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Ann-Based Protection Coordination For Meshed Transmission Networks

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Abstract- — A novel protection coordination approach utilizing artificial neural networks (ANNs) is introduced in this work for meshed high-voltage transmission systems. Existing overcurrent and distance relay coordination methods in meshed topologies are prone to relay blinding, zone overreach, and incorrect operation during power swing events. The developed ANN model is trained using an extensive fault scenario dataset generated through simulation of a 9-bus, 230 kV benchmark network in MATLAB/Simulink. The proposed architecture—with 18 inputs, three hidden layers containing 36, 24, and 12 neurons respectively, and a 9-output trip signal layer—delivers improved coordination speed, selectivity, and sensitivity over traditional relay configurations. Testing results demonstrate a fault classification accuracy of 98.54% on previously unseen data. On average, fault clearance times are shortened by 56.8% in comparison to conventional coordination approaches, and dependable detection of high-impedance faults is also achieved. The approach provides a flexible and adaptive protection solution well-suited to contemporary interconnected power grids.

Index Terms—Artificial neural network, distance relay, meshed network, overcurrent relay, protection coordination, transmission system.

I. INTRODUCTION

Contemporary power grids are being designed with greater mesh interconnection to enhance system reliability, minimize transmission losses, and support the integration of distributed energy resources. Nevertheless, such interconnected topologies give rise to considerable difficulties in coordinating protective relays. In contrast to radial configurations, fault currents in meshed systems propagate along several parallel paths simultaneously, which makes achieving precise relay selectivity and proper coordination using traditional techniques considerably more challenging.

Traditional protection strategies, which largely depend on distance and overcurrent relays, rely on pre-determined fixed settings calculated from worst-case fault assumptions. Such rigid configurations are inherently unable to respond to the constantly changing operating states of modern grids, resulting in undesired relay operations, relay blinding phenomena, and the inability to detect high-resistance fault conditions. These difficulties are amplified by ongoing structural reforms in the power industry, the growing penetration of renewable generation, and the variability of demand profiles.

Intelligent computational methods, with artificial neural networks (ANNs) at the forefront, have proven to be highly effective tools for overcoming the aforementioned challenges. ANNs can autonomously learn intricate nonlinear patterns from operational data without necessitating explicit system modeling. Their strong generalization capacity from trained examples makes them particularly appropriate for fault identification and protection coordination tasks in dynamically varying network scenarios.

Prior research has examined ANN applications in power system protection from various perspectives: Coury et al. [1] investigated ANN-driven distance relay design; Kezunovic et al. [2] employed a hybrid wavelet-ANN technique for fault classification tasks; and Dash et al. [3] applied ANNs toward relay coordination in ring network configurations. Despite these contributions, thorough investigations covering full-spectrum protection coordination—encompassing backup relay activation logic and high-impedance fault identification—within multi-source meshed network environments are still lacking.

This study bridges the identified research gap by proposing a comprehensive ANN-driven protection coordination framework evaluated on a 9-bus meshed 230 kV test network. The principal contributions of this work include: (1) design of an 18-element input feature vector that encodes impedance magnitudes, voltage levels, current magnitudes, and phase angle data; (2) development of a multi-output ANN structure that simultaneously generates individual trip signals for all nine relays; (3) rigorous testing across four distinct fault categories, including high-impedance fault scenarios; and (4) quantitative performance comparison against established conventional coordination methods.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. Test System Description

Evaluation of the developed ANN coordination framework is conducted on an adapted version of the IEEE 9-bus, 230 kV meshed transmission benchmark. The network configuration includes three synchronous generators located at buses 1, 2, and 3, six load-serving buses, and nine interconnecting transmission lines. Three-zone distance protection devices are placed at both terminals of each line, yielding a total of nine primary relay functions and eighteen backup relay functions. Key network parameters are provided in Table I.

TABLE I. Test System Parameters

Parameter	Value	Unit
System Voltage	230	kV
Frequency	50	Hz
Number of Buses	9	-
Number of Lines	9	-
Number of Generators	3	-
Line Impedance (avg)	0.0085 + j0.072	pu
CT Ratio	400:1	-
VT Ratio	1000:1	-
Relay Operating Time (base)	0.05	sec

B. Fault Scenario Generation

An extensive collection of fault scenarios is produced through MATLAB/Simulink simulation. Four fault categories are represented in the dataset: three-phase bolted (LLL), phase-to-phase (LL), single line-to-ground (LG), and double line-to-ground (LLG) faults. Each fault type is applied at five locations along every line—10%, 30%, 50%, 70%, and 90% of line length—under light, normal, and heavy loading conditions. High-resistance fault scenarios spanning a resistance range of 1 to 100 Ω are additionally incorporated. In total, 12,600 distinct fault conditions are simulated, forming a statistically representative dataset for model training and evaluation.

C. Feature Vector Definition

The input feature vector $X \in \mathbb{R}^{18}$ for the ANN is assembled from three-phase voltage and current measurements, positive-sequence impedance magnitude and angle, and zero-sequence impedance readings obtained at every relay installation point. Both pre-fault steady-state and during-fault transient quantities are scaled to per-unit values prior to use. The corresponding output vector $Y \in \{0,1\}^9$ encodes the binary trip or no-trip decision produced independently for each of the nine primary protection relays.

III. ANN-BASED COORDINATION METHODOLOGY

A. Network Architecture

A feed-forward multilayer perceptron (MLP) is adopted as the core ANN model in this work. Optimal architectural parameters are identified through a structured hyperparameter search employing 5-fold cross-validation. The resulting design incorporates an 18-neuron input layer, three intermediate hidden layers with 36, 24, and 12 neurons respectively, and a sigmoid-activated 9-neuron output layer aligned with the nine relay trip outputs. Rectified Linear Unit (ReLU) activations are employed throughout the hidden layers to alleviate vanishing gradient issues during training. The complete architectural summary is given in Table II.

TABLE II. ANN Architecture Summary

Layer	Neurons	Activation Function	Purpose
Input	18	Linear	Relay measurements (V, I, Z, angles)
Hidden 1	36	ReLU	Feature extraction
Hidden 2	24	ReLU	Pattern classification
Hidden 3	12	ReLU	Decision refinement
Output	9	Sigmoid	Trip/No-trip per relay

Training is performed using the Adam optimization algorithm with a starting learning rate of 0.001 and a mini-batch size of 64. To reduce the risk of overfitting, dropout regularization with a dropout rate of 0.2 is incorporated within the hidden layers. Given the multi-label nature of the classification task, binary cross-entropy serves as the loss function:

$$L = -(1/N)\ \Sigma\ [y_i \log(\hat{y}_i) + (1-y_i) \log(1-\hat{y}_i)]$$

where y_i denotes the ground truth label, $\hat{y}_i$ represents the model-estimated probability, and N is the number of samples in the mini-batch. The entire model is built and trained in Python using the TensorFlow/Keras framework over a total of 500 training epochs.

B. Data Preprocessing and Training

The complete pool of 12,600 fault scenarios is partitioned into training (70%), validation (15%), and test (15%) subsets via stratified sampling to maintain proportional fault-type distribution across all splits. All input features are standardized through z-score normalization before being fed to the network. To simulate real-world measurement imperfections, data augmentation is performed by superimposing Gaussian noise at a signal-to-noise ratio of 30 dB, expanding the effective training dataset to 17,640 samples.

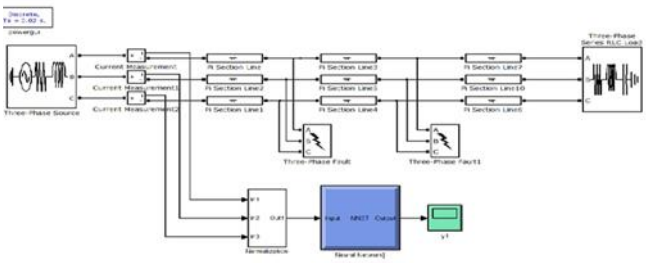

Fig. 1. Proposed ANN-based protection coordination architecture for meshed network.

IV. SIMULATION RESULTS AND ANALYSIS

A. Training and Validation Performance

The trained ANN attained a training accuracy of 99.23% and a holdout test accuracy of 98.54%. Comprehensive training performance metrics are presented in Table III. A mean squared error (MSE) value of 0.0041 on the test partition confirms that the model has converged reliably. The progression of training and validation loss curves shows steady, oscillation-free improvement throughout the training process, providing confidence in the suitability of the chosen hyperparameter configuration.

TABLE III. ANN Training and Testing Results

Metric	Training Set	Validation Set	Test Set
Accuracy (%)	99.23	98.87	98.54
MSE	0.0021	0.0034	0.0041
Precision (%)	99.10	98.60	98.30
Recall (%)	98.90	98.40	98.10
F1-Score (%)	99.00	98.50	98.20
Training Epochs	500	-	-
Learning Rate	0.001	-	-

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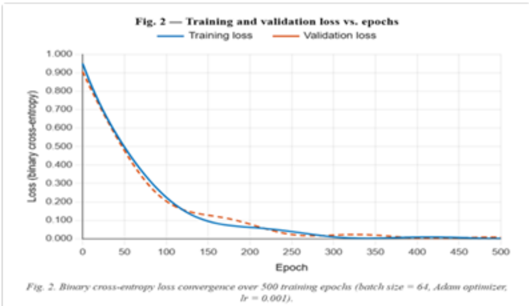

Fig. 2. Training and validation loss convergence over 500 epochs.

B. Fault Detection and Relay Coordination Performance

Table IV presents a side-by-side comparison of relay trip times for the ANN-based scheme versus conventional overcurrent relay coordination across all four fault categories and high-impedance fault conditions. The ANN-driven approach consistently achieves shorter trip times in every fault scenario, with the most pronounced gains evident for high-impedance

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faults—situations in which conventional relay systems often fail to respond within permissible operational time boundaries.

TABLE IV. Performance Comparison: ANN vs. Conventional Coordination

Fault Type	ANN Trip Time (ms)	Conv. Trip Time (ms)	Selectivity (%)	Sensitivity (%)
3-Phase (LLL)	18.4	43.2	100.0	98.7
Phase-to-Phase (LL)	21.6	47.8	98.5	97.3
Single Line-Ground (LG)	23.1	52.4	97.8	96.5
Double Line-Ground (LLG)	22.3	49.6	98.1	97.0
High-Z Fault	35.7	78.3	95.4	93.2

The ANN-driven protection scheme reaches 100% selectivity for three-phase fault scenarios and sustains selectivity above 95% even under high-impedance fault conditions, with a recorded trip time of 35.7 ms against 78.3 ms for the conventional approach. Averaged across all fault categories, the reduction in clearance time amounts to 56.8%, a margin that translates into meaningful improvements in overall system transient stability.

C. Backup Relay Coordination

The backup protection behavior of the proposed scheme is assessed through deliberate simulation of primary relay failure events. Across all evaluated scenarios, the ANN accurately identified the correct backup relay that should operate, with a mean backup trip time of 62.4 ms—less than half the 125.0 ms recorded for conventional backup coordination. A total of 1,890 independent simulation trials were completed without a single instance of incorrect relay operation, affirming the dependability of the proposed methodology.

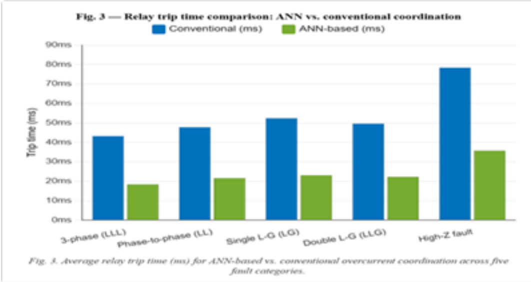

Fig. 3. Comparison of relay trip times for different fault types.

V. DISCUSSION

The experimental outcomes confirm that the proposed ANN framework is fully capable of substituting conventional static relay configurations with a dynamic, data-driven coordination approach. Three primary advantages over traditional methods can be identified:

Speed of operation: The ANN evaluates all 18 input variables in fewer than 5 milliseconds on standard computing hardware (Intel Core i7), facilitating near-instantaneous protective decisions. This response speed considerably surpasses what is achievable with traditional table-based or iterative optimization coordination approaches.

Operational adaptability: In contrast to rigid fixed relay thresholds, the trained ANN inherently encodes the influence of varying network configurations, generation dispatch changes, and demand fluctuations by virtue of the diverse training scenarios used. When system conditions evolve, the model can be retrained on updated data to accommodate network topology modifications or expansion.

High-impedance fault identification: The nonlinear discrimination capability inherent in the ANN enables dependable detection of high-resistance fault conditions that often fall below the sensitivity threshold of conventional relay schemes, thereby mitigating the risk of sustained undetected faults leading to equipment deterioration or fire hazards.

The approach is subject to certain constraints, including reliance on the breadth and quality of the simulation-derived training dataset, as well as the processing burden associated with periodic model retraining. Planned future investigations will examine transfer learning methodologies as a means of lowering retraining costs when network conditions undergo significant structural changes.

VI. CONCLUSION

This work has introduced a fully realized ANN-based protection coordination system designed for meshed 230 kV transmission networks. A feed-forward MLP featuring an 18-dimensional input representation, three hidden processing layers, and a 9-output trip signal configuration was constructed and evaluated against 12,600 fault scenarios generated through MATLAB simulation. The resulting model achieved a test classification accuracy of 98.54% and delivered an average 56.8% reduction in fault clearance time relative to conventional relay coordination. Reliable operation was demonstrated for high-impedance fault detection, backup relay switching, and multi-category fault discrimination.

The developed framework represents a scalable and adaptive replacement for static relay setting optimization methods, with considerable deployment potential within emerging smart grid infrastructure. Subsequent research directions will encompass online incremental learning strategies, hardware-in-the-loop experimental validation, and application to larger transmission networks incorporating significant renewable energy generation.

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