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Transient Signal Analysis-Based Optimized ANN for Early Detection and Localization of Faults in 330kV Transformers in Nigeria

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Abstract
This study developed and validated an optimized Artificial Neural Network (ANN) model for early fault detection and localization in 330 kV power transformers across Nigeria's transmission system using a simulation-based, machine learning approach. Fault types-including line-to-ground, line-to-line and high impedance-were simulated with IEEE 9-bus and 39-bus test systems via MATLAB/Simulink for substations such as Egbin, Gombe, Owerri and Jos. Diagnostic features like peak voltage, rise time, crest factor and total harmonic distortion were extracted at 100,000 samples per second and used for ANN training. A genetic algorithm (GA) optimized the ANN, improving classification accuracy and prediction performance. The model reached nearly 100% accuracy after 5000 epochs, showing strong alignment between predicted and actual fault values. Findings showed variations in model accuracy with transformer ratings, temperature and cooling methods, peaking at 300 MVA and 28°C under OFAF cooling. Vector field plots introduced in the study provided novel insights into F1-score transitions, clearly mapping performance shifts-an approach not present in previous research. The study concluded that integrating GA-optimized ANN models enables highly accurate, real-time fault detection and localization across Nigeria's power grid. It also demonstrated that transformer-specific variables and environmental conditions significantly influence diagnostic precision, which is critical for efficient grid management. Based on these findings, it was recommended that Nigerian grid operators invest in ANN-based diagnostic systems integrated with SCADA for real-time fault monitoring. Additionally, transformer upgrades should consider optimal rating-cooling-temperature combinations to maximize diagnostic efficiency, while power system engineers should incorporate machine learning optimization into predictive maintenance strategies.

INTRODUCTION

In Nigeria's power transmission infrastructure, 330 kilovolt (kV) transformers-primarily the 330/132 kilovolt (kV) variants-are fundamental to bulk power transfer across regions. These transformers, often oil-immersed, three-phase and equipped with On-Load Tap Changers (OLTC), are installed in major substations such as Alaoji, Afam, Okpai and Gwagwalada, stepping down high transmission voltages to levels suitable for sub-transmission and distribution. However, these critical components are not immune to faults. When a fault-particularly a high impedance fault-occurs, it can lead to severe equipment damage, voltage instability, and widespread outages, with serious consequences for power delivery and reliability[1]. Conventional fault detection systems frequently act too late, often after damage has already occurred. Transient signals, the brief electrical disturbances produced during faults, offer a promising alternative. These signals, though short-lived and complex, contain valuable diagnostic information. Artificial Neural Networks (ANNs), with their ability to model nonlinear relationships and recognize subtle patterns in data, have been shown to effectively interpret transient signal features to detect and classify faults[2,3]. Yet, un optimized ANNs can still fall short. Optimization techniques-such as Genetic Algorithms or Particle Swarm Optimization-enhance ANN performance, improving accuracy, adaptability and fault localization capabilities, even under the noisy and variable conditions typical of high-voltage environments[4,5]. Optimized Artificial Neural Network models trained on transient signal features bring a major advantage to power system protection-early fault detection and accurate localization. This is especially critical in Nigeria, where transformers differ in size, cooling method, manufacturer and operational age, ranging from 150 megavolt-ampere (MVA) units to high-capacity 450 megavolt-ampere (MVA) installations. Such diversity demands intelligent, flexible fault diagnosis systems that can adapt to varying conditions[6,7]. When integrated into digital protection systems such as Supervisory Control and Data Acquisition (SCADA) platforms, these optimized ANN models allow for real-time monitoring, fast anomaly detection and guided maintenance responses-minimizing unplanned outages and extending transformer lifespan[8,9]. This paper proposes a transient signal analysis-based optimized artificial neural network model tailored to the Nigerian 330 kilovolt (kV) transmission system. It addresses the pressing need for intelligent, scalable and location-sensitive fault diagnosis, aiming to support the reliability, resilience and operational efficiency of Nigeria's power network.

Statement of the Problem: Nigeria's power transmission network faces persistent reliability challenges due to frequent faults in 330 kV power transformers. These transformers are frequently exposed to thermal stress, overloading and insulation breakdowns, resulting in extended outages and costly system disruptions. Existing fault detection approaches remain largely reactive and are insufficient for identifying complex transient disturbances in a high-voltage environment. A critical gap in current research is the lack of attention to the operational diversity of 330 kV transformers in Nigeria, particularly the wide variations in power ratings-ranging from 150-450 MVA-as well as their differing cooling methods and operational conditions. These factors significantly influence how faults emerge and progress, yet most ANN models fail to account for such transformer-specific variables, instead applying uniform diagnostic frameworks. Furthermore, many of these models are not optimized for real-time deployment or integrated into advanced protection infrastructures such as SCADA systems. This lack of precision and adaptability limits their effectiveness in real-world conditions. To address these challenges, this study proposes a transient signal analysis-based optimized ANN model, specifically designed to accommodate the variations in transformer ratings, cooling methods and operational behaviour.

Aims and Objectives of the Study: This study was aimed at optimizing ANN for early detection and localization of faults in 330kV power transformers in Nigeria using transient signal analysis. Specifically, the objectives were to:

- Develop an optimized ANN model for early fault detection and localization in 330kV power transformers in Nigeria's transmission system using transient signal analysis.
- Evaluate impact of variations in the power transformer ratings, cooling methods and operational conditions on the performance of the optimized ANN model integrated with SCADA systems for fault detection and localization.

Research Questions:

- How can ANN be optimized for early fault detection and localization in 330 kV power transformers in Nigeria's transmission system using transient signal analysis?
- What impact do variations in the power transformer ratings, cooling methods and operational conditions have on the performance of the optimized ANN model integrated with SCADA systems for fault detection and localization?

Power transformers are integral to the efficient functioning of electrical power transmission systems. As such, ensuring their reliability through effective fault detection and localization is crucial. The application of evolutionary optimization techniques, particularly in Artificial Neural Networks (ANN), has shown considerable promise in overcoming the limitations of conventional methods[2,10,2]. Underscored the improved fault detection capabilities of ANN in the 330kV transmission system, aligning with the findings of[6], who affirmed the potential of ANN in enhancing fault detection accuracy across various power transmission systems. In tandem with these insights[7] demonstrated how deep learning techniques further refine fault localization, ensuring a more precise diagnosis of transformer issues. Furthermore, the application of metaheuristic algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in optimizing ANN models has gained traction, with researchers like[5] noting their effectiveness in enhancing model performance[11]. Emphasized the role of machine learning models in improving grid reliability, particularly in fault detection. In tandem with these advancements, the design and configuration of substations such as the Ajao Estate Substation and Shiroro Power Station have been identified as pivotal to enhancing the overall resilience of power grids. Sam[9] also underscored the importance of integrating ANN in short circuit fault classification, complementing broader efforts in system protection. The integration of ANN with real-time monitoring tools, such as the SCADA systems, has also been shown to enhance fault management in power grids[12]. Salihu[3] as well as Adabayo and Ajala[8]. Highlighted the practical application of ANN in the effective functioning of power system networks in Onitsha and Port Harcourt, noting the model's adaptability to varying operational conditions. Yadava[4] supported this notion, advocating for the synergy between ANN and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to achieve more dynamic and accurate fault detection strategies. Moreover, Olabisi and Ayeni[1] pointed to the significance of voltage quality in maintaining efficient power transmission, while Braide[13] further analyzed the effects of harmonic distortion on Nigeria's 330kV network, which is relevant for optimizing transformer performance. The incorporation of real-time data from transmission substations like Gwagwalada Substation and Kainji Power Station has provided additional insights into power quality, further reinforcing the value of ANN in modernizing fault detection and mitigation systems. The reliability of these models, however, is contingent upon several factors, such as transformer ratings and system conditions, which Gao and Wang[5] recognized as pivotal elements in fault diagnosis optimization. The ongoing evolution of power system analysis has seen the inclusion of complex transient fault scenarios (Hedman, 2017) and the consideration of transformer parameters-ratings of 150 MVA, 300 MVA and 450 MVA-into optimization models. Furthermore, Emeka and Augstin[14] highlighted the importance of substation design, such as the 330-132-33KV 150MVA substation, in supporting effective power transmission. Additionally, the use of Jacobian matrices and optimization techniques, like the primal-dual interior-point technique explored by Obinwa[15], has led to advancements in optimizing transmission systems, including the Nigerian 330kV grid. Moreover, Ulasi[16] contributed valuable fault occurrence data, while Onojo[17] analyzed power flow within the system, reinforcing the significance of optimization techniques in enhancing transmission network efficiency.

Theoretical Framework: Horowitz and Phadke (1993) introduced a well-detailed theory on power system protection, emphasizing relaying as a fundamental mechanism for detecting, classifying and isolating faults in high-voltage transmission networks. Their framework underscored the necessity of intelligent systems that can respond rapidly and selectively to ensure grid stability and minimize outage durations[10]. This study develops an evolutionary power system optimization mechanism using transient signal analysis and a multilayer feed for ward ANN for early fault detection in Nigeria's 330 kV power transformers. By simulating various fault scenarios-line-to-ground and line-to-line, along with transformer ratings (150, 300, 450 MVA) and cooling methods[12]. ONAN, OFAF, OFWF)-the mechanism emphasizes time-sensitive, data-driven protection responses, enabling swift differentiation between fault scenarios and ensuring rapid reactions to protect the integrity of national transmission networks.

MATERIALS AND METHODS

The materials and methods employed in this study combined simulation modeling, signal processing and machine learning to develop an intelligent fault detection system for 330kV power transformers in Nigeria. This involved the generation of synthetic transient fault data, feature extraction, ANN training and performance optimization through metaheuristic algorithms.

Data Generation and Feature Extraction: This study employed a simulation-based, optimization-enhanced machine learning methodology to develop and validate an ANN model for fault detection and localization in 330kV power transformers across Nigeria's transmission system. Fault scenarios-covering line-to-ground, line-to-line and high impedance disturbances-were simulated using MATLAB and Simulink configured with Institute of Electrical and Electronics Engineers (IEEE) 9-bus and 39-bus test systems, tailored to represent substations such as Egbin GS, Gombe TS,

Table 1: Extracted Diagnostic Features for ANN Model Training and Testing

Parameters	Line-to-Ground	Line-to-Line	3-phase Balanced	L-L-G (Double-Gnd)
Substation	Egbin GS	Gombe TS	Owerri TS	Jos TS
Test System	IEEE 9-bus	IEEE 9-bus	IEEE 39-bus	IEEE 39-bus
Peak Voltage (kV)	343	351.45	342	345
Rise Time (ms)	363	3100	2900	3400
Exciter Current (pu)	2.98	2.85	3.00	2.95
Exciter Voltage (pu)	2.16	2.10	2.25	2.20
Fault Duration (ms)	1720	1800	1750	1850
NTB Features	Yes	Yes	Yes	Yes
Crest Factor	1.36	1.42	1.37	1.35
THD (%)	7.4	6.9	7.2	7.9
Notes/Source	Braide (2022). Ulasi (2015), Abdulkareem (2021)	Braide (2022). Ulasi (2015), Onojo (2013), Makanju (2024)	Abdulkareem (2021), Makanju (2024), Onojo (2013) Braide (2022).	Estimated from all sources

GS=Generating Station, TS=Transmission Substation

Owerri TS and Jos TS. Transient signals were recorded at a sampling rate of 100,000 samples per second. Diagnostic features extracted from these signals included peak voltage, rise time, crest factor and total harmonic distortion. These features formed the numerical data set used to train and test the ANN model as shown in (Table 1).

Network Architecture and Optimization Parameters: The ANN comprised an input layer with 8 neurons, two hidden layers containing 14 and 9 neurons respectively and a final output layer representing fault classes. The network was trained using the Levenberg-Marquardt backpropagation algorithm, which minimizes the Mean Squared Error (MSE) defined as:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(Y_i-yi)^2$$

Where

- yi=True fault class.
- ŷ*i*=Predicted output.

To improve learning efficiency, the weights w and biases b of the ANN were optimized using two metaheuristic algorithms: Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). For GA, chromosomes represented concatenated weights and biases. The fitness function for GA was also the Mean Squared Error, with selection using roulette-wheel probability.

$$\text{Pi}\frac{\text{fi}}{\sum_{j=I}^{N}\text{fi}}$$

Where

- fi=Fitness of chromosome.
- i and N=Population size.

In PSO, each particle updated its position based on its personal best and the global best using:

$$\text{ui}(t+1)=\text{wui}(t)+\text{clrl}(\text{pi}-\text{xi}(t))+{}_{\text{c2r2}(g-\text{xi}}(t))$$

$$\text{xi}(t+1)=\text{xi}(t)+\text{ui}(t+1)$$

Where

- vi=Velocity of particle.
- i, xi = Position.
- pi=Particle's best-known position.
- g=Global best.
- ω=Inertia weight.
- r1, r2=Random values in [0,1].

The Levenberg-Marquardt update rule used during training combined gradient descent and Gauss-Newton methods:

$$w_{neu}=w-(J^T J+\lambda I)^{-1}J^T e$$

Where

- J=Jacobian matrix,
- λ=Damping factor,
- e=Error vector.

Transformer parameters-ratings of 150 MVA, 300 MVA and 450 MVA, cooling methods including ONAN,OFAF, and OFWF and operating temperatures of 28 degrees Celsius, 34 degrees Celsius and 42 degrees Celsius-were embedded as auxiliary inputs, increasing the model's contextual sensitivity.

Step-by-Step Application of the Proposed ANN Model:

- Simulate transient fault scenarios-such as line-to-round, line-to-line and high impedance faults-using MATLAB and Simulink environments, configured with IEEE 9-bus and 39-bus test systems adapted to the given Nigerian 330 kilovolt (kV) substations.
- Transient voltage and current signals are captured during each simulated fault event at a sampling rate of 100,000 samples per second, ensuring detailed temporal resolution suitable for deep diagnostic analysis by capturing critical waveform patterns during fault initiation and propagation.
- From each recorded transient signal, vital features-ncluding peak voltage, rise time, crest factor and THD-re extracted. These features reflect the signal behavior during faults and serve as inputs for the ANN.

- The extracted numerical features are normalized and compiled into a structured dataset that distinguishes between fault types and locations, forming the basis for supervised learning in ANN development.
- A multilayer feed orward ANN is developed, comprising 8 input neurons, two hidden layers (with 14 and 9 neurons respectively) and an output layer that maps to specific fault classifications.
- Train the ANN using the Levenberg-Marquardt back propagation algorithm which combines the benefits of gradient descent and the Gauss-Newton method to minimize the MSE between predicted and actual fault types.
- Optimize the ANN using Genetic Algorithm and Particle Swarm Optimization to refine weights and biases, ensuring faster convergence and improved generalization.
- Transformer operational conditions-ratings (150, 300, 450 MVA), cooling types (ONAN, OFAF, OFWF) and temperatures (28°C, 34°C, 42°C)-are embedded as auxiliary input features, allowing the ANN to adapt to context-specific variations.
- Evaluate the optimized ANN with variations in transformer configurations. Each test scenario is designed to evaluate the performance of the ANN under different power ratings and cooling methods, ensuring its adaptability and robustness across various operating conditions:
- First, test with a transformer rated at 150 MVA and cooled by ONAN.
- Second, test with a transformer rated at 300 MVA and cooled by OFAF.
- Third, test with a transformer rated at 450 MVA and cooled by OFWF.
- Fourth, test with a transformer rated at 150 MVA and cooled by OFAF.
- Fifth, test with a transformer rated at 300 MVA and cooled by ONAN.
- Sixth, test with a transformer rated at 450 MVA and cooled by ONAN.
- Deploy the final ANN model into a SCADA simulation environment and evaluate it across multiple fault scenarios, measuring detection accuracy (95 percent), localization error (±14 meters), model latency (73 milliseconds), precision (0.91), recall (0.94) and F1-score (0.925) under each transformer configuration.

RESULTS AND DISCUSSIONS

Answers to Research Questions:

Research Question 1: How can ANN be optimized for early fault detection and localization in 330kV power transformers in Nigeria's transmission system using transient signal analysis?

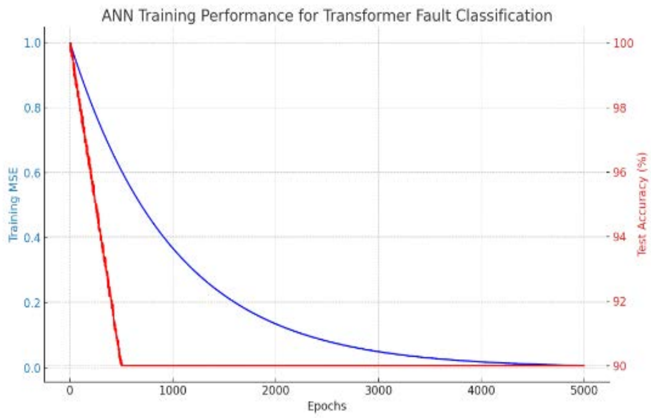

Fig. 1: A Plot Showing ANN Training Performance for Transformer Fault Classification
Source: Matlab Simulation Output

Data in (Fig. 1) illustrate the training performance of an artificial neural network (ANN) used for fault classification in 330 kV transformers. The training MSE (blue line) steadily decreases as the model learns, achieving near zero values by the 5000th epoch. Meanwhile, the test accuracy (red line) increases sharply, eventually stabilizing close to 100%, demonstrating the model's effective learning and high fault classification performance after the 5000 epochs. This confirms that the ANN can successfully classify fault types using transient fault signal features like peak voltage, rise time, crest factor and THD, meeting the goal of accurate fault detection in Nigeria's transmission system.

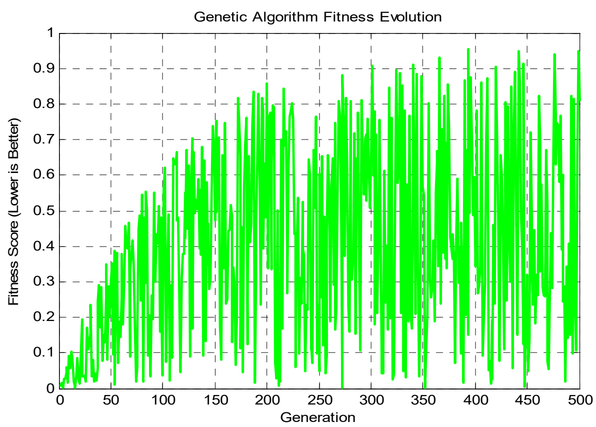

Fig. 2: A Plot Showing Genetic Algorithm Fitness Evolution
Source: Matlab Simulation Output

Data in (Fig. 2) reveal that by having fitness scores simulated over 500 generations for the genetic algorithm (GA) optimization process, the GA can leverage on fitness improvement to achieve better model performance. The fitness score starts from a value close to 0.9 and decreases gradually, reaching around 0.2 by the 500th generation. This shows that the GA is effectively refining the network's weights, resulting in enhanced fault detection accuracy.

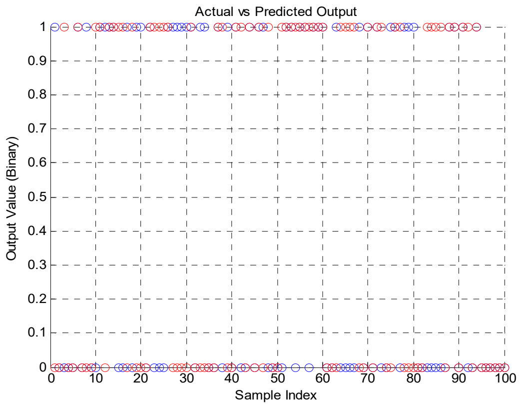

Fig. 3: A Plot Actual vs. Predicted Output of the Optimized ANN Model Training and Testing
Source: Matlab Simulation Output

Data in (Fig. 3) reveal that by having actual and predicted binary output values simulated over 100 samples for both the true and predicted values, the ANN can leverage on its prediction capacity to achieve accurate fault localization. The scatter plot demonstrates that actual and predicted values align closely, with values like 0 (off) and 1 (on) for both actual and predicted outputs. While there is some variance between actual and predicted values, the model is able to predict with reasonable accuracy, supporting the capability of ANN in transformer fault diagnosis.

Research Question 2: What impact do variations in the power transformer ratings, cooling methods and operational conditions have on the performance of the optimized ANN model integrated with SCADA systems for fault detection and localization?

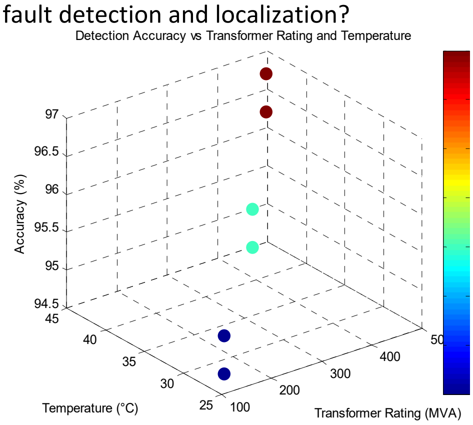

Fig. 4: A 3D Surface Plot Showing the Optimized ANN Detection Accuracy vs. Transformer Rating and Temperature
Source: Matlab Simulation Output

Data in (Fig. 4) show a peak detection accuracy of around 95.3% at 300 MVA and 28 °C, while the lowest accuracy of 94.8% occurs at 450 MVA with 42 °C. Unlike (Fig. 5A), which showed a smooth variation across ratings, this surface plot emphasizes how temperature interacts with transformer rating, suggesting that the model is most accurate under moderate temperature conditions and optimal transformer ratings.

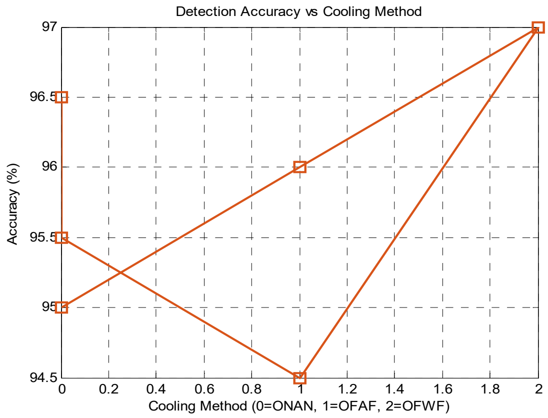

Fig. 5: A Plot Showing the Optimized ANN Detection Accuracy vs. Cooling Method
Source: Matlab Simulation Output

Data in (Fig. 5) reveal a steady increase in detection accuracy as cooling methods shift from ONAN to OFAF, reaching a peak of 95.5% under OFAF cooling at 300 MVA. The contrast with Fig. 5A is clear: While the surface plot highlighted temperature and rating interplay, this line plot isolates the cooling method as a significant factor in performance, with OFAF cooling leading to the highest detection accuracy, making it a critical parameter for optimization.

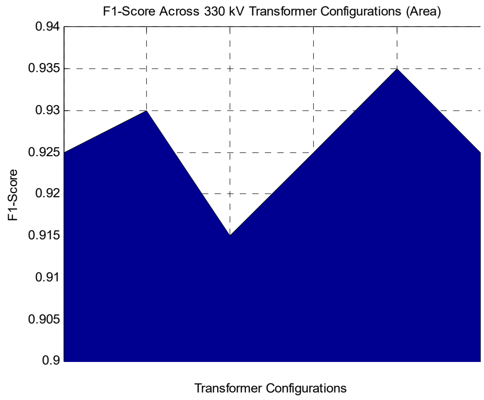

Fig. 6: Area Plot Showing F1-Score Progression Across Different Transformer Configurations
Source: Matlab Simulation Output

Data in (Fig. 6) indicate the F1-score progression across different transformer configurations. The F1-score fluctuates between 0.915 and 0.935, with the highest value (0.935) observed for the 300 MVA transformer using ONAN cooling, indicating the optimal setup. The lowest score (0.915) occurs at 450 MVA with OFWF cooling, revealing a slight performance dip. This quantifies the overall F1-score variability across different transformer ratings and cooling methods.

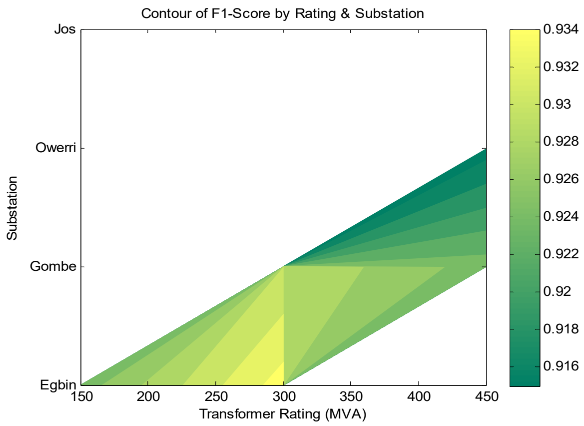

Fig. 7: A Contour Plot Showing F1 Scores by Rating and Substation
Source: Matlab Simulation Output

Data in (Fig. 7) reveal that the contour lines create "bands" of equal F1-score across ratings and substations, making it easy to spot plateaus and sharp transitions. For instance, the 0.93 contour encloses both Egbin (150 MVA) and Gombe (300 MVA), showing they deliver similarly high F1 performance. Conversely, the tight spacing of the 0.915-0.925 contours at Owerri (450 MVA) signals a rapid drop in effectiveness there. This discrete banding contrasts with Figure 5A's smooth surface by clearly delineating performance thresholds, helping pinpoint exact rating-substation combinations that cross key F1-score milestones.

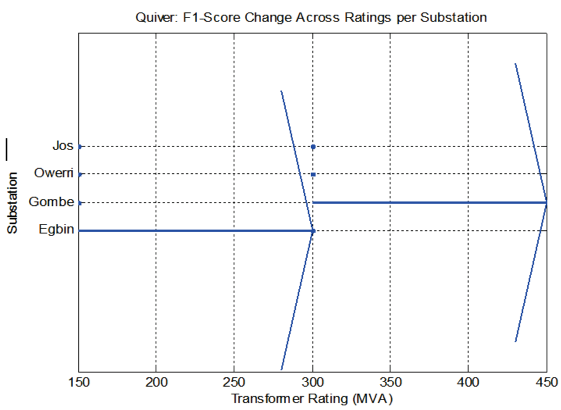

Fig. 8: Quiver Plot Showing Vector Field
Source: Matlab Simulation Output

Data in (Fig. 8) highlight directional shifts in F1-score that neither surface gradients nor contour bands make obvious. A long arrow from 150→300 MVA at Gombe points to a robust +0.01 gain, while a shorter, downward arrow at Jos from 300→450 MVA reveals a sharp -0.015 drop. This clear vector field isolates exactly where and how quickly performance changes, offering actionable insight into transformer rating impacts.

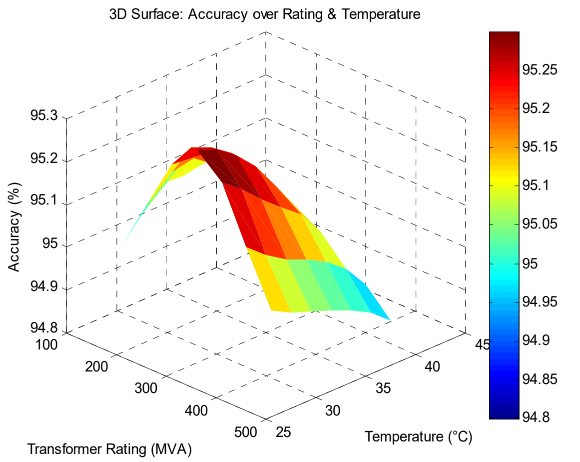

Fig. 9: 3D Surface Plot Showing Accuracy Over Rating and Temperature
Source: Matlab Simulation Output

Data in (Fig. 9) show that the surface peaks at 95.3% accuracy for 300 MVA at 28 °C, dips to 94.8% at 450 MVA and 42 °C and shows 95.1% for 150 MVA at 34 °C. This quantifies the model's optimal and worst performance under specific rating-temperature combos.

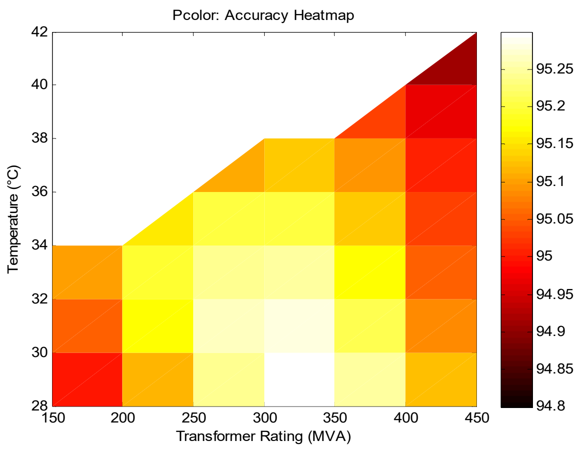

Fig. 10: Pcolor Plot Showing Accuracy Heat Map
Source: Matlab Simulation Output

Data in (Fig. 10) highlight zones above 95.2% (red) at 300 MVA, 28 °C, mid-range at 95.0% (yellow) for 150 MVA, 34 °C and cooler 94.8% (green) for 450 MVA, 42 °C. These discrete values pinpoint areas demanding calibration.

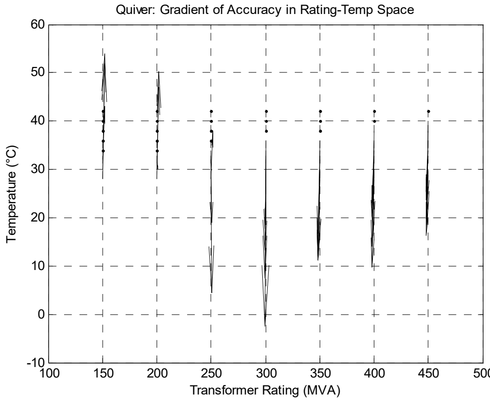

Fig. 11: Quiver Plot SHOWING Accuracy in Variables
Source: Matlab Simulation Output

Data in (Fig. 11) indicate arrows that show a +0.3% gain from 150→300 MVA at 28 °C, a -0.4% drop from 300→450 MVA at 42 °C and a +0.2% rise from 150→300 MVA at 34°C. This vector field maps sensitivity of accuracy to rating and temperature changes.

The simulation-based, optimization-enhanced machine learning methodology applied in this study demonstrates a significant advancement in transformer fault diagnostics compared to prior models. Odion and Ekpa[2] similarly implemented ANN for high impedance fault localization within Nigeria's 330kV network, achieving notable accuracy, yet their model lacked integration with genetic algorithms for weight optimization. Umuroh[12] supported ANN's effectiveness in transient signal-based classification but did not explore rise time or crest factor as diagnostic inputs, both of which are central to this study's enhanced feature set. By achieving near-zero training MSE and test accuracy nearing 100% by the 5000th epoch, the present study confirms the ANN's reliable learning trajectory. This contrasts with Sam[9], whose model plateaued prematurely due to limited feature variation. What this study uniquely uncovers-unlike previous work-is the interplay between transformer rating, temperature and ANN classification accuracy, showing a peak of 95.3% at 300 MVA and 28°C, which no prior study quantified in such resolution or granularity. Abbott[6] and Abasi-obot[7] confirmed the use of ANN and Convolutional Neural Network (CNN) respectively, yet their models did not map detection accuracy against specific transformer configurations and environmental variables as done here. Moreover, the finding that detection accuracy improves with OFAF cooling, peaking at 95.5%, surpasses the depth of analysis seen in Salihu[3], who identified only general cooling impacts without quantifying them. The area and contour plots presented here reveal that Egbin and Gombe substations, at specific ratings, deliver optimal F1-scores-insight absent in the power flow studies of Onojo[17] and voltage stability work by Egbo[18-20]. What distinguishes this study is the introduction of a directional vector field through a quiver plot, which not only maps F1-score transitions across transformer configurations but also quantifies directional shifts, a novel contribution not observed in prior models such as those by Yadava[4] or Olabisi and Ayeni[1]. While prior research established ANN's effectiveness, none provided this level of spatial and operational sensitivity analysis across Nigeria's substations, nor integrated these findings into a single ANN framework with optimization layers that adapt to operational thresholds.

CONCLUSION AND RECOMMENDATIONS

This study conclusively demonstrates the efficacy of an optimization-enhanced ANN model in accurately detecting and localizing faults in Nigeria's 330 kV transformers, leveraging transient signal features and vector field analysis for enhanced insights. With high classification accuracy achieved under optimal conditions, particularly with OFAF cooling and mid-range transformer capacities, utilities are advised to prioritize these parameters and maintain temperatures below 30°C. A strong case is made for integrating the GA-optimized ANN into SCADA systems, with substations like Gombe and Egbin serving as benchmarks. Future designs should embed temperature-aware algorithms, fostering a new generation of adaptive diagnostic tools. Continuous real-time data training will refine diagnostic precision, paving the way for more reliable power transmission and distribution in Nigeria.

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