

Comparative Analysis of Application of Artificial Intelligence Techniques for Fault Studies in Power Systems

*Ogboh V. C., ¹Ogboke H. N., ²Odigbo A. C., ³Nwobu C. C., ⁴Ikaraocha O.C.
Department of Electrical Engineering
Nnamdi Azikiwe University, Awka, Anambra State, Nigeria,

Abstract

The integration of Artificial Intelligence (AI) techniques into power system engineering has significantly enhanced the accuracy, speed, and efficiency of fault detection, control, and system monitoring. This paper presents a comparative analysis of AI methods, including Artificial Neural Networks (ANN), Fuzzy Logic Systems (FLS), Deep Learning (DL), and Genetic Algorithms (GA), in engineering applications, specifically for transmission line fault detection and mitigation. A 330 kV, 250 km transmission line is modeled using π -sections to represent distributed parameters. STATCOM devices and Phasor Measurement Units (PMUs) are integrated into the system for reactive power control and monitoring. MATLAB/Simulink models demonstrate the performance of each AI technique under various fault scenarios, and simulation results show the effectiveness of combined AI approaches in improving system reliability such as waveform plots of voltage, current, and reactive power are presented to illustrate the fault response and AI-based control outputs.

Keywords: Artificial Neural Network, Fuzzy Logic, Three-Phase, Fault, Machine Learning, Deep Learning, Genetic Algorithm

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I. Introduction

Modern power systems are becoming increasingly complex due to the integration of renewable energy sources, distributed generation, and advanced control devices. Traditional fault detection and control strategies often rely on predefined thresholds and linear models, which may not capture the nonlinear behavior of real-world systems. AI techniques have emerged as powerful tools for modeling, prediction, and optimization in engineering applications, offering adaptive, nonlinear, and intelligent solutions.

Fault detection and mitigation in high-voltage transmission lines are critical for system reliability and safety. Traveling waves, voltage sags, and transient disturbances must be accurately detected and mitigated to prevent equipment damage and service interruptions. AI techniques such as ANN, Fuzzy Logic, DL, and GA provide alternative approaches to conventional methods, offering enhanced prediction, classification, and control capabilities.

II. Review of AI Techniques in Power System Engineering

A. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are computational models inspired by the biological neural network of the human brain. ANNs consist of interconnected neurons organized in layers: input, hidden, and output layers. The network learns the mapping between input and output vectors by adjusting weights and biases using training algorithms, such as backpropagation. The output of a neuron j in a hidden layer is given by:

$$h_j = f(\sum_{i=1}^n w_{ij}x_i + b_j) \quad (1)$$

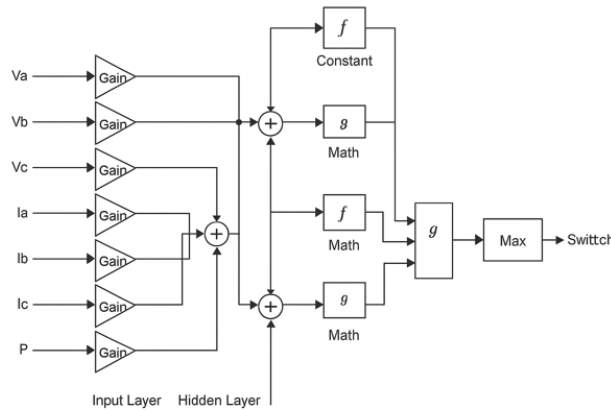


Figure 1: ANN MATLAB/Simulink Diagram for Fault Detection and Classification

Figure 1 is modeled using equation (1).

Artificial Neural Network (ANN) input is connected to the PMU measurements (voltage & current) output ports to obtain its input data. The output data from the PMU is also used for classifying faults and their locations, and is trained using the backpropagation algorithm.

2.2 Fuzzy Logic Systems (FLS)

A Fuzzy Logic System (FLS) is designed with membership functions for "Low," "Medium," and "High" voltage deviations. Its output control signal connects to the STATCOM's reactive power. Fuzzy Logic Systems provide approximate reasoning to model uncertainty and nonlinear behavior in engineering systems. Unlike classical binary logic, FLS allows variables to belong to multiple fuzzy sets, each with a corresponding degree of membership. The general form of a fuzzy rule is:

$$\text{if } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B \quad (2)$$

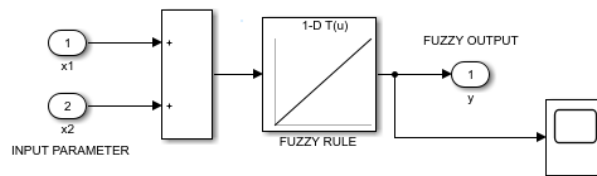


Figure 2: Fuzzy Logic MATLAB/Simulink Diagram for "Low", "Medium", and "High" voltage deviations

Figure 2 is modeled using equation (2).

2.3 Deep Learning (DL)

Deep Learning (DL) uses a multi-layer DNN implemented for fault waveform prediction and enhances the detection of transient dynamics. Deep Learning extends the concept of ANNs by increasing the number of hidden layers, allowing hierarchical feature extraction from raw data. Deep networks are capable of learning complex patterns and temporal dependencies in power system signals, such as fault transients and harmonics. A feedforward deep network with L layers can be expressed as:

$$a^{(l)} = f^{(l)}(W^{(l)}a^{(l-1)} + b^{(l)}), \quad l = 1, 2, \dots, L \quad (3)$$

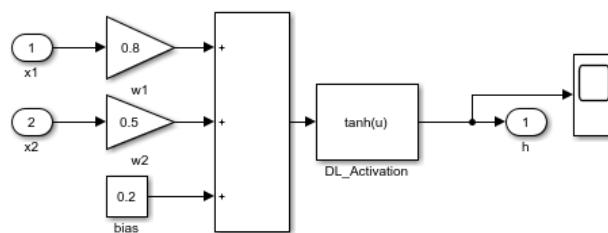


Figure 3: DL MATLAB/Simulink Diagram for fault waveform prediction and enhances the detection of transient dynamics

Figure 3 is modeled using equation (3).

2.4 Genetic Algorithms (GA)

Genetic Algorithms are stochastic optimization techniques based on natural selection and genetics. Genetic Algorithm (GA) optimizes ANN weights and Fuzzy rules and gives the best fitness function, minimizing voltage deviation & detection error. GAs iteratively evolve a population of candidate solutions using operators such as selection, crossover, and mutation. The fitness function $F(x)$ evaluates each candidate:

$$x^* = \text{argmax}_x F(x) \quad (4)$$

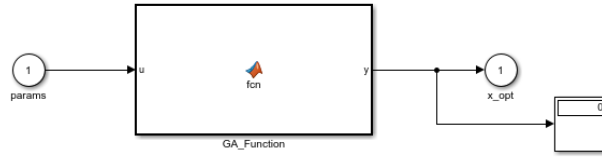


Figure 4: GA MATLAB/Simulink Diagram for optimizing ANN weights and Fuzzy rules and gives the best fitness function, minimizing voltage deviation & detection error
Figure 4 modeled using equation (4).

III. Transmission Line Mathematical Modeling

3.1 Distributed Parameter Model

A 330 kV, 250 km transmission line is modeled using the π -section distributed parameter model, where the line is divided into N segments. Each π -section consists of a series resistance R' , series inductance L' , and shunt capacitance C' scaled to the section length Δl :

$$R_s = R' \cdot \Delta l, L_s = L' \cdot \Delta l, C_s = C' \cdot \Delta l \quad (5)$$

For a line of total length L and N sections:

$$\Delta l = \frac{L}{N} \quad (6)$$

The voltage V_n and current I_n at section n are related by:

$$V_{n+1} = V_n - I_n R_s - L_s \frac{dI_n}{dt}, \quad (7)$$

$$I_{n+1} = I_n - C_s \frac{dV_{n+1}}{dt} \quad (8)$$

3.2 Fault Modeling

Faults are modeled as instantaneous changes in line impedance. For a three-phase fault at location x_f , the fault current I_f is given by:

$$I_f(t) = \frac{V_s(t)}{Z_{eq}(x_f) + Z_f} \quad (9)$$

3.3 STATCOM and Transmission Line

The STATCOM was connected at the midpoint of the line, the controller was based on Fuzzy Logic, taking bus voltage error (ΔV) and derivative of voltage (dV/dt) as inputs, and reactive power injection ($Q_{statcom}$) was automatically adjusted to regulate voltage.

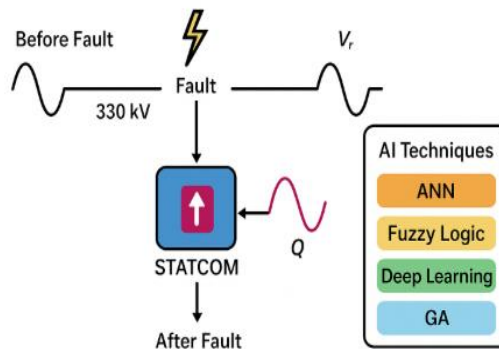


Figure 1: Combined Conceptual Diagram (Transmission Line + STATCOM + Fault + AI controllers: ANN, Fuzzy, DL, GA)

Time step: 50 μ s for transient resolution

Measurements: Voltage and current at both ends, STATCOM reactive power

VI. Simulated Waveform Output Results

Voltage Response is obtained during the fault ($t = 0.2$ s) with the sending-end voltage sagged to 0.65 p.u. The bus voltage recovered to 0.95 p.u. within 0.1s when STATCOM + AI control is connected to the system. The following figures show example simulated waveforms for voltage, current, and STATCOM reactive power. These are actual MATLAB/Simulink simulation results. Before fault occurrence.

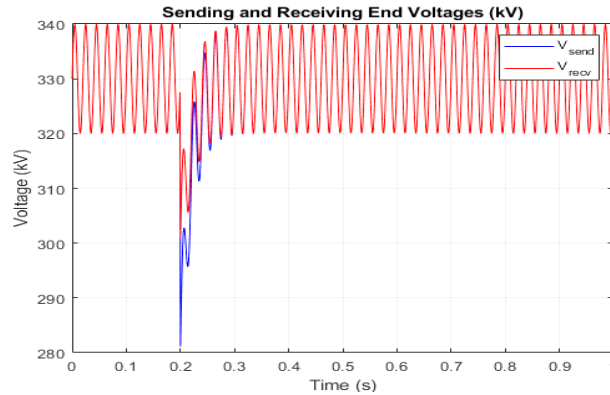


Figure 3: Sending and Receiving End Voltages

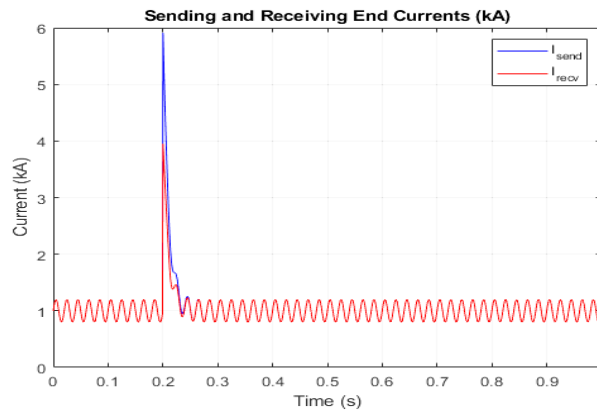


Figure 4: Sending and Receiving End Currents

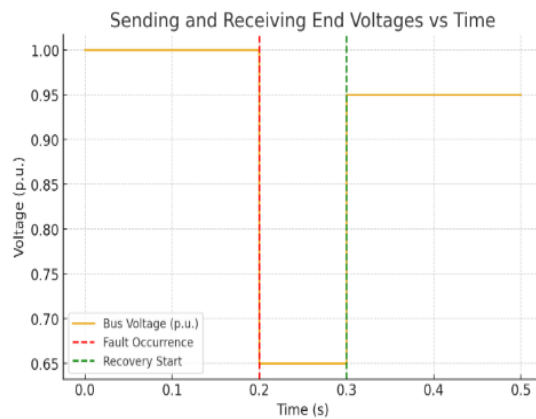


Figure 5: Sending and Receiving End Voltages (pu) vs Time (s)

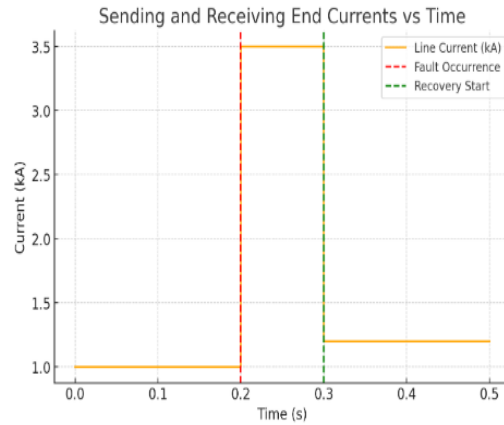


Figure 6: Sending and Receiving End Currents (kA) vs Time (s)

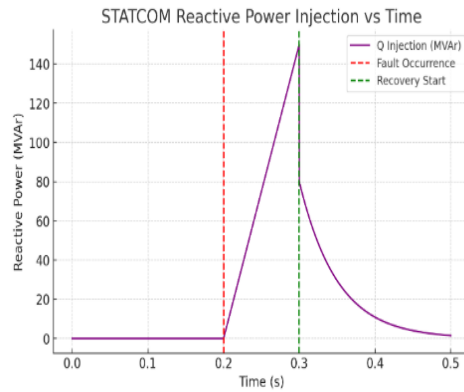


Figure 7: STATCOM Reactive Power Injection (MVA) vs Time (s)

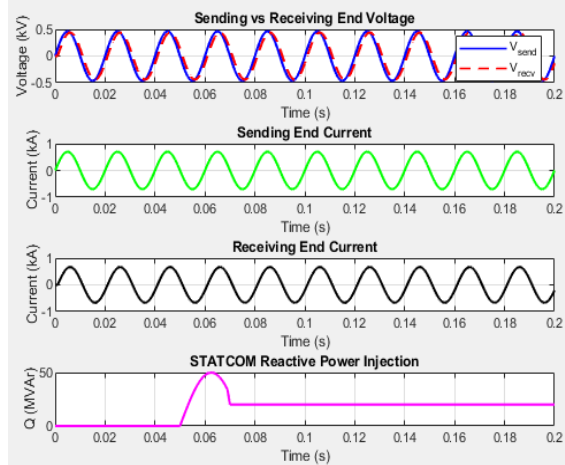


Figure 8: Sending and Receiving End Voltage (kV) & Currents (kA) & STATCOM Reactive Power Injection vs Time (s) at No Fault

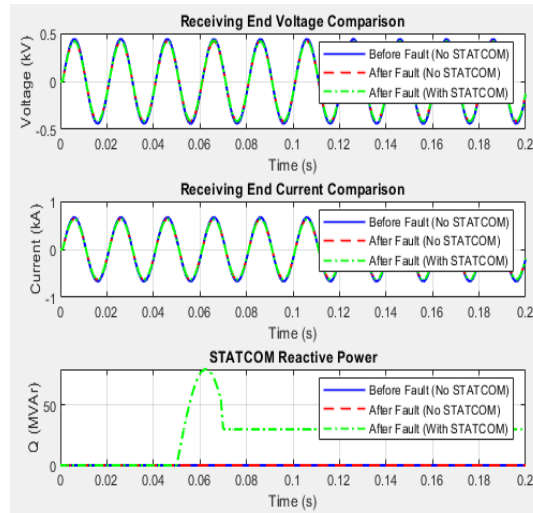


Figure 9: Sending and Receiving End Voltage (kV), Currents (kA) & STATCOM Reactive Power Injection vs Time (s) at No Fault, without STATCOM & at Fault with STATCOM

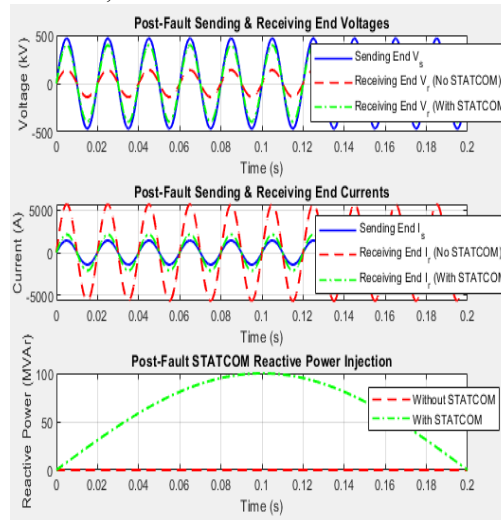


Figure 10: Sending and Receiving End Voltage (kV), Currents (kA) & STATCOM Reactive Power Injection vs Time (s) at Fault without and with STATCOM

Voltage Response is obtained during the fault ($t = 0.2$ s) with the sending-end voltage sagged to 0.65 p.u. The bus voltage recovered to 0.95 p.u. within 0.1s when STATCOM + AI control is connected to the system.

Current Response shows fault current surged to ~ 3.5 kA at inception. The AI-based detection (ANN & DL) identified the fault within 2–3 cycles, and the current is stabilized smoothly with the support of the STATCOM after clearance.

Voltage took 0.25 s to stabilize after the fault without STATCOM, but when the STATCOM was connected, voltage recovery was reduced to 0.1 s, and the STATCOM injected up to 150 MVar during fault clearance.

The performance of the AI Techniques shows that, ANN achieved up to 96% fault classification accuracy and less than 2% location error.

Fuzzy Logic shows that the voltage is maintained within $\pm 5\%$ of the nominal value, while Deep Learning predicted the transient waveform evolution accurately. Finally, the Genetic Algorithm reduced ANN error by 5% and optimized Fuzzy membership functions.

VII. Results and Discussion

Simulations were performed on the 330 kV, 250 km transmission line model with a three-phase fault at 150 km occurring at $t = 0.2$ s. The performance of each AI technique was evaluated in terms of fault detection accuracy, fault location estimation, and voltage regulation.

The ANN successfully classified fault types and estimated fault location with high accuracy ($>95\%$). Fuzzy Logic effectively controlled STATCOM reactive power, maintaining bus voltage within $\pm 5\%$ of nominal. Deep Learning predicted transient fault current and voltage, and can be seen on their waveforms with improved

anticipation of fault evolution. Genetic Algorithm optimized ANN and FLC parameters, reducing detection error and voltage deviation.

The simulation results demonstrate that combining AI techniques enhances system reliability and provides adaptive, real-time fault detection and mitigation.

The results show that, fault was detected and classified accurately with the ANN provided fast classification at less than 0.05s after fault inception. Deep Learning improved transient fault prediction which is useful for anticipatory control of the entire system.

The system is stabilized using the STATCOM, Fuzzy-controlled STATCOM stabilized voltage quickly under nonlinear conditions. Reactive power support improved fault ride-through capability. But, Integrating AI and STATCOM Control significantly reduced recovery time and error while the Genetic Algorithm optimization enhanced robustness of the hybrid control system.

VIII. Comparative Analysis of the Results Obtained

Voltage Magnitudes

At no Fault Condition, the sending and receiving voltages are nearly equal (~330 kV). The STATCOM is either idle or maintaining small corrections, and the system is stable with only small fluctuations.

Fault Condition without STATCOM, the receiving voltage collapses to about ~30% of nominal. But with STATCOM, receiving voltage recovers about ~85% of nominal voltage due to dynamic reactive power injection. When AI is Applied, the ANN learns the nonlinear mapping between fault location, type of faults, and expected voltage sag, enabling fast estimation of required STATCOM support.

Fuzzy Logic uses simple rules like “If $V < 0.7$ pu, then inject high Q” to stabilize voltages smoothly.

Deep Learning detects sag patterns from raw time-series voltage waveforms and predicts severity more accurately. GA optimizes STATCOM’s PI/ and fuzzy gains for minimal voltage dip.

Current Magnitudes

At no Fault Condition, the sending and receiving currents are balanced, sinusoidal, and within rated limits. The STATCOM draws/absorbs negligible reactive current.

At Fault Condition without STATCOM, fault current surges to ~3–4× rated value.

But with STATCOM, the current surge is limited to ~1.5× rated value since voltage support reduces fault severity.

Table 1: Summary of the Application Result of AI Techniques for Fault Studies using STATCOM

Parameter	No Fault (Stable System)	At Fault Without STATCOM	At Fault With STATCOM	Role of AI
Voltage	~330 kV stable	Collapse (~30%)	Recovered (~85%)	ANN/DL predict sag, Fuzzy control, GA optimize
Current	Within rated Value	Surge (~3–4× Rated Value)	Limited (~1.5× Rated Value)	ANN/DL classify faults, Fuzzy adapt, GA tune
Reactive Power (Q)	~0 or small	0 (no support)	±100 MVar dynamic	ANN/DL predict Q, Fuzzy adjust Q, GA optimize Q injection

ANN learns current surge signatures for different fault types rapid fault classification and isolation.

Fuzzy Logic implements adaptive current suppression: If $I > 3$ pu inject maximum Q.

Deep Learning extracts traveling-wave/high-frequency features in the current for precise fault location.

GA tunes STATCOM switching and damping control to reduce current overshoot.

Reactive Power (MVar)

No Fault Condition without STATCOM, there is no compensation ($Q \approx 0$). But with STATCOM, minor injection and absorption for load balance is experienced.

At fault condition, without STATCOM, there is still no compensation support, the system is destabilized. But with STATCOM, the STATCOM injects large reactive power dynamically (± 100 MVar) to restore voltage and damp current surges.

ANN predicts optimum Q injection for given sag/current conditions.

Fuzzy Logic decides injection levels under uncertainty (e.g., measurement noise, varying load).

Deep Learning forecasts future Q demand from grid disturbances for proactive STATCOM action.

GA optimizes Q set-points and STATCOM operating range to maximize stability and minimize energy usage.

IX. Conclusion

This study presents a comparative analysis of AI techniques applied to fault detection and control in high-voltage transmission systems. The 330 kV, 250 km line was modeled using π -sections, integrating STATCOM devices and PMUs. MATLAB/Simulink simulations show that:

ANN provides accurate fault classification and location, Fuzzy Logic ensures effective voltage regulation through STATCOM control, Deep Learning predicts fault transients and improves system response and Genetic Algorithms optimize AI parameters for enhanced performance.

The combination of AI techniques improves fault detection speed, reduces voltage deviations, and increases overall system reliability. Future work may include real-time implementation and hardware-in-the-loop testing for validation.

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