is Matern 5/2. The formula of this kernel is expressed in Eq. 7, where σ_f is signal standard deviation and σ_l is characteristic length scale [29, 30]. GPR has been applied in different fields recently [31-33]. It is easier to implement in practice compared to ANN and performs more robust predictions than SVM [34].

$$f(x) \sim GP(m(x), k(x, x')) \tag{4}$$

$$y = f(x) + \in \tag{5}$$

$$\in \sim N(0, \sigma^2) \tag{6}$$

$$k(x, x') = \sigma_f^2 \left(1 + \frac{\sqrt{5}r}{\sigma_l} + \frac{\sqrt{5}r^2}{3\sigma_l^2}\right) exp\ exp\left(-\frac{\sqrt{5}r}{\sigma_l}\right) \tag{7}$$

3. Result and Discussion

N_p, V_p and A_c input parameters are used for ANSYS/ MAXwell parametric analysis. As a result of the time-dependent parametric analysis, the core loss, used as the output parameter, was obtained. The necessary dataset for the prediction was created using all parameters. The max-min values of V_p and N_p and the values of A_c are shown in table 3. The variation of V_p voltages time-dependent for each parametric value is given in figure 2. Figure 3 shows the core loss graphs obtained due to the parametric analysis. The single-core loss graphs on the right side are the core loss graphs corresponding to each A_c value for a constant V_p and N_p values.

In addition to obtaining the data set with FEA analysis, it also allows us to see the change in the magnetic characteristic of the transformer. The most important of these is the magnetic flux distribution. The instantaneous magnetic flux distributions at the same time t for three different A_c values are shown in figure 4.

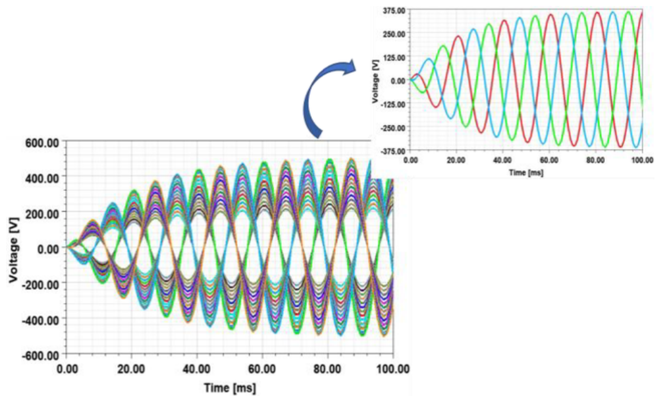
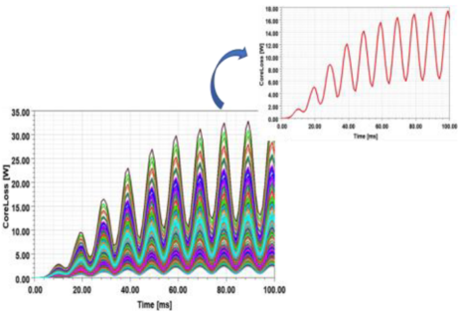
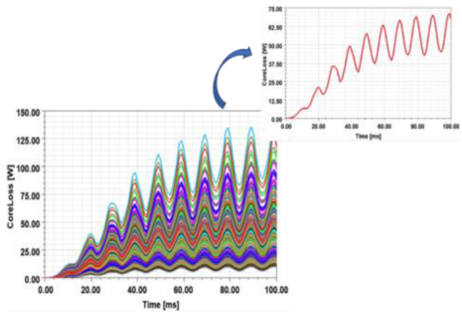


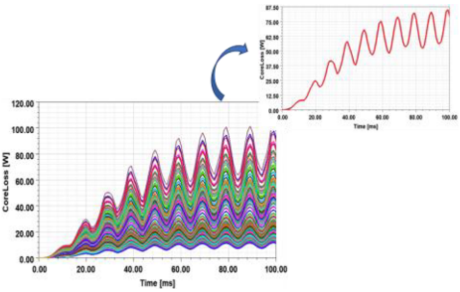
Figure 2. Time-dependent primary voltage (V_p).



a) $A_c = 0.0153\ m^2$



b) $A_c = 0.0105\ m^2$



c) $A_c = 0.0084\ m^2$

Figure 3. Time-dependent core losses for various cross section area values.

In the estimation process performed with GPR, 80% of 506 data is selected as training. The rest is reserved for testing. This selection is made randomly. After the training process, the trained model is tested with the test data, and the performance is measured. As a result, high accuracies are obtained for the test data, as seen in table 4. Table 4 calculates the error in the prediction values using three different metrics. These metrics are often used in regression applications. Equations of these metrics are shown between Eq.8 – Eq. 10. As a result of the estimation made by the GPR, the error values in the test data are 0.0102, 0.0029 and 0.0534 for MAE, MSE and RMSE, respectively.

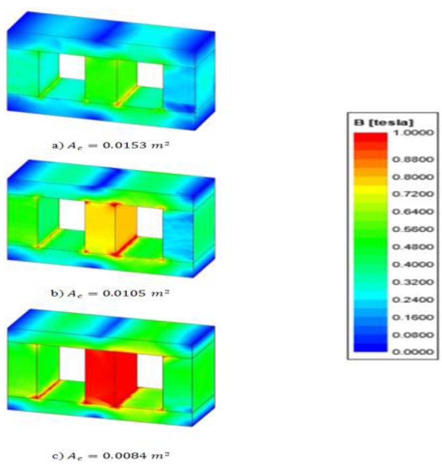


Figure 4. Time-dependent core losses for various cross section area values.

Table 4. The transformer's fea parametric analysis variables.

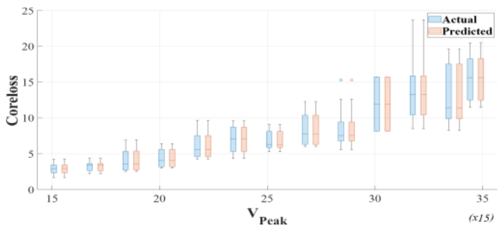
Metrics	MAE	MSE	RMSE
Test Error	0.0102	0.0029	0.0534

$$Mean\ absolute\ error\ (MAE) = \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{N} \tag{8}$$

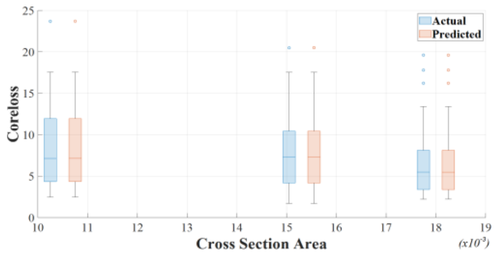
$$Mean\ Square\ error\ (MSE) = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{9}$$

$$Root\ mean\ square\ error\ (RMSE) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{10}$$

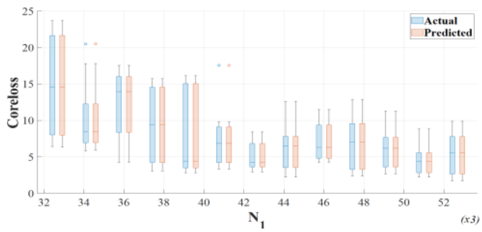
According to table 4, all three error values are quite low. To better illustrate the low errors in table 4, figure 5 shows the actual and predicted values of each input's core-loss value in boxplots. It can be seen that the estimations made according to the cross-section area, excitation voltage and primary turn numbers inputs are very close to the actual values, and the mean values are almost the same.



a) V_p



b) A_c



c) N_1

Figure 5. The boxplot of actual and predicted core loss values for each parameter.

4. Conclusion

This study introduces the use of the GPR) technique to estimate core losses in a three-phase dry-type transformer through FEA. The core losses are determined based on three input parameters. The dataset required for estimating core losses using GPR is generated via the parametric analysis function of the Ansys/Maxwell software, utilizing these input parameters. Three input features are used for this study, and the number of samples is 506 (506×3). The small amount of data is poor performance for most AI algorithms (such as machine learning, deep learning), while GPR based on Bayesian inference is stronger for small data. Ultimately, the estimation results of this study prove that GPR successfully performs core loss estimation with little data. Thus, it is important to predict transformer core losses in nonlinear behavior during the design and optimization phase before production. Core losses may not be accurately predicted in the classical design approach, and in this case, parameter analysis based on pre-prototype simulation provides useful information. Estimation of core power losses with parametric variational approach provides extremely accurate and fast information. Finally, as a future work, estimations can be made based on the harmonic analysis of the power losses occurring in the transformer windings and a decision can be made for the most appropriate winding structure and conductor type.

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