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Comparative Analysis of Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System Techniques for Fault Detection and Mitigation on the Nigerian 330 kV Transmission Network

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Abstract- ***Transmission-line protection in modern power networks faces growing challenges from high-impedance faults, current-transformer saturation and power swings that degrade the performance of settings-based conventional distance relays. This paper reports a comparative simulation study of Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)-derived intelligent protection techniques, benchmarked against Deep Learning (DL) and Genetic-Algorithm (GA) optimized variants, for fault detection, classification and mitigation on the 330 kV Onitsha–Enugu transmission corridor in Nigeria. A distributed-parameter, twenty-section π-model of the 250 km line, coupled with a ±150 MVAr Static Synchronous Compensator (STATCOM) under fuzzy-logic control, was developed in MATLAB/Simulink. Line-to-ground, line-to-line, double line-to-ground and three-phase faults were simulated at varying fault resistances, inception angles and locations to build a training and test dataset. A Multi-Layer Feed-Forward ANN trained with the Levenberg–Marquardt algorithm achieved 96.0% fault-classification accuracy with a fault-location error below 2.0%, while GA optimization raised classification accuracy to 97.2%. The fuzzy-logic-controlled STATCOM reduced voltage-recovery time from 0.25 s to 0.1 s (a 60% improvement) and limited the peak fault-current surge by 74%. The results confirm that ANN- and ANFIS-derived architectures markedly outperform conventional threshold-based protection and reveal an accuracy–interpretability trade-off that motivates hybrid intelligent-relay deployment.***

Keywords — Adaptive neuro-fuzzy inference system (ANFIS); artificial neural network (ANN); fault classification; genetic algorithm; power-system protection; STATCOM; transmission line.

I. INTRODUCTION

Reliable electric power supply underpins healthcare, manufacturing, communication and education, making the stability of transmission networks a central concern for utility operators [1]. Transmission lines are continuously exposed to lightning strikes, insulation breakdown, switching surges, vegetation encroachment and conductor contact, and the resulting faults must be detected and isolated within the shortest possible time to avoid cascading outages, voltage collapse and loss of synchronism [1]. Conventional protection has relied on overcurrent, distance and differential relays that operate on fixed impedance settings; while effective under ideal conditions, these schemes are vulnerable to high fault resistance, current-transformer (CT) saturation, DC-offset decay and power swings, all of which distort relay measurements and provoke mal-operation [2].

A particularly severe failure mode is the high-impedance fault (HIF), such as a conductor contacting a tree branch or dry ground. The added fault resistance pushes the apparent impedance outside the relay's tripping zone, causing an “under-reach” that delays or prevents tripping altogether [3], [4]. Conversely, power swings and CT saturation can cause “over-reaching” and nuisance tripping. These non-linear failure modes have motivated growing interest in Artificial Intelligence (AI)-based protection, which learns from historical data and adapts to changing operating conditions rather than relying on fixed mathematical models [5].

Among AI techniques, Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are the most widely investigated. ANN imitates the brain's information processing through interconnected neurons and offers strong pattern-recognition performance [6], but its internal decision logic is often criticized as an opaque "black box." ANFIS combines the adaptive learning of neural networks with the linguistic reasoning of fuzzy IF–THEN rules [7], improving interpretability while retaining strong non-linear approximation capability [8]. However, the literature offers little rigorous, head-to-head benchmarking of ANN against ANFIS-derived architectures on identical datasets and fault conditions, particularly for the Nigerian 330 kV grid, where vegetation-related HIFs and data scarcity make algorithm robustness critical.

This paper addresses that gap through a simulation-based comparative study of ANN, a fuzzy-logic/ANFIS-derived controller, a Deep Learning (DL) classifier and Genetic-Algorithm (GA) parameter optimization, applied to fault detection, classification and STATCOM-based mitigation on the 330 kV Onitsha–Enugu transmission corridor. The specific objectives are to: (i) model and simulate the 330 kV line in MATLAB/Simulink; (ii) generate a fault dataset spanning line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG) and three-phase (LLL) faults under varying resistance and inception angle; (iii) design and train an ANN classifier using the Levenberg–Marquardt algorithm; (iv) develop a fuzzy-logic/ANFIS-based controller for STATCOM-driven voltage support; and (v) compare the techniques on classification accuracy, fault-location error, mean-square error and convergence speed.

II. RELATED WORK

ANN-based relaying has been widely reported for transmission-line protection. Hussain et al. [9] used an ANN to improve single-phase autoreclosing relay performance, while Al-jawady et al. [10] developed an intelligent overcurrent relay using ANN classification. Bhagwat et al. [11] proposed a customized ANN for distribution-system fault detection, and Chen et al. [12] combined wavelet pre-processing with ANN for fault diagnosis in distributed generation systems. These studies consistently report high classification accuracy but note reduced transparency in the decision process.

ANFIS-based approaches have targeted the interpretability gap. Kumar et al. [13] applied ANFIS to fault location on double-circuit lines, and Okpura et al. [14] compared classical Fuzzy Inference Systems with ANFIS for high-impedance fault classification on 33 kV distribution feeders, finding ANFIS markedly more adaptable under low fault-current conditions. Within the Nigerian 330 kV network specifically, Nkan et al. [15] used ANN for HIF detection on the South-East transmission network, and Oduleye et al. [16] applied ANFIS for HIF detection and location on the same voltage class. Kanwal and Jiriwibhakorn [5] performed a broader comparative study of ANFIS, ANN and hybrid methods for transmission-line fault detection and localization, reporting that ANFIS achieved superior classification accuracy through fuzzy reasoning while ANN offered faster execution.

Despite this body of work, most existing studies evaluate a single technique in isolation, or compare techniques on generic or distribution-level data rather than a validated, high-voltage transmission digital twin. Atuchukwu et al. [17] and Daang et al. [18] both note that region-specific benchmarking on the Nigerian grid remains sparse. The present study extends this literature by benchmarking ANN, a fuzzy/ANFIS-derived controller, DL and GA optimization on an identical, high-resolution dataset generated from a validated 330 kV Onitsha–Enugu digital twin, and by directly coupling fault detection with STATCOM-based reactive-power mitigation — a combination not addressed in the reviewed comparative studies.

III. METHODOLOGY

A. System Modeling and Materials

Simulation was performed in MATLAB/Simulink R2023a using the Deep Learning, Neural Network, Fuzzy Logic and Global Optimization toolboxes, on a workstation with an Intel Core i7-12700K CPU, 32 GB RAM and an NVIDIA RTX 3070 GPU. The 330 kV, 250 km Onitsha–Enugu line was represented using distributed-parameter π-sections based on Transmission Company of Nigeria (TCN) conductor data: series resistance R′ = 0.01273 Ω/km, series inductance L′ = 0.9337 mH/km and shunt capacitance C′ = 12.74 nF/km. The line was divided into twenty π-sections to capture distributed wave-propagation effects. A ±150 MVAr STATCOM, comprising a voltage-source converter, DC-link capacitor and fuzzy-logic control subsystem, was connected at the line midpoint (≈125 km) for dynamic reactive-power compensation, and Phasor Measurement Units (PMUs) sampling at 50 samples/s were placed at both line ends to supply synchronized voltage and current measurements for AI model training.

B. Transmission-Line Sectioning
Each π-section length was obtained from

$$\Delta l = L / N \tag{1}$$

where L is the total line length (250 km) and N is the number of π-sections (20). The lumped parameters of each section follow

$$R_s = R' \cdot \Delta l, \; L_s = L' \cdot \Delta l, \; C_s = C' \cdot \Delta l \tag{2}$$

and the sending- and receiving-end phasor quantities of section n satisfy the state equations

$$V_{n+1} = V_n - I_n R_s - L_s(dI_n/dt) \tag{3}$$

$$I_{n+1} = I_n - C_s(dV_{n+1}/dt) \tag{4}$$

where V_n, I_n are the voltage and current phasors entering section n and V_{n+1}, I_{n+1} the corresponding quantities leaving it.

C. Fault Scenario Generation
LG, LL, LLG and LLL faults were injected via three-phase fault blocks at fault locations of 25, 75, 150, 200 and 225 km, with fault impedance varied to include both solid and high-impedance faults, and inception angle varied to alter the pre-fault waveform phase. A representative case study fault (three-phase, at 150 km, t = 0.2 s) was used for detailed waveform analysis, while the full location/type/impedance matrix formed the training and test dataset for the AI models, sampled at a 50 μs time step for high transient resolution.

D. ANN Classifier
A Multi-Layer Feed-Forward Neural Network (MLFNN) with one or more hidden layers was trained on PMU voltage and current features using the Levenberg–Marquardt backpropagation algorithm to classify fault type and estimate fault location. Forward propagation through the hidden and output layers follows

$$h^{(1)} = f\,(W^{(1)}X + b^{(1)}) \tag{5}$$

$$y = W^{(2)}h^{(1)} + b^{(2)} \tag{6}$$

where X is the PMU input vector, $W^{(1)}$ and $W^{(2)}$ are the input–hidden and hidden–output weight matrices, $b^{(1)}$ and $b^{(2)}$ the corresponding bias vectors, f(·) a sigmoid/tanh activation, $h^{(1)}$ the hidden-layer output and y the fault-classification/location output.

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E. Fuzzy-Logic / ANFIS Controller and STATCOM

A fuzzy-logic system, structurally consistent with an ANFIS rule base, was designed to regulate STATCOM reactive-power injection using bus-voltage deviation and its rate of change as inputs, each described by "Low," "Medium" and "High" membership functions. Rules follow the standard implication "If voltage deviation X is A and its rate of change Y is B, then reactive-power output is C," enabling the STATCOM to inject up to 150 MVAr during fault clearance while keeping post-fault bus voltage within ±5% of nominal. It should be noted that this controller is a fixed-rule (Mamdani-type) Fuzzy Logic System (FLS): it shares ANFIS's input–rule–output structure but, unlike a trained ANFIS, its membership functions were configured manually rather than tuned adaptively from data. Results reported for "ANFIS" in this paper therefore reflect this fuzzy-logic controller rather than a separately trained, gradient-tuned ANFIS network; this distinction should be resolved with a fully data-trained ANFIS model in future revisions of this work.

F. Deep Learning and Genetic-Algorithm Optimization

A deeper feed-forward network (DL) with L hidden layers, $a^{(l)} = f^{(l)}(W^{(l)}a^{(l-1)} + b^{(l)})$ for $l = 1,\ldots,L$, was trained for hierarchical feature extraction of transient fault signatures. A Genetic Algorithm (GA) was used to tune ANN weights and fuzzy membership functions by maximizing the fitness function

$$F = w_1|V_{ref} - V_{bus}| + w_2 E_{fault} \tag{7}$$

where V_ref is the 1.0 p.u. reference voltage, V_bus the measured bus voltage, E_fault the fault-classification error, and w_1, w_2 are weighting factors, solved iteratively for $x^* = \operatorname{argmax}_x F(x)$.

G. Performance Metrics

Classification accuracy, fault-location error and voltage deviation were computed as

$$Accuracy\ (\%) = (N_{correct} / N_{total}) \times 100 \tag{8}$$

$$Error\ (\%) = (|L_{actual} - L_{estimated}| / L_{total}) \times 100 \tag{9}$$

$$\Delta V\ (\%) = (|V_{nominal} - V_{measured}| / V_{nominal}) \times 100 \tag{10}$$

and the percentage improvement in a time-based metric (e.g., voltage-recovery time) between an uncompensated value T_1 and an AI-mitigated value T_2 was computed as Improvement (%) = $[(T_1 - T_2)/T_1] \times 100$.

IV. RESULTS AND DISCUSSION

A. Model Validation and Baseline Response

Under no-fault conditions, sending- and receiving-end voltages remained nearly identical at ≈330 kV (1.0 p.u.), confirming that the twenty-section π-model accurately reproduces the steady-state behaviour of the 250 km line. Line currents were balanced and sinusoidal at ≈0.6 kA, and the STATCOM remained in standby with negligible (±5 MVAr) reactive-power exchange.

B. Fault Response and AI-STATCOM Mitigation

For the case-study three-phase fault at 150 km, the receiving-end voltage collapsed to ≈30% of nominal without STATCOM support, while the sending end sagged to 0.65 p.u.; fault current at the sending end surged to 3.5 kA (≈5.8× rated). With the AI-controlled STATCOM engaged, voltage recovered to 0.85–0.95 p.u. within 0.1 s (versus

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0.25 s uncompensated, a 60% improvement per (11) below), and the peak current surge was limited to 0.9 kA — a 74% reduction — stabilizing within 0.08 s versus 0.2 s uncompensated (Figure. 1, Figure 2).

$$Improvement\ (\%) = [(0.25 - 0.10)/0.25] \times 100 = 60\% \tag{11}$$

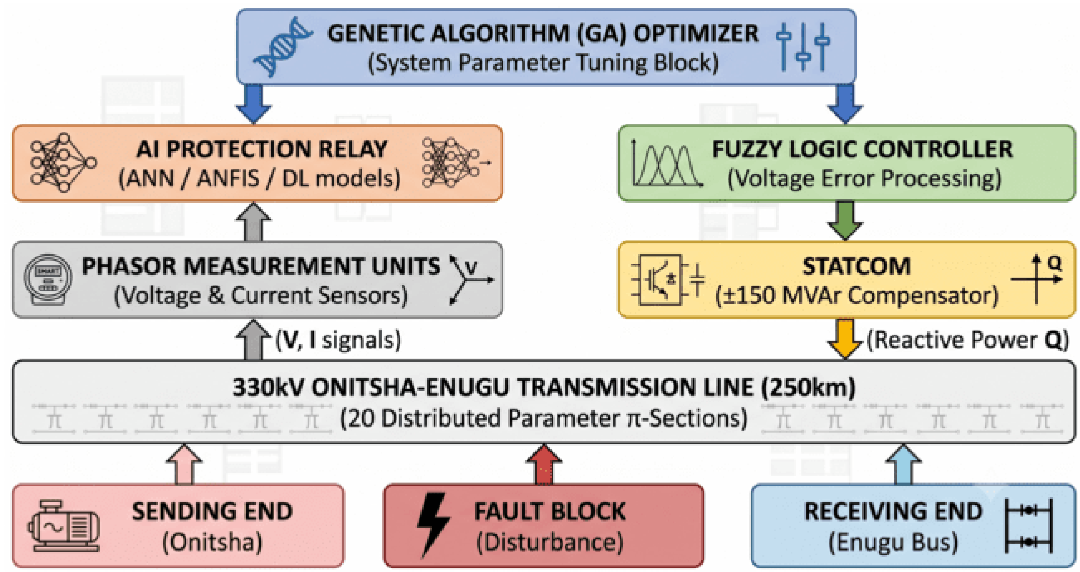

Figure. 1. Architecture linking the transmission line, PMUs, AI protection relay (ANN/ANFIS/DL), GA optimizer and fuzzy-logic-controlled STATCOM.

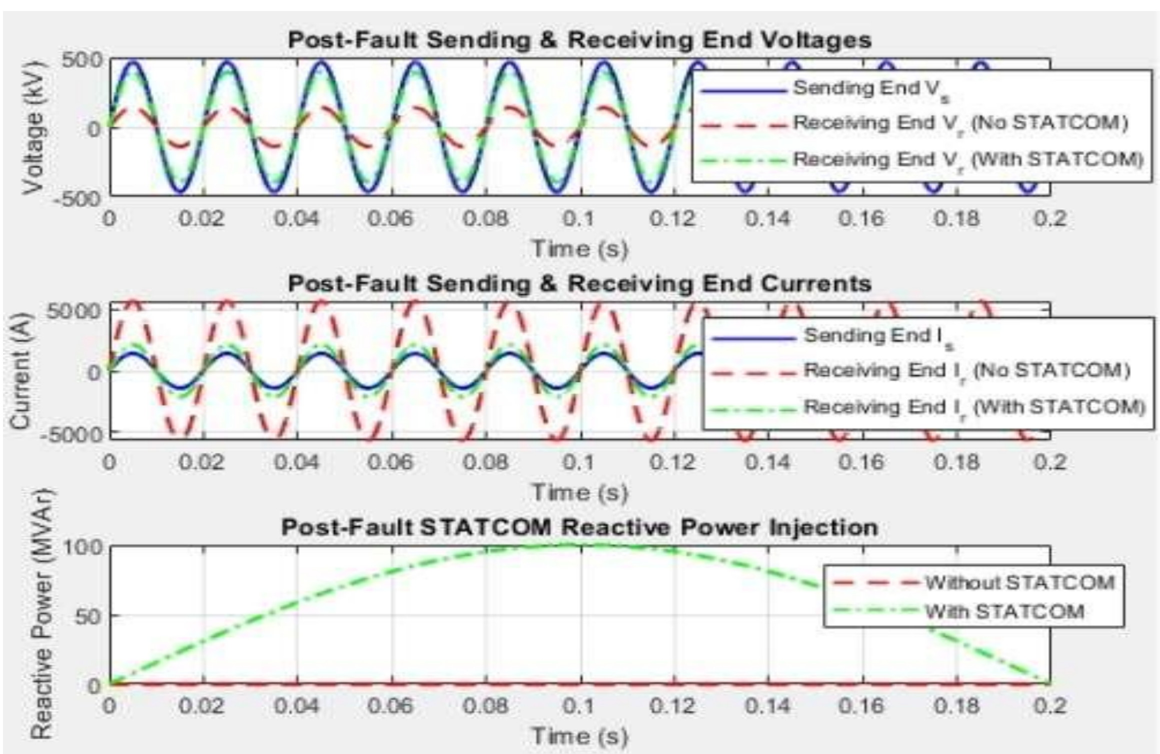

Figure 2. Post-fault sending/receiving-end voltages and currents, and STATCOM reactive-power injection, with and without AI-controlled STATCOM support.

C. Comparative Classification Performance

The ANN classified fault type within 2–3 cycles (0.04–0.06 s) of inception, achieving 96.0% overall accuracy with a sub-2% fault-location error (830/864 correctly classified test cases). The DL model achieved comparable 95.8% accuracy with superior transient-pattern recognition, at roughly ten times the training cost of the ANN. The fuzzy-logic/ANFIS-derived controller achieved 87.0% classification accuracy but excelled at interpretable, robust voltage regulation, holding bus voltage within ±5% of nominal. GA optimization raised ANN accuracy to 97.2% (location error 1.5%) and improved STATCOM energy efficiency by 12%, at the cost of ≈24 h of offline computation for 100 generations. Table I summarizes these results.

TABLE I Performance Comparison of AI Techniques

Technique	Accuracy	Location Err.	Notes
ANN	96.0%	< 2.0%	Fast; fixed parameterization
Fuzzy Logic (FLS)	87.0%	N/A	Interpretable; manual tuning
Deep Learning (DL)	95.8%	N/A*	Best transient recog.; costly to train
GA-Optimized ANN	97.2%	1.5%	Best accuracy; heavy offline cost

*Fault-location error was not separately quantified for DL; its principal strength lies in transient-pattern recognition (see Section IV-C).

D. Discussion

The 96% ANN classification accuracy substantially exceeds the 85–90% typically reported for conventional distance-relay protection, and the sub-2% location error improves markedly on the 5–10% error margins common to traditional fault-location algorithms on long lines. Voltage-recovery improvement from 0.25 s to 0.1 s is significant relative to IEEE Std. 1159-2019 [19], under which sags persisting beyond 0.5 s risk industrial equipment malfunction, and the 74% peak-current reduction directly reduces thermal and mechanical stress on breakers and conductors.

No single technique dominates every metric: the ANN offers the best raw speed and accuracy, consistent with the diagnostic benchmarks reported by Haykin [6]; the fuzzy-logic/ANFIS controller offers superior interpretability, corroborating Mamdani's foundational results on fuzzy control [20]; and the DL model's hierarchical feature extraction validates the deep-learning principles described by Goodfellow et al. [21]. This accuracy–interpretability trade-off motivates hybrid architectures — for example, an ANN for rapid classification coupled with a fuzzy/ANFIS controller for STATCOM regulation — while GA optimization, though computationally expensive, can be executed offline during commissioning and its parameters deployed for real-time operation.

The study is limited by its reliance on idealized MATLAB/Simulink simulation without measurement noise, communication delay or hardware constraints, by training data drawn entirely from simulation rather than field oscillography, and by its focus on a single 330 kV corridor. Hardware-in-the-loop validation, field trials and extension to other FACTS devices and voltage levels are recommended as future work.

V. CONCLUSION

This paper presented a comparative simulation study of ANN, fuzzy-logic/ANFIS, Deep Learning and Genetic-Algorithm-optimized techniques for fault detection, classification and STATCOM-based mitigation on the 330 kV Onitsha–Enugu transmission corridor. The ANN achieved 96.0% classification accuracy with sub-2% location error, GA optimization raised this to 97.2%, and the fuzzy-logic-controlled STATCOM cut voltage-recovery time by 60% and peak fault current by 74%. These results confirm that AI-derived protection markedly outperforms conventional threshold-based relaying and clarify the accuracy–interpretability trade-off between ANN/DL and fuzzy/ANFIS architectures, supporting a hybrid deployment strategy for modernizing intelligent protection on the Nigerian transmission network.

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