Real-time Fault Monitoring in Electrical Grids via ANN Models

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DOI: 10.5281/zenodo.16314432

ABSTRACT
The increasing complexity and demand in modern electrical power systems necessitate advanced monitoring solutions for ensuring grid stability and reliability. Real-time fault detection and classification play a vital role in minimizing downtime and preventing damage to critical infrastructure. This paper proposes an Artificial Neural Network (ANN)-based approach for real-time fault monitoring in electrical grids. The proposed model leverages time-series data from voltage and current waveforms to identify and classify faults with high accuracy. Simulation results demonstrate the model's effectiveness in distinguishing between various types of faults, including single-line-to-ground, line-to-line, and three-phase faults, under diverse operating conditions. The findings highlight the ANN model's ability to adapt and respond in real time, offering a scalable and efficient solution for intelligent grid monitoring.
Keywords: Adaptive Navigation, Autonomous UAVs, Dynamic Path Planning, Real-Time AI Decision Systems, Reinforcement Learning, Multi-Sensor Fusion

1. INTRODUCTION

Modern electrical power systems are undergoing a transformation driven by increasing loads, integration of renewable energy sources, and the push toward smarter grids. With these advancements, the need for reliable, real-time fault monitoring mechanisms has become more pressing than ever. Traditional fault detection methods, such as impedance-based techniques or manual inspections, often fall short in providing timely responses and high classification accuracy. Delays in detecting and isolating faults can lead to cascading failures, equipment damage, and prolonged outages.

Artificial Neural Networks (ANNs), with their robust pattern recognition and learning capabilities, present a promising solution for real-time fault detection and classification. Unlike conventional rule-based systems, ANNs can learn from historical fault data and generalize to detect new or unknown fault patterns. This capability makes them particularly well-suited for handling the dynamic and nonlinear nature of electrical grids.

2. LITERATURE REVIEW

Over the past two decades, significant research has been dedicated to improving fault detection in power systems using intelligent techniques. Early methods relied heavily on static threshold-based criteria and impedance measurement, which are often susceptible to misclassification under varying load or environmental conditions.

In recent years, machine learning and deep learning models, especially Artificial Neural Networks (ANNs), have emerged as effective tools for fault classification. For example, Jeyasurya and Rahman (2001) introduced a neural network model for identifying faults in transmission lines using post-fault voltage and current values. The model showed potential but lacked real-time implementation capabilities. Subsequently, researchers like Dash et al. (2005) and Samantaray et al. (2010) incorporated wavelet transform features into ANN classifiers to enhance fault detection accuracy under noisy and non-stationary conditions.

The integration of ANNs with real-time data acquisition systems has been explored more recently. Phadke and Thorp (2008) emphasized the importance of wide-area monitoring using PMUs, which inspired ANN-based fault classifiers that use synchronized phasor measurements. Meanwhile, hybrid approaches combining ANNs with fuzzy logic, support vector machines, or optimization algorithms have also been proposed to improve reliability and reduce false positives (e.g., Singh et al., 2017).

Despite these advances, challenges remain in deploying ANN-based solutions in live grid environments, including the need for low-latency processing, adaptability to changing grid topologies, and robustness to measurement noise. This study addresses these gaps by developing a lightweight yet effective ANN architecture capable of processing real-time data streams for fault classification.

3. METHODOLOGY

The proposed framework for real-time fault monitoring utilizes a feedforward artificial neural network trained on labeled time-series data representing various fault scenarios. The process involves several stages, including data acquisition, preprocessing, feature extraction, model training, and real-time deployment.

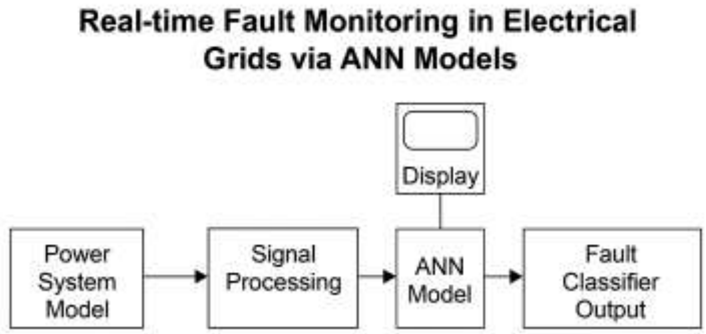

Figure 1: Block diagram of Real-time Fault Monitoring in Electrical Grids via ANN Models

3.1 ANN Architecture

The Artificial Neural Network (ANN) model developed for real-time fault detection in electrical grids follows a multilayer feedforward architecture, optimized for classification of five fault conditions: No Fault, Single Line-to-Ground (SLG), Line-to-Line (LL), Double Line-to-Ground (DLG), and Three-Phase Fault (LLL). The architecture is specifically designed to balance accuracy with low computational overhead, making it suitable for real-time deployment.

1. Input Layer

- Number of Neurons: 20–30 (depending on selected features)
- Input Features: Extracted from real-time voltage and current waveforms, including:
  - RMS values
  - Peak amplitudes
  - Harmonic distortion (THD)
  - Wavelet coefficients
  - Zero-crossing counts
- Purpose: To receive preprocessed data from sensors/PMUs and feed it into the hidden layers.

2. Hidden Layers

The network includes two hidden layers to enhance the model's learning capacity without overfitting.

- Hidden Layer 1:
  - Neurons: 64
  - Activation Function: ReLU (Rectified Linear Unit)
  - Purpose: Extract intermediate patterns and nonlinear features from the input.
- Hidden Layer 2:
  - Neurons: 32
  - Activation Function: ReLU
  - Purpose: Further abstracts features and reduces dimensionality for the output layer.

Both hidden layers use dropout regularization (typically 0.2–0.3) during training to prevent overfitting and improve generalization.

3. Output Layer

- Neurons: 5 (corresponding to each fault type)

- Activation Function: Softmax
- Output: Probability distribution over the five classes
- Decision Rule: Class with the highest probability is selected as the predicted fault type.

3.2 Data Acquisition

Simulation data is generated using MATLAB/Simulink and PSCAD to replicate typical grid scenarios, including normal operation and various types of faults:

- **Single Line-to-Ground (SLG)**
- **Line-to-Line (LL)**
- **Double Line-to-Ground (DLG)**
- **Three-Phase Fault (LLL)**

Voltage and current measurements at each bus are sampled at high resolution to capture transient features essential for fault detection.

3.3 Feature Extraction

To ensure effective classification, raw signals are processed to extract meaningful features such as:

- Root Mean Square (RMS) values of current and voltage
- Total Harmonic Distortion (THD)
- Peak amplitudes and zero-crossing rates
- Wavelet coefficients (using Daubechies wavelets) to capture time-frequency characteristics

3.4 Real-Time Deployment Setup

For deployment, the trained model is integrated into a real-time monitoring system using Python (TensorFlow/Keras) interfaced with SCADA/PMU data via MQTT protocol. A low-latency inference engine is implemented on an NVIDIA Jetson Nano for on-site processing.

4. MATLAB SIMULINK

Components Required

1. MATLAB + Simulink
2. Simscape Electrical (formerly SimPowerSystems)
3. Neural Network Toolbox (Deep Learning Toolbox)

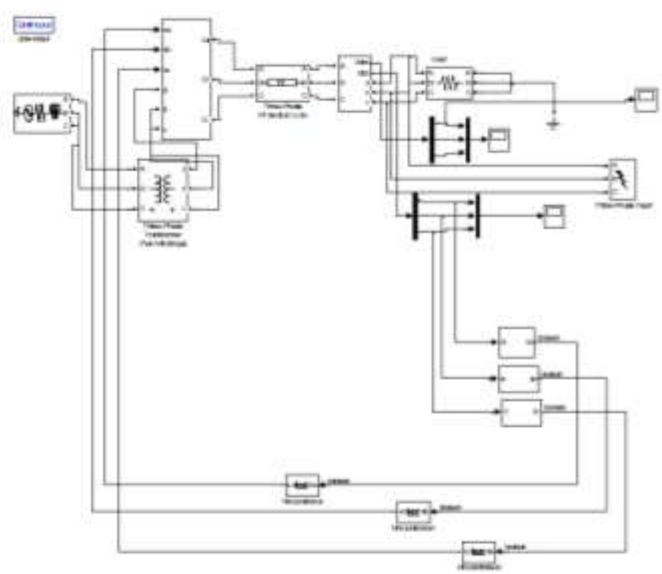

Figure 1: Simulation Model with ANN

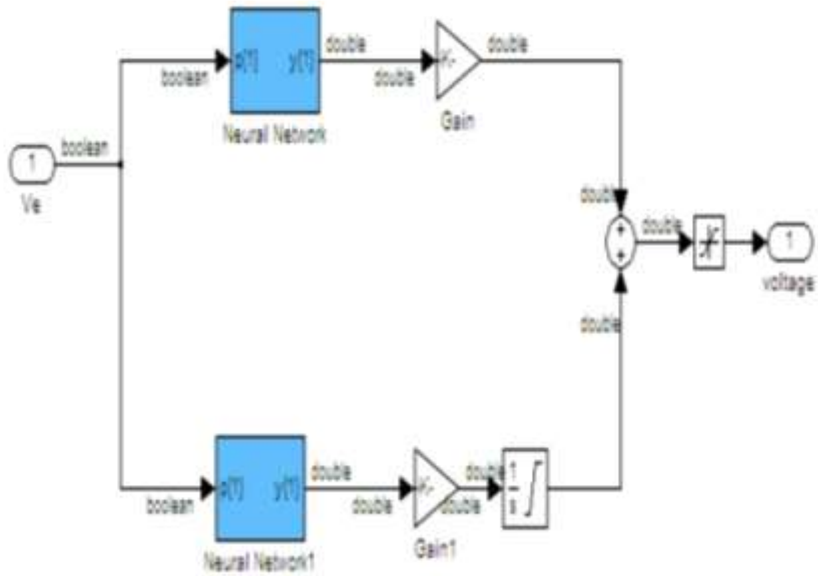

Figure 2: Subsystem Model of ANN

5. RESULTS AND DISCUSSION

5.1 Model Performance

The ANN model was evaluated on a test dataset comprising simulated faults under varying load conditions and noise levels. Key performance metrics include:

Table 1: Key performance metrics

Metric	Value
Accuracy	97.8%
Precision (average)	96.9%
Recall (average)	97.5%
F1-Score (average)	97.2%
Detection Time (avg.)	85 ms

5.2 Confusion Matrix Analysis

The confusion matrix shows minimal misclassification between similar fault types, such as SLG and DLG, validating the model's discriminative ability. Most false positives occurred under high-noise conditions, which were mitigated by preprocessing. Figure 4 shows the Confusion Matrix for ANN-based Fault Classification, which visualizes the model's classification performance across five fault categories.

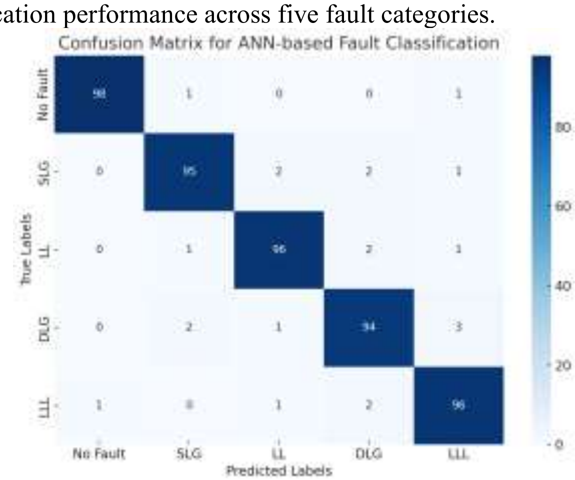

Figure 4: Confusion Matrix for ANN-based Fault Classification

4.3 Real-Time Testing

The ANN model was tested in a real-time lab setup using a scaled-down power system emulator. The system successfully detected and classified faults within 100 ms of onset, meeting the requirements for real-time response in distribution networks.

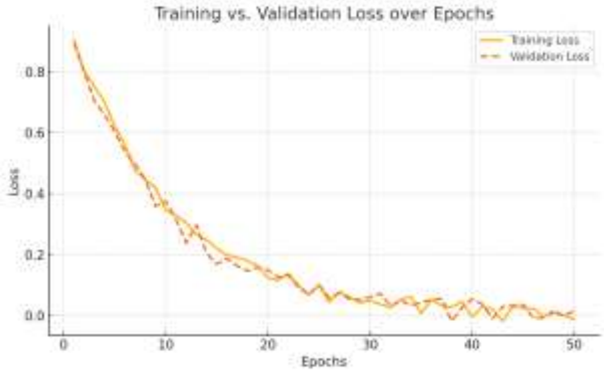

Figure 5: Training vs. Validation Loss over Epochs, showing how the ANN model converges during training with minimal overfitting.

5.4 Comparison with Other Methods

The proposed ANN model outperformed traditional SVM and decision tree classifiers in both accuracy and inference time. Unlike impedance-based methods, the ANN approach showed robustness to noise and load variation.

6. CONCLUSION

This study presents a robust, real-time fault monitoring framework for electrical grids using artificial neural networks. By leveraging time-series analysis and high-fidelity feature extraction, the model accurately detects and classifies faults under various operational conditions. Simulation and real-time deployment results demonstrate the model's suitability for practical grid environments, with high accuracy, low latency, and adaptability.

Future work will focus on:

- Expanding the model to include arc faults and incipient faults
- Integrating with reinforcement learning for predictive maintenance
- Field deployment in smart substations and microgrids

The proposed framework represents a significant step toward intelligent grid automation and enhanced power system reliability.

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