Artificial Intelligence-Based Transformer Fault Identification Using Frequency Response Analysis

Joshua Ottens*, Ali Doostmohammadi*, Amir Ameli*, Mohammad N. Uddin*, Siavash Jamshidi†,
*Dept. of Electrical and Computer Engineering, Lakehead University, Thunder Bay, Ontario, Canada
{jaottens, adoostmo, aameli, muddin}@lakeheadu.ca
†Dept. of Electrical Engineering, Arya Transfo Factory, Semnan, Iran
s.jamshidi@arya-transfo.com

***Abstract*—Transformer failures significantly disrupt power system reliability and impose considerable economic costs. Rapid and accurate fault diagnosis following transformer faults is crucial to minimize downtime and facilitate effective repair decisions. Transformer failures disrupt power-system reliability and impose significant economic costs, motivating rapid, non-invasive fault diagnosis. This paper presents a diagnostic framework that combines a FEM-based digital twin, a lumped-parameter winding model, and phase-angle FRA to generate labeled fault signatures for supervised learning. Parameters extracted in ANSYS Maxwell populate an eight-section Simulink equivalent circuit, and simulated FRA phase features are used to train an XGBoost classifier. Validation on a real manufactured 63 kV disc-type HV winding demonstrates high classification accuracy for axial vs. radial deformation and supports future extension toward fault localization.**

***Index Terms*—Power transformer, winding, digital twin, fault, frequency response analysis, finite element modelling, machine learning**

I. Introduction

Transformers are essential to power system operation, supporting voltage regulation, efficient transmission, and reliable power delivery. Faults in transformers can interrupt this function, leading to outages, equipment damage, and cascading failures that compromise system stability and result in significant economic losses [1]. Prompt detection, type identification, and localization of faults are therefore critical. Knowing the specific fault type early can avoid invasive inspections—such as oil draining or internal disassembly—thereby reducing maintenance time, minimizing costs, and accelerating restoration. Accurate and timely fault diagnosis ultimately supports faster decision-making, improves operational efficiency, and enhances system resilience.

Among diagnostic techniques, Frequency Response Analysis (FRA), first introduced by Dick and Erven [2], is widely recognized as one of the most effective methods for detecting mechanical and structural faults in transformer windings, such as axial displacement and radial deformation [3]. FRA applies a swept-frequency voltage across the windings and analyzes the resulting response. Mechanical faults alter winding geometry, affecting electrical parameters such as capacitance and inductance and producing measurable shifts in the frequency response that enable non-invasive fault identification.

Previous research has studied how different transformer faults influence internal electrical parameters. Radial deformation faults are known to primarily cause a reduction in series capacitance as well as a minor effect on ground capacitance and mutual inductance, with the latter typically considered the most sensitive indicator of radial faults [5]. In contrast, axial displacement faults predominantly affect series capacitance, significantly reducing series capacitance and, to a lesser extent, ground capacitance and mutual inductances. These fault-specific parameter changes produce characteristic shifts in both the magnitude and phase components of FRA curves, enabling engineers to reliably differentiate fault types by analyzing distinct FRA signatures [6].

Despite the proven sensitivity of FRA to transformer winding faults, conventional diagnostic practices depend heavily on visual interpretation of FRA curves. Such an analysis is inherently subjective, susceptible to human error, and requires substantial expertise, which can limit diagnostic consistency and scalability. To address these limitations, recent studies have applied machine learning (ML) techniques to automate FRA interpretation, enabling objective, reproducible, and highly accurate fault classification [7]. By learning complex, non-linear relationships within FRA data, ML algorithms reduce dependence on individual expert judgment and significantly improve diagnostic speed and reliability.

Previous research has explored various ML approaches for automating transformer fault classification using FRA data. For example, in [8] Zhao *et al.* introduced a method combining Finite Element Modelling (FEM) and lumped parameter equivalent circuits to simulate FRA signatures under diverse fault scenarios. Subsequently, several clustering-based ML techniques were applied for fault classification. Although this methodology provided promising results, it primarily utilized FRA magnitude data and basic ML models. There remains potential for further improvement in fault classification accuracy by incorporating FRA phase angle data, as well as utilizing more advanced ML models which are capable of identifying more complex relationships in the data to accurately classify the fault types.

This research systematically investigates the effects of axial and radial winding deformations on transformer FRA signatures by integrating FEM, lumped parameter circuit simulation, and machine learning based classification. First, a detailed digital twin model in ANSYS Maxwell is used to extract key electrical parameters such as series and ground capacitances, series and mutual inductances, and winding resistance, for both

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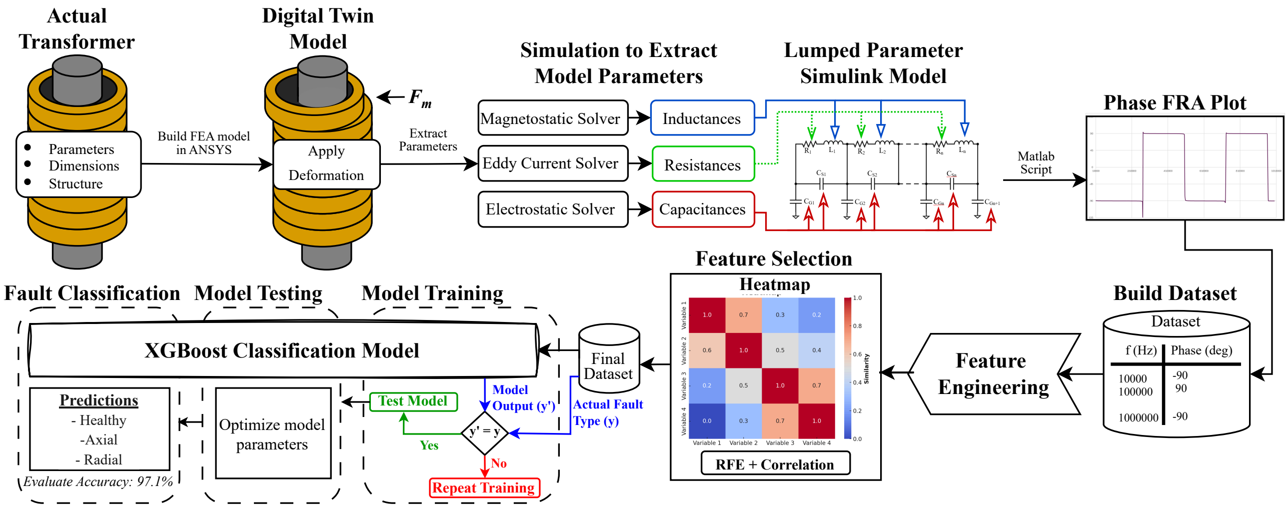


Fig. 1: Flowchart of Fault Classification Process.

healthy and faulted conditions. These parameters are then used in a lumped parameter equivalent circuit model in Simulink to generate realistic FRA responses. Finally, the simulated FRA data is processed and fed into an XGBoost classifier, which reliably distinguishes fault types based on characteristic FRA deviations.

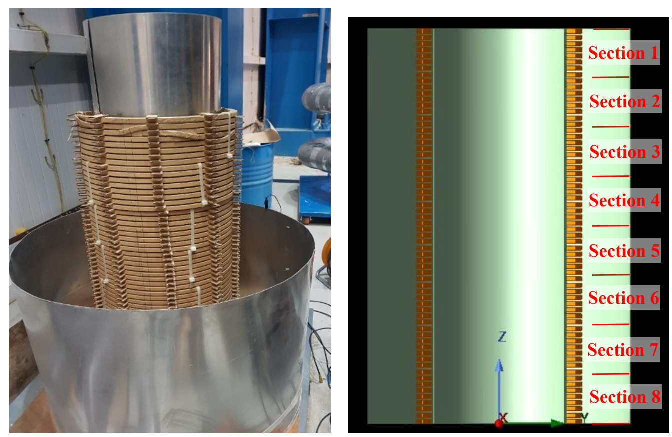
The main contributions of this paper are as follows:

- Systematic generation and characterization of FRA phase signatures for multiple fault scenarios, demonstrating clear, non-invasive differentiation between axial and radial faults.
- Development of an optimized machine learning pipeline, incorporating data processing, feature engineering and feature selection, to automate FRA interpretation and achieve objective and accurate fault classification.

The remainder of this paper is organized as follows. Section II describes the transformer FEM modeling, parameter extraction, lumped-circuit implementation, FRA simulation, data processing and ML model creation procedures. Section III presents the classification performance and analyzes key findings. Section IV concludes the paper and outlines directions for future work.

II. Methodology

This section describes the approach undertaken to investigate the impact of axial and radial winding faults on transformer FRA signatures. The methodology comprises five main stages: transformer modelling and parameter extraction using FEM, construction of a lumped parameter equivalent circuit model in Simulink, automated FRA data extraction from the lumped parameter model, data processing and feature selection, and finally machine learning based fault classification using the extracted FRA data. The flowchart in Figure 1 visualizes the process used in this research to accurately classify the transformer faults.



(a) Actual Transformer (b) Digital Twin Transformer

Fig. 2: Transformer Windings.

A. Transformer Modeling and Parameter Extraction using FEM

The transformer geometry and internal winding arrangement were modelled in ANSYS Maxwell FEM software. The winding consists of 64 discs, each with six copper turns insulated by cellulose paper, while the core and tank are represented as concentric steel cylinders surrounding the winding. For effective extraction of electrical parameters, the transformer's 64 discs were segmented into eight distinct sections, each containing eight separate discs. This segmentation facilitated the efficient extraction of electrical parameters and simplified their subsequent integration into the lumped parameter equivalent circuit model.

The actual winding from the manufacturing facility is depicted in Fig.2a, while a cross section displaying the eight sections of the FEM based transformer model is shown in Fig.2b.

Three specialized FEM solvers in ANSYS Maxwell were utilized to extract precise electrical parameters:

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- **Electrostatic solver:** Extracts series capacitances between winding turns and discs, as well as ground capacitances between windings and transformer tank and core.
- **Magnetostatic solver:** Calculates series inductances for individual winding section and mutual inductances between winding sections.
- **Eddy-current solver:** Determines the AC resistance for each winding section, completing the impedance profile required for the lumped equivalent circuit.

Initially, parameters are extracted from the model of a healthy transformer. Subsequently, the digital model is adjusted to simulate axial and radial deformation faults with varying extents applied individually to each of the eight transformer sections. To simulate an axial displacement fault, the faulted winding is shifted vertically by the defined extent distance. Ten evenly spaced fault displacement extents are modelled for the axial faults, ranging from 1 to 11 mm displacement. To simulate a radial displacement fault, the faulted winding is shifted horizontally by the defined extent distance. Ten evenly spaced fault displacement extents are modelled for the radial faults, ranging from 2 to 22 mm displacement. By extracting the data for all fault extents and each of the 8 windings, a comprehensive dataset is constructed to later be used for training and validating the ML fault classification model.

It should be noted that the present study focuses exclusively on a disc-type transformer winding, which is a common configuration for high-voltage windings. The FEM model is constructed in a fully geometry-driven and parameterized manner, where winding dimensions, spacing, insulation thickness, number of turns, and material properties are defined as independent parameters. As a result, the same modelling framework can be reconfigured to represent other winding types, such as layer or helical windings, by modifying the geometric definitions and winding arrangement while preserving the overall parameter extraction procedure. In this work, a disc winding is selected to validate the proposed framework using a real manufactured winding and measured FRA data.

B. Lumped Parameter Model Development in Simulink

A lumped parameter equivalent circuit for a single winding as proposed by Shintemirov [9] represents the transformer's electrical characteristics and is developed using MATLAB's Simulink software. The lumped parameter method involves discretizing the transformer's complex internal structure into interconnected capacitive, inductive and resistive elements, forming an equivalent circuit that closely emulates the real transformer's electrical behavior. The lumped parameter model for a n-section transformer is shown in Figure 3. The transformer in this work is modelled using a lumped parameter model with $n = 8$, meaning that the transformer is composed of eight individual sections, each with their own capacitances, inductances and resistances.

In the Simulink model, each of the eight winding sections is represented by dedicated lumped parameter circuit blocks,

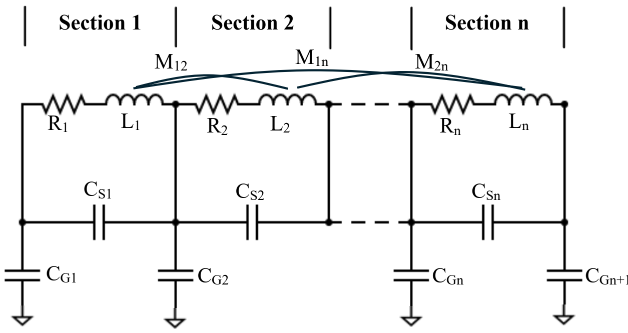

Fig. 3: Transformer Lumped Parameter Equivalent Circuit.

precisely configured according to their actual physical and electrical interconnections. After constructing the lumped circuit, a variable frequency AC voltage source is applied to the top winding. A voltage measurement block is also connected to the bottom winding to measure the output response. The input sinusoidal voltage frequency sweep and the corresponding output voltage measurement are used to generate FRA data.

C. FRA Simulation and Data Extraction

The FRA simulation and data extraction process involved applying a sinusoidal voltage sweep across the lumped parameter model and measuring the corresponding output response. The frequency sweep ranged from 10 kHz to 1 MHz and consisted of 801 equally logarithmically spaced frequency steps to ensure high resolution across the entire frequency spectrum. For each simulation scenario, defined by specific fault types and deformation extents, the MATLAB script automatically executed the Simulink lumped parameter model, systematically updating the model parameters according to the FEM-derived fault conditions. The output voltage measured at the bottom winding, along with the corresponding input frequency, was recorded to generate the FRA phase angle curves. Each FRA dataset comprised 801 frequency phase angle data pairs, stored as individual MATLAB files for subsequent use in fault analysis and machine learning based fault classification.

D. Data Processing

Data processing is critical to ensure that only relevant, informative data is used to train the ML model, improving both model accuracy and computational efficiency. The data processing workflow for this research involves three stages: data integration, feature engineering, and feature selection.

The data integration stage began by loading the FRA phase data and merging each FRA data file into a single unified dataset. This combined dataset included rows representing each extent of each type of transformer fault scenario, with the first column containing the corresponding fault type labels and the remaining columns containing FRA phase data associated with specific frequency points.

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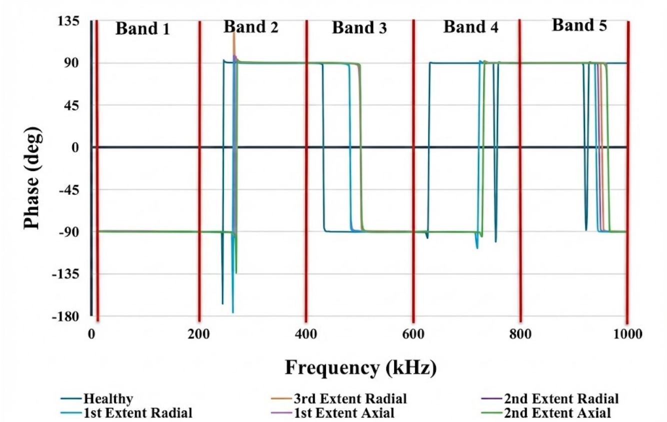

Fig. 4: Frequency Bands Labeled on Transformer Phase FRA.

Feature engineering begins by calculating the difference between the FRA phase data of faulted conditions and the healthy baseline condition, thereby quantifying deviations introduced by transformer faults. This generates an error dataset explicitly highlighting frequency dependent changes induced by each fault scenario. To enhance the informational content of the dataset, statistical features such as maximum error, minimum error, and standard deviation are extracted across defined frequency bands: 10–200 kHz, 200–400 kHz, 400–600 kHz, 600–800 kHz, and 800–1000 kHz. These statistical features enable the capture of broader frequency characteristics by summarizing error trends within each frequency band, rather than relying solely on individual frequency points. By segmenting the overall frequency spectrum into five distinct 200 kHz wide bands, each of the four significant phase transitions between the -90° and 90° phase extremes could be isolated effectively. The frequency bands are shown on the FRA plot displayed in Fig. 4. Notably, the lowest frequency band of 10–200 kHz, which did not include a phase transition, was expected to hold minimal diagnostic value, as this frequency range primarily indicates changes associated with transformer core damage rather than winding faults.

Since the dataset contains numerous features relative to the available data samples, feature selection is performed to reduce complexity and avoid overfitting. A hybrid feature selection method using Recursive Feature Elimination (RFE) and correlation analysis identifies the most informative subset of 17 features. These 17 features are displayed in table I. Notably, the selected features predominantly occupy the 500–1000 kHz frequency band, aligning with expectations since transformer winding faults typically affect FRA signatures within the 100 kHz to 1 MHz range.

After feature selection, the dataset is divided into training and testing subsets using an 80/20 split. Finally, these subsets are further separated into features and target variable labels.

E. Machine Learning Fault Classification

Lastly, a machine learning model is employed to classify transformer fault types based on the processed FRA data. The Extreme Gradient Boosting algorithm was proposed by Chen *et al.* [10] and is often referred to as XGBoost model. It is commonly used due to its high classification accuracy, computational efficiency, and robustness in handling complex and nonlinear classification problems. Additionally, the XGBoost models' inherent capability to handle datasets with missing data points makes it ideal for this study, where many of the frequency-phase data pairs are removed due to the feature selection process. Furthermore, XGBoost incorporates built-in regularization techniques, such as L1 and L2 penalties, significantly reducing the risk of overfitting. This regularization capability is essential given the limited number of available FRA fault samples. These attributes collectively make XGBoost well suited for transformer fault diagnosis based on FRA data, allowing for accurate, efficient and reliable classification. This algorithm operates by building an ensemble of gradient-boosted decision trees, iteratively refining predictions by minimizing errors and effectively capturing subtle and intricate data patterns.

To further improve the classification accuracy of the XGboost model, hyper-parameter tuning is conducted with the set of hyper-parameters providing the most accurate result summarized in table III.

TABLE I: Selected Features.

No.	Metric	Frequency (Hz)	No.	Metric	Frequency (Hz)
1	Phase angle	537 031.80	10	Phase angle	927 897.49
2	Phase angle	549 540.87	11	Phase angle	933 254.30
3	Phase angle	767 361.49	12	Phase angle	966 050.88
4	Phase angle	771 791.52	13	Phase angle	971 627.95
5	Phase angle	780 728.44	14	Phase angle	994 260.07
6	Phase angle	789 768.85	15	Std. dev. of error	200–400 kHz
7	Phase angle	794 328.23	16	Max error	600–800 kHz
8	Phase angle	803 526.12	17	Min error	200–400 kHz
9	Phase angle	922 571.43			

TABLE II: Comparison of Classification Model Accuracies.

Model	Accuracy	Model	Accuracy
XGBoost	**95.4%**	KNN	84.1%
LightGBM	92.3%	Decision Tree	79.9%
SVM	87.3%	ANN	89.6%

III. Performance Evaluation

This work begins by creating a digital twin model of an actual, single-phase, 63kV transformer winding which has an internal diameter of 43 cm and a winding height of 110 cm. This model is then used to extract the transformer parameters, which are then applied to the transformer lumped parameter equivalent circuit to obtain the FRA data of the transformer. This data is then processed and used to train a machine learning model to classify transformer axial and radial faults.

Several machine learning models are trained and tested with the processed data and then compared to each other to determine which type of model was best suited to accurately classify the transformer fault types. The models used are XGBoost, LightGBM, Support Vector Machine, K-Nearest Neighbor, Decision Trees and an Artificial Neural Network where the results are displayed in table II. The XGboost model displays the highest classification accuracy and thus is chosen to classify the faults in this research.

TABLE III: Hyperparameter Setting of XGBoost Model.

Hyperparameter	Value	Hyperparameter	Value
max_depth	9	reg_lambda	4.953
learning_rate	0.046	min_child_weight	6
n_estimators	122	subsample	0.73
gamma	2.372	colsample_bytree	0.98
reg_alpha	0.966		

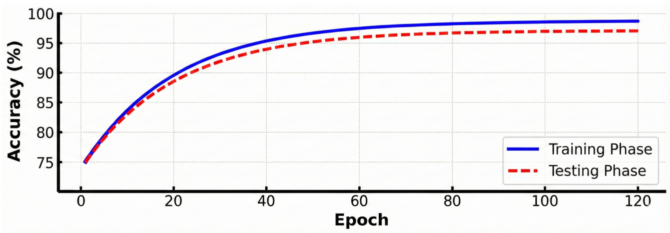

Fig. 5: Learning Curve of XGBoost Model.

To further improve the prediction accuracy of the XGBoost model, hyperparameter tuning is conducted with the set of hyper-parameters providing the most accurate result summarized in table III.

The performance of the proposed fault classification framework is evaluated using a dataset comprising 34 fault scenarios, 17 of which were axial faults and 17 of which were radial faults. These cases are generated from the FEM based digital twin model by applying varying fault extents across different winding sections. The trained XGBoost model is tested on this unseen dataset to assess its generalization ability and classification accuracy. The model successfully classifies all 17 axial faults and 16 out of 17 radial faults, achieving an overall accuracy of 97.1%. This result demonstrates the reliability and precision of the proposed approach in distinguishing between fault types based on their corresponding FRA phase signatures.

Figure 5 presents the learning curve of the XGBoost model over training epochs. The curve shows that both training and testing errors converge after approximately 80 epochs, indicating that the model is well-tuned and not overfitting or underfitting. The close alignment between training and testing accuracy suggests good generalization performance. These findings confirm that integrating FEM-based simulation, advanced feature selection, and XGBoost classification enables accurate, consistent, and non-invasive transformer fault diagnosis.

IV. Conclusion

This paper presents a novel framework for transformer fault diagnosis that integrates FRA with FEM, lumped parameter simulations in MATLAB/Simulink, and machine learning techniques. By leveraging accurate FEM-based transformer models and combining them with carefully engineered features and an XGBoost classifier, the proposed method achieves a fault classification accuracy of 97.1%. This significantly outperforms traditional visual FRA interpretation and shows notable improvements over existing machine learning approaches in the literature. The developed digital twin model enables realistic simulation of various fault scenarios, while the machine learning component ensures consistent and rapid classification. Together, these elements offer a non-invasive, reliable, and efficient diagnostic tool capable of reducing transformer downtime and maintenance costs.

Future work extends this framework in several directions. While this study employs Recursive Feature Elimination for feature selection, alternative dimensionality reduction techniques such as Principal Components Analysis may be investigated to explore relationships among FRA frequency features prior to feature removal and to further enhance model interpretability. In addition, the proposed framework will be applied to transformer windings with different geometries and construction types, including layer and helical windings. Evaluating the methodology across a broader range of winding configurations and operating conditions will strengthen the generality of the FEM-based digital twin, the lumped-parameter model, and the machine learning classifier, and will support future development toward a more widely applicable transformer diagnostic framework.

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