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Methodological Framework and System Modeling for ANN-Based Transmission Line Fault Detection

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Abstract—Following the comprehensive review of machine learning applications in power systems, the next critical phase in developing an intelligent fault diagnosis system is the establishment of a robust simulation framework. This paper presents the methodological progress and system modeling required to generate a training dataset for an Artificial Neural Network (ANN). A detailed 11kV three-phase transmission line model is designed using the MATLAB/Simulink environment. The primary objective of this phase is to establish a controlled digital environment where various asymmetrical and symmetrical shunt faults can be simulated under varying conditions. Furthermore, this paper outlines the data acquisition strategy, focusing on the extraction of Root Mean Square (RMS) values of three-phase voltages and currents, which will serve as the foundational feature vectors for the proposed ANN architecture. This framework bridges the gap between theoretical literature and final empirical analysis, setting the stage for intelligent fault classification.

Index Terms—Transmission Line Modeling, MATLAB/Simulink, Data Acquisition, Artificial Neural Networks, Fault Simulation.

I. INTRODUCTION

The transition from traditional, impedance-based relay protection to adaptive, AI-driven fault detection requires a meticulous intermediate phase: the generation of high-quality, reliable data. As established in prior literature reviews, Machine Learning (ML) algorithms, particularly Artificial Neural Networks (ANN), possess the capability to identify and classify transmission line faults with unprecedented accuracy. However, an ANN is fundamentally reliant on the quality and comprehensiveness of the data it is trained on.

Since it is neither safe nor economically feasible to induce physical faults on live commercial transmission networks to gather training data, electrical engineers must rely on highly accurate digital twin simulations. This progress paper details the development of an 11kV transmission line simulation model utilizing MATLAB/Simulink. By outlining the system parameters, the fault injection methodology, and the feature extraction techniques, this paper documents the critical preparatory steps taken prior to the final training, validation, and performance analysis of the ANN model.

II. PROPOSED SYSTEM ARCHITECTURE AND MODELING

To accurately replicate the transient and steady-state behaviors of a real-world power grid during a fault, a comprehensive three-phase electrical network was constructed in the MATLAB/Simulink Simscape Electrical environment.

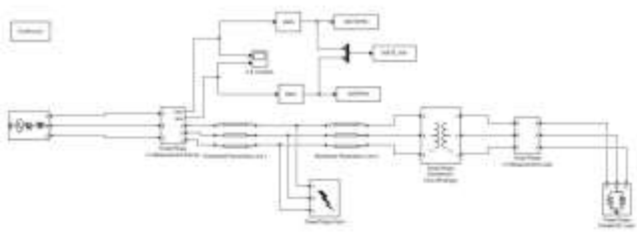

Fig. 1. MATLAB/Simulink Model of the 11kV Three-Phase Transmission Line System.

A. Transmission Line Parameters

The simulated network represents a standard 11kV distribution/transmission grid. The core component of the simulation is the Three-Phase Distributed Parameter Line block, which is mathematically modeled to reflect the real-world resistance, inductance, and capacitance of physical overhead conductors. Unlike simple PI-section models, the distributed parameter model accurately captures the high-frequency traveling waves generated during sudden fault transients, providing a

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much more realistic dataset for the neural network to learn from.

B. Power Source and Load Configuration

The system is powered by a Three-Phase Programmable Voltage Source configured to deliver an 11kV (RMS) phaseto-phase voltage at a standard grid frequency of 50 Hz. At the receiving end of the transmission line, a Three-Phase Parallel RLC Load is connected to simulate the typical power draw of a municipal or industrial sector.

III. FAULT SIMULATION AND DATA ACQUISITION STRATEGY

The primary purpose of the Simulink model is to act as a data generator. To train an ANN to recognize every possible fault scenario, the model must experience a wide variety of disturbances.

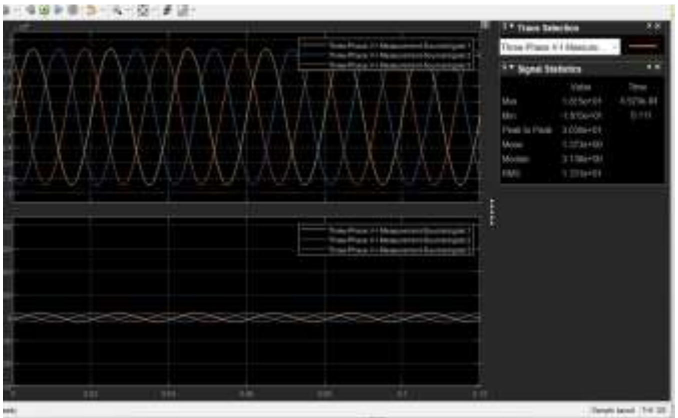

Fig. 2. Simulink Scope Output: Normal Operating Condition (Pre-Fault), establishing the baseline for AI training.

A. Fault Injection Methodology

A Three-Phase Fault Block is integrated into the middle of the transmission line model. This block is programmed to systematically trigger different types of shunt faults (baseline shown in Fig. 2):

- Single Line-to-Ground (LG): Simulating a single conductor falling to the earth or touching a grounded structure. The transient response is captured in Fig. 3.
- Line-to-Line (LL) and Double Line-to-Ground (LLG): Simulating two phases short-circuiting due to wind or mechanical failure, or two phases simultaneously touching the ground. Fig. 4 demonstrates the associated voltage drops and current spikes.
- Three-Phase Symmetrical (LLL/LLLG): A complete collapse of the three-phase spacing, resulting in severe transients across all phases as shown in Fig. 5.

To ensure the ANN learns to generalize rather than memorize, these faults will be simulated across different physical locations on the line and with varying fault resistances (e.g., 0.001Ω for bolted faults and higher resistances for arcing faults).

B. Feature Extraction

Raw waveform data contains millions of data points per second, which is computationally overwhelming for a standard ANN. Therefore, a feature extraction strategy

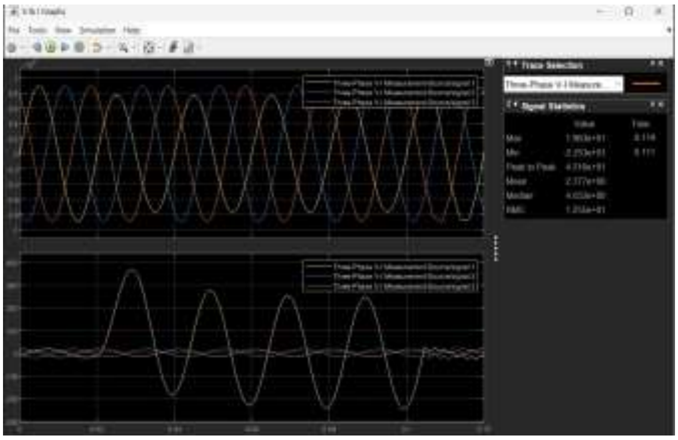

Fig. 3. Simulink Scope Output: Single Line-to-Ground (LG) Fault Transient initiated at $t = 0.02s$.

has been established. Three-Phase V-I Measurement blocks are installed at the sending end of the transmission line. Instead of feeding raw sinusoidal waves into the AI, the system calculates the Root Mean Square (RMS) values of the three phase voltages (V_a, V_b, V_c) and the three phase currents (I_a, I_b, I_c) over a specific moving window (visible in the signal statistics panels of the provided scope figures). These six discrete RMS values will form the input feature vector for the neural network.

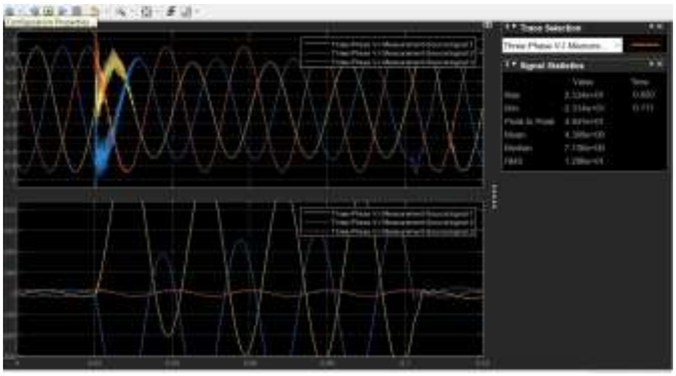

Fig. 4. Simulink Scope Output: Double Phase (LL/LLG) Fault Transient initiated at t =0.02s.

IV. PROPOSED ARTIFICIAL NEURAL NETWORK FRAMEWORK

With the data generation strategy finalized, the architecture for the pattern recognition system has been designed. The proposed system will utilize a Multi-Layer Perceptron (MLP) Feedforward Neural Network.

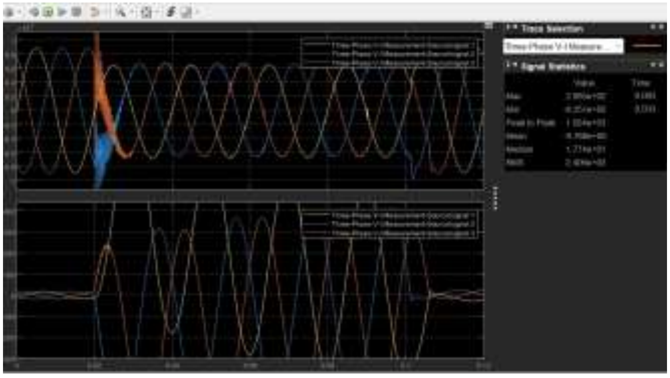

Fig. 5. Simulink Scope Output: Three-Phase Symmetrical (LLL) Fault Transient initiated at t =0.02s.

A. Network Topology

The network is structured as follows:

- Input Layer: Consists of 6 neurons, corresponding to the extracted RMS values of the 3-phase voltages and currents.
- Hidden Layer(s): Designed to map the non-linear relationships between the sudden voltage drops and current spikes during a fault. The exact number of neurons will be optimized during the final testing phase to prevent overfitting.
- Output Layer: Configured to output a classification matrix identifying the exact nature of the fault (e.g., Normal, LG, LL, LLG, LLL).

B. Training Algorithm Selection

Based on preliminary theoretical analysis, the LevenbergMarquardt (LM) backpropagation algorithm has been selected for the upcoming training phase. The LM algorithm mathematically blends the speed of the Gauss-Newton algorithm with the stability of gradient descent. It is highly optimized for networks of moderate size and is expected to yield rapid convergence and minimal Mean Squared Error (MSE) when processing the electrical transient data.

V. CURRENT STATUS AND FUTURE SCOPE

At the current stage of the project, the theoretical literature review is complete, and the MATLAB/Simulink digital twin has been successfully designed and parameterized. The feature extraction logic utilizing RMS values has been finalized.

The immediate future scope involves executing the batch simulations to generate a massive dataset containing thousands of fault and non-fault scenarios. Once the dataset is exported to the MATLAB workspace, it will be divided into training, validation, and testing subsets. The final phase of the project will focus on feeding this data into the proposed LevenbergMarquardt ANN, tuning the hidden layer hyperparameters, and rigorously analyzing the final classification accuracy, regression plots, and error histograms.

VI. CONCLUSION

Developing a machine learning-based fault detection system requires a highly structured methodology bridging theoretical concepts and final data analysis. This progress paper has detailed the critical intermediate steps of the project: the construction of a reliable 11kV transmission line simulation in MATLAB/Simulink and the establishment of a robust feature extraction protocol. By successfully designing the data generation pipeline and defining the architecture of the LevenbergMarquardt Artificial Neural Network, the project is now fully prepared to enter the final stages of model training, empirical validation, and fault analysis.

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