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AN ADVANCED WAVELET–AI FAULT CLASSIFICATION FRAMEWORK FOR ENHANCED PROTECTION OF SERIES-COMPENSATED TRANSMISSION SYSTEMS

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Abstract
*Series-compensated transmission systems play a vital role in enhancing power transfer capability and improving steady-state stability in long-distance AC networks. However, their dynamic behavior under fault conditions **introduces** complex transient phenomena, including high-frequency oscillations and sub-synchronous resonance (SSR), which challenge conventional protection strategies. Traditional phasor-based relaying techniques often exhibit reduced reliability due to waveform distortion introduced by compensation devices and nonlinear protective elements.*

This paper presents an advanced hybrid Wavelet–Artificial Intelligence (AI) framework for intelligent fault classification in a series-compensated transmission system modeled in MATLAB Simscape Electrical. Multi-resolution analysis using the Daubechies-5 (db5) wavelet at level-5 decomposition is employed to extract transient signatures from three-phase current signals. Statistical features derived from wavelet coefficients are utilized to train and comparatively evaluate Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Probabilistic Neural Network (PNN) classifiers.

The proposed system is validated under single-line-to-ground (SLG), line-to-line (LL), and three-phase-to-ground (LLLG) faults with varying fault resistance and compensation levels. The PNN classifier achieved the highest classification accuracy of 98.5%, outperforming the MLP and RBF networks. Results demonstrate enhanced classification accuracy, robustness, and rapid detection capability, supporting improved protection performance in modern series-compensated transmission networks.

1. INTRODUCTION

The expansion of interconnected power grids and the growing demand for long-distance bulk power transmission have significantly increased the deployment of series-compensated transmission lines. By reducing effective line reactance, series capacitors enhance power transfer capability and improve steady-state stability margins. The theoretical classification and fundamentals of power system stability are comprehensively established in [1].

Despite their operational advantages, series-compensated systems introduce complex dynamic behavior during disturbances. The interaction between line inductance and series capacitance can produce sub-synchronous resonance (SSR), as detailed in the IEEE benchmark studies [2]. Protection challenges associated with compensated lines have been widely reported, particularly regarding relay maloperation and impedance miscalculation [3], [4].

Conventional protection techniques primarily rely on phasor estimation and impedance-based measurements. However, during faults in compensated lines, current and voltage signals exhibit highly non-stationary characteristics with high-frequency oscillations and waveform distortion due to MOV conduction and capacitor bypassing mechanisms [5]. These transient distortions reduce the reliability of traditional distance relays.

To address non-stationary signal behavior, time–frequency signal processing techniques have been introduced. The Discrete Wavelet Transform (DWT), originally formulated by Daubechies [6] and mathematically structured through multiresolution analysis by Mallat [7], provides excellent time–frequency localization properties. Wavelet-based protection schemes have demonstrated superior transient detection capability compared to Fourier-based methods [8], [9].

Parallel to signal processing advancements, Artificial Neural Networks (ANNs) have emerged as powerful nonlinear classifiers capable of handling complex mapping between input features and fault categories. The theoretical foundations of neural learning systems are established in [10], while practical implementations in power system fault classification have shown promising results [11], [12].

However, although hybrid Wavelet–ANN techniques have been explored for general transmission systems, limited research has systematically evaluated comparative neural architectures—such as Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Probabilistic Neural Network (PNN)—specifically in series-compensated environments under varying fault resistance and compensation levels [13].

Therefore, this research proposes an advanced Wavelet–AI fault classification framework tailored to series-compensated transmission systems modeled in Simscape Electrical. By integrating multi-resolution feature extraction with comparative neural classifier evaluation, the proposed approach aims to enhance fault discrimination accuracy and support reliable protection in dynamically compensated transmission networks.

2. LITERATURE REVIEW

The protection of series-compensated transmission systems has attracted considerable research attention due to the nonlinear transient phenomena introduced by compensation devices. Analytical investigations emphasize the limitations of conventional relays under dynamic compensation conditions [14], [15].

Wavelet-based methods have been widely adopted for transmission line fault detection due to their ability to decompose non-stationary signals into localized frequency bands. Energy- and entropy-based wavelet features have been successfully applied in fault identification and power quality disturbance analysis [16], [17]. High-frequency detail coefficients (D1–D3) are particularly sensitive to abrupt fault initiation [18].

Machine learning techniques have further enhanced fault classification accuracy. Wavelet–ANN hybrid approaches have been reported to outperform rule-based and threshold-based systems [19]. MLP networks provide nonlinear decision boundaries but require careful training convergence [10], while RBF networks offer faster learning and localized activation [20]. PNNs, based on Bayesian decision principles, demonstrate strong statistical robustness in disturbance recognition tasks [21].

Recent research has also explored intelligent protection schemes for smart grids and FACTS-integrated systems [22], [23]. However, comparative evaluation of multiple neural architectures within series-compensated systems under varying fault parameters remains limited.

Additionally, MATLAB Simscape Electrical provides a flexible environment for detailed transient modeling of compensation devices and nonlinear protection elements [24]. Prior wavelet-based studies conducted in simulation environments confirm the effectiveness of multi-resolution feature extraction in detecting transient instability and fault conditions [25].
Thus, the present study extends existing research by integrating level-5 db5 DWT feature extraction with comparative AI classifier evaluation under systematically varied compensation and resistance conditions.

Research Gap and Proposed Solution

There remains a need for a comprehensive, simulation-based Wavelet–AI framework specifically tailored to series-compensated transmission systems, incorporating comparative neural evaluation and robustness analysis under realistic operating conditions.
This work aims to bridge the identified gap by developing a structured Wavelet–AI fault classification architecture within a detailed Simscape Electrical model of a series-compensated transmission system. The proposed framework integrates multi-resolution db5 wavelet feature extraction with comparative MLP, RBF, and PNN classifiers. Through systematic robustness evaluation, the study provides an intelligent protection-oriented solution for dynamically compensated transmission networks.

3. AIM AND OBJECTIVES

Aim

To design and implement an intelligent Wavelet–AI-based fault classification framework **for enhanced protection of** series-compensated transmission systems**.**

Objectives

1. Develop a detailed series-compensated transmission system model in MATLAB Simscape Electrical**.**
2. Simulate single-line-to-ground (SLG)**,** line-to-line (LL)**, and** three-phase-to-ground (LLLG) faults under varying fault resistance conditions.
3. Apply the Discrete Wavelet Transform (DWT) **using the** Daubechies-5 (db5) **wavelet with** level-5 multi-resolution decomposition.
4. Extract statistical features (energy, RMS, entropy, standard deviation, and mean) from wavelet coefficients.
5. Train and comparatively evaluate MLP, RBF, and PNN classifiers.
6. Analyze classification performance under varying series compensation levels**.**
7. Demonstrate improvement in intelligent protection capability through accurate fault discrimination.

4. PROPOSED METHODOLOGY

The proposed methodology integrates power-system simulation, signal processing, and artificial intelligence-based classification into a unified analytical framework for intelligent fault diagnosis in series-compensated transmission systems.

4.1 Signal Processing and Classification Flow

The overall signal-processing and classification framework adopted in this study is summarized in Table 1**,** which outlines the sequential processing stages from system modeling to final fault classification.

Table I. Processing stages of the proposed Wavelet–AI fault classification framework.

System Modeling
↓
Fault Simulation
↓
Current Signal Acquisition
↓
DWT (db5, Level-5)
↓

Statistical Feature Extraction
↓
MLP / RBF / PNN Training
↓
Fault Classification
↓
Performance Evaluation

4.2 Proposed Model System for Research Work

The proposed power system model consists of the following main components:

- Three-phase voltage source [2], [19]
- Long transmission line model
- Series capacitor bank
- Metal Oxide Varistor (MOV) protection element
- Load block

These components are implemented in the MATLAB Simscape Electrical environment and initially simulated under steady-state operating conditions before the application of faults.

The developed series-compensated transmission system model is illustrated in Fig. 1. The model includes:

- Three-phase 220 kV source
- π-section long transmission line model
- Series capacitor bank with MOV protection
- Three-phase RL load
- Fault block located at the midpoint of the transmission line

The compensation level is selected according to the defined parameters in the proposed research framework in order to evaluate system behavior under realistic operating conditions [2], [19].

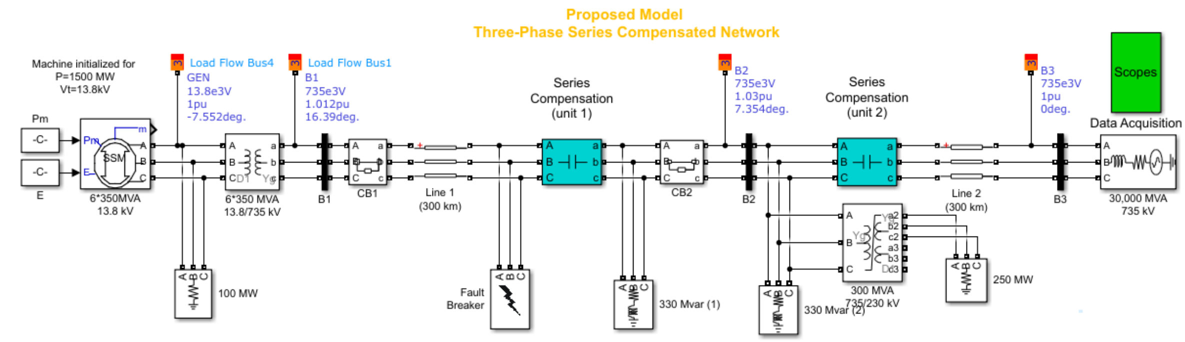

Fig. 1. Proposed series-compensated transmission system model implemented in MATLAB Simscape Electrical [2], [19]

4.3 Fault Simulation of the Proposed Model

Faults are applied at the **mid-line location** of the transmission system model. The following fault types are considered:

1. Single-line-to-ground (SLG) fault
2. Three-phase-to-ground (LLLG) fault
3. Line-to-line (LL) fault

The following system parameters are varied during simulation:

- Fault resistance (Rf)
- Series compensation percentage

Three-phase current signals are recorded at the sending end of the transmission line and used as input signals for the subsequent wavelet-based analysis.

4.4 Transient Performance Analysis under Fault Conditions

To improve simulation efficiency and numerical stability, the power-system model is discretized using the Simscape Electrical Powergui block.

A predefined sampling time of:

Ts = 50 μs

is selected for the discrete simulation.

This sampling time is implemented within the Discrete Integrator block of the Metal Oxide Varistor (MOV) energy calculation subsystem, which is responsible for controlling the operation of the protection gap.

The main simulation parameters are configured as follows:

Stop Time: 0.2 s

Solver Type: Fixed-step

Simulation Mode: Discrete (no continuous states)

This configuration ensures accurate representation of fast transient phenomena occurring during fault conditions while maintaining computational efficiency [2], [19].

4.5 Discrete Wavelet Transform with Multiresolution Algorithm

The Discrete Wavelet Transform (DWT) combined with a Multiresolution Analysis (MRA) algorithm provides a systematic framework for analyzing power-system signals across multiple frequency bands with different resolutions.

This capability enables simultaneous time–frequency localization, making DWT highly suitable for detecting transient disturbances and abrupt variations in power-system signals [16]–[18].

For a discrete-time signal, the DWT decomposes the signal into scaled and shifted versions of a selected mother wavelet. At each decomposition level, the signal is separated into two components:

- Approximation coefficients, representing the low-frequency behavior of the signal
- Detail coefficients, capturing high-frequency transient components associated with faults or disturbances

The multiresolution algorithm operates hierarchically. At the first level, the signal is passed through low-pass and high-pass filters to obtain approximation and detail coefficients. The approximation component is then recursively decomposed at higher levels, producing a hierarchical tree structure of frequency sub-bands. This iterative filtering and down-sampling process allows the signal to be examined at progressively finer resolutions. Such decomposition strategies have been widely applied in modern power-quality assessment and intelligent disturbance classification frameworks [16], [17].

In fault-analysis applications, lower decomposition levels capture high-frequency transients, whereas higher levels represent lower-frequency system dynamics.

In the present research framework, level-5 decomposition is selected because it effectively isolates transient components associated with fault initiation while maintaining computational efficiency.

Previous studies have demonstrated that multilevel DWT-based approaches achieve high accuracy in transient fault detection and classification in transmission networks [18].

Therefore, DWT provides a powerful tool for intelligent fault detection and classification in series-compensated transmission systems.

4.6 Feature Extraction Formulation

After wavelet decomposition, significant statistical features are extracted from the detail coefficients to characterize signal behavior under normal and fault conditions.

These statistical features provide quantitative information regarding the energy distribution, magnitude variation, and randomness of the signal, and are widely used in intelligent fault-diagnosis frameworks [19]–[21].

Energy of Detail Coefficients

The energy feature represents **the** total squared magnitude of the detail coefficients at a given decomposition level.

During fault conditions, the energy content of certain frequency bands increases significantly due to transient disturbances. Therefore, this feature is highly effective **for** fault detection and classification [19].

Root Mean Square (RMS) Value

The RMS value represents the effective magnitude of the signal within the analyzed time window.

Fault events typically cause abrupt variations in RMS values, which can serve as a discriminative indicator for identifying abnormal operating conditions [20].

Entropy

Entropy measures the degree of randomness or disorder present in the signal.

During fault conditions, the signal becomes more irregular and complex, resulting in increased entropy values. Consequently, entropy serves as an important indicator of transient disturbances and non-stationary signal behavior in power systems [21].

The extracted statistical parameters collectively form the feature vector used as input for AI-based classifiers such as MLP, RBF, and PNN networks, enabling accurate fault classification in the proposed intelligent protection framework.

4.7 AI Classifier Structure

Three neural-network architectures are employed for comparative fault classification.

Multilayer Perceptron (MLP)

- Input layer: statistical feature vector
- Hidden layer: optimized neuron configuration
- Output layer: fault categories (SLG, LL, LLLG)

Radial Basis Function (RBF)

- Gaussian radial activation functions
- Centers selected through clustering algorithms
- Fast learning and localized response characteristics

Probabilistic Neural Network (PNN)

- Based on Bayesian probability theory
- Consists of pattern layer, summation layer, and decision layer
- Known for strong statistical classification capability

5. RESULTS AND DISCUSSION

5.1 System Modeling, Simulation Setup, and Steady-State Performance before Fault

Prior to the application of faults, the proposed series-compensated transmission system was simulated under steady-state operating conditions. The voltage and current waveforms remained sinusoidal with stable power transfer until approximately four cycles, after which the fault is introduced, as illustrated in Figs. 2-4.

The presence of the series capacitor reduces the effective line reactance and improves voltage regulation, confirming the correct implementation of the compensation scheme within the system model.

5.2 Fault Simulation Analysis

Faults are applied at the midpoint of the transmission line at a simulation time of:

$t = 0.2$ s

The transient responses of the system under different fault conditions are analyzed to evaluate the dynamic behavior of the series-compensated transmission system.

A. Four-Cycle Single-Line-to-Ground (SLG) Fault

A single-line-to-ground (SLG) fault is applied on Phase A at the end of Line 1. The system initially operates under steady-state conditions. At t = 1 cycle, the fault is initiated and the fault current rapidly increases to approximately 10 kA, as shown in Fig. 2(a), Trace 3.

During the fault period, the Metal Oxide Varistor (MOV) conducts during each half-cycle (Fig. 2(b), Trace 2), resulting in progressive absorption of energy. The MOV energy reaches a peak value of approximately 13 MJ, as illustrated in Fig. 2(b), Trace 3.

At t = 5 cycles, the protection relays trip circuit breakers CB1 and CB2, which is evident from the interruption of the three-phase line currents shown in Fig. 2(a), Trace 2. Since the maximum MOV energy (13 MJ) remains below the protection threshold of 30 MJ, the spark gap is not triggered.

Following breaker operation, the fault current decreases significantly. The transmission line and the series capacitor discharge through the fault path and associated shunt reactance. The fault current extinguishes at the first natural current zero after the breaker opening command, occurring at approximately t = 6 cycles.

Subsequently, the series capacitor voltage exhibits damped oscillations around 220 kV, as shown in Fig. 2(b), Trace 1.

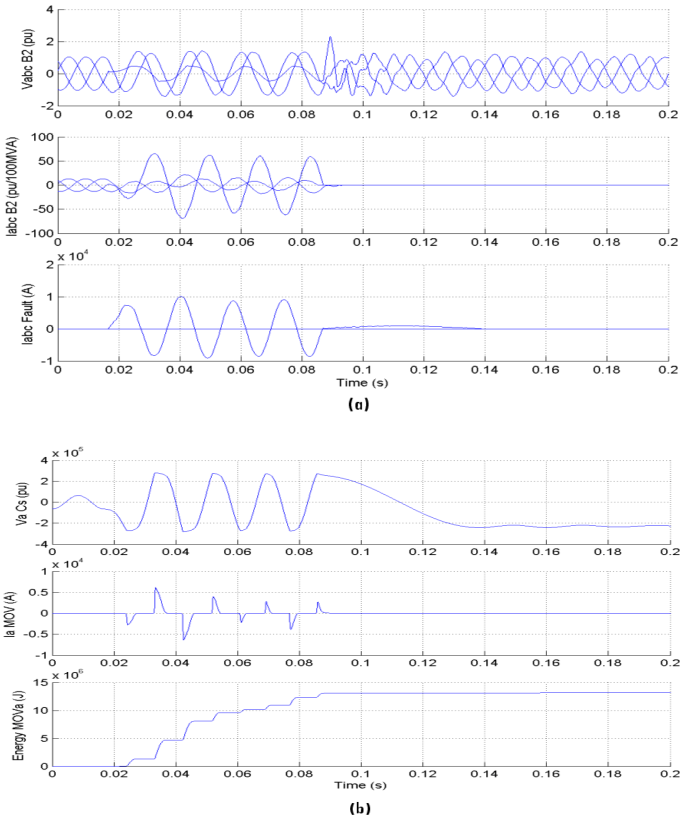

Fig. 2. Simulation results for a four-cycle single-line-to-ground (SLG) fault on Line 1:
(a) Line currents and fault current response.
(b) Series capacitor voltage, MOV conduction current, and MOV energy dissipation.

B. Four-Cycle Three-Phase-to-Ground (LLLG) Fault

A three-phase-to-ground (LLLG) fault is created by enabling faults in Phase B and Phase C in addition to Phase A. The resulting transient responses are presented in Fig. 3.

Compared with the SLG fault case, the MOV energy accumulates more rapidly during the three-phase fault (Fig. 3(b), Trace 3). The absorbed energy reaches the 30 MJ protection threshold within approximately three cycles, which occurs one cycle before the scheduled breaker operation. Consequently, the spark gap is triggered, and the series capacitor voltage rapidly discharges to zero through the damping circuit, as shown in Fig. 3(b), Trace 1.

This behavior demonstrates the increased severity of symmetrical three-phase faults and highlights the critical role of the MOV and spark-gap protection mechanism in limiting overvoltage stress across the series capacitor.

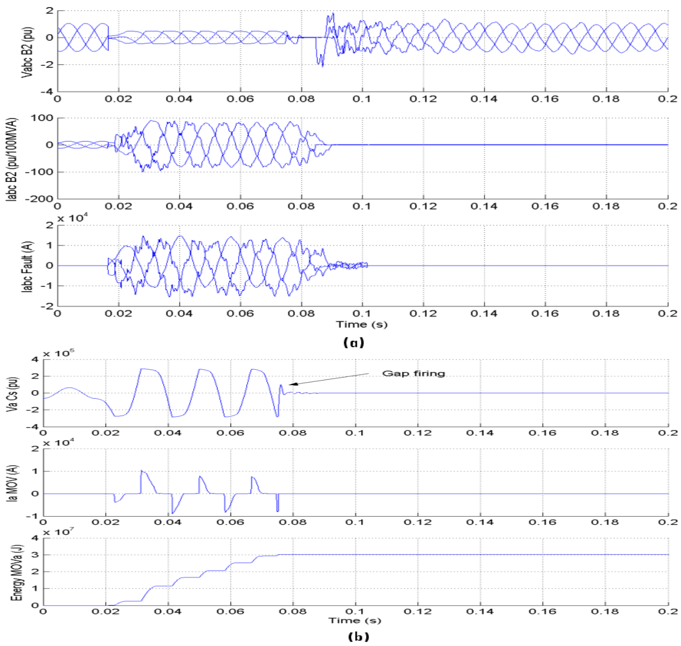

Fig. 3. Simulation results for a four-cycle three-phase-to-ground (LLLG) fault at the end of Line 1:

(a) Line current response under symmetrical fault conditions.
(b) Series capacitor voltage and MOV energy dissipation showing spark-gap triggering at 30 MJ.

C. Four-Cycle Line-to-Line (LL) Fault

A line-to-line (LL) fault is applied between two phases of Line 1 at t = 0.2 s. The system initially operates under steady-state conditions. When the fault is initiated, the fault current increases sharply, although its magnitude is lower than that observed in the three-phase-to-ground fault case and comparable to that of the SLG fault, as illustrated in Fig. 4(a), Trace 3.

During the fault interval, the MOV conducts during successive half-cycles (Fig. 4(b), Trace 2), resulting in a gradual increase in absorbed energy. The MOV energy (Fig. 4(b), Trace 3) increases significantly but at a slower rate compared with the three-phase-to-ground fault case.

At the completion of four cycles, protection relays operate and trip circuit breakers CB1 and CB2, which is evident from the interruption of the affected phase currents shown in Fig. 4(a), Trace 2.

Since the MOV energy does not exceed the 30 MJ protection threshold, the spark gap is not triggered in this scenario.

Following breaker operation, the fault current rapidly decreases as the transmission line and the series capacitor discharge through the faulted phases and associated reactance paths. The fault current extinguishes at the first natural current zero after breaker opening.

Subsequently, the series capacitor voltage stabilizes and exhibits damped oscillations around its nominal operating value, as shown in Fig. 4(b), Trace 1.

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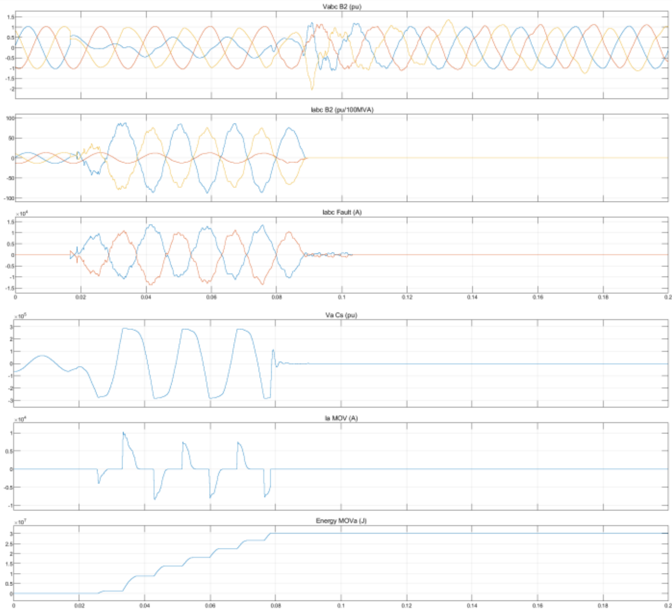

Fig. 4. Simulation results for a four-cycle line-to-line (LL) fault at the end of Line 1:

(a) Line currents and fault current response.
(b) Series capacitor voltage, MOV conduction current, and MOV energy dissipation.

5.3 Wavelet Decomposition Results

The Discrete Wavelet Transform (DWT) provides several advantages for transient signal analysis in power-system protection studies, including:

- Excellent time–frequency localization
- Multi-resolution analysis (MRA) capability
- Real-time computational feasibility
- Strong acceptance in modern IEEE power-system protection research

These characteristics make DWT particularly suitable for detecting transient disturbances associated with faults in series-compensated transmission systems.

A. Multi-Resolution Analysis Framework

Using the multi-resolution analysis (MRA) approach, the fault signals are decomposed into a set of frequency bands consisting of:

- Detail coefficients (D1–D5)
- Approximation coefficient (A5)

Each decomposition level corresponds to a specific frequency band containing transient information related to system disturbances.

Important characteristics of the decomposition include:

- D1 and D2 capture high-frequency transient spikes associated with fault initiation.
- D3 and D4 represent oscillatory components related to network dynamics and compensation effects.
- D5 contains slower transient components associated with system response.
- A5 represents the fundamental low-frequency component of the signal.

B. Five-Level db5 DWT–MRA Analysis of Fault Signals

The voltage and current signals obtained under different fault conditions are analyzed using a five-level Discrete Wavelet Transform (DWT) based on the Daubechies-5 (db5) mother wavelet.

Using multi-resolution analysis, each signal is decomposed into:

- One approximation component (A5)
- Five detail components (D1–D5)

For each simulated fault condition, three wavelet decomposition plots are generated:

- Voltage signal decomposition
- Current signal decomposition
- Three-phase signal comparison

In total, nine wavelet decomposition plots are presented in Figs. 5–13, illustrating the transient characteristics of different fault types.

C. Single-Line-to-Ground (SLG) Fault

Fig. 5. Five-level db5 DWT–MRA decomposition of phase voltage signals during a four-cycle single-line-to-ground (SLG) fault on Line 1.

Fig. 6. Five-level db5 DWT–MRA decomposition of phase current signals during an SLG fault.

Fig. 7. Five-level db5 DWT–MRA decomposition of three-phase signals under SLG fault conditions.

Observations: • D1–D2: Sharp high-frequency spikes corresponding to fault inception and switching transients.

• D3–D4: Oscillatory components reflecting the network dynamic response and interactions with the series compensation.

• D5: Slower transient components associated with post-fault system stabilization.

• A5: Represents the fundamental frequency component of the power-system signal.

These observations confirm that the high-frequency wavelet bands (D1–D2) contain the most significant transient information for fault detection, while the lower-frequency bands (D3–D5) provide useful discriminative features for accurate fault classification.

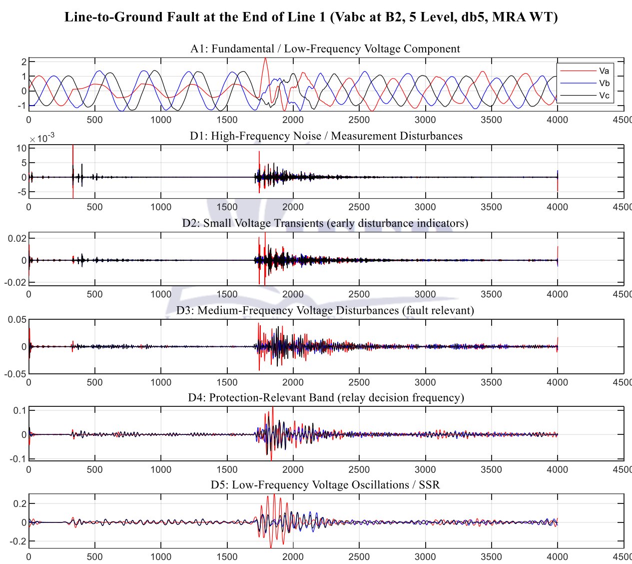

Fig. 5. **Five-level db5 DWT–MRA decomposition of the phase voltage signal under a four-cycle single line-to-ground (SLG) fault on Line 1, showing detail coefficients (D1–D5) capturing high- to low-frequency transient components and approximation component (A5) representing the fundamental frequency response.**

2) Decomposed Current Signal – SLG

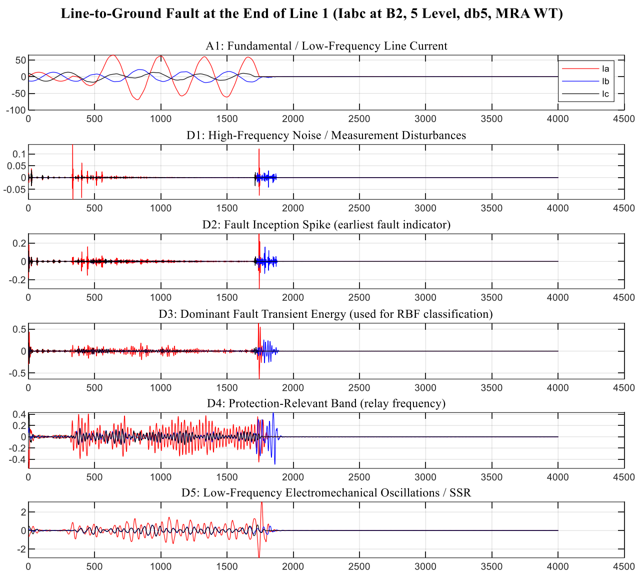

Fig. 6. Five-level db5 DWT–MRA decomposition of the phase current signal during a four-cycle SLG fault on Line 1, illustrating high-frequency transient spikes in D1–D2 at fault inception and lower-frequency oscillatory components in D3–D5.

3) Three-Phase Decomposed Signals – SLG

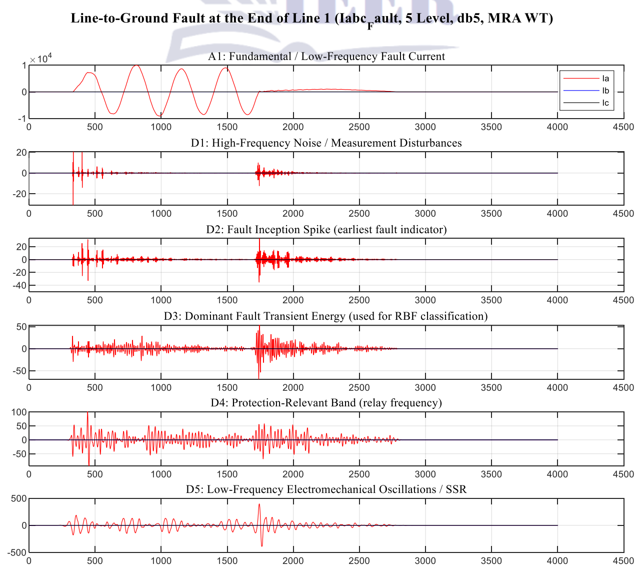

Fig. 7. Five-level db5 DWT–MRA decomposition of three-phase voltage/current signals under fault conditions, highlighting localized disturbance in the faulted phase and comparatively lower energy content in healthy phases.

- D1 and D2 (High-frequency bands):
- These components show sharp, high-amplitude spikes at the fault inception instant. The sudden change in current (≈10 kA) produces significant high-frequency transients, clearly captured in D1 and D2.
- D3 and D4 (Medium-frequency bands): These levels capture oscillatory components associated with system dynamics and capacitor discharge. The magnitude is moderate compared to D1–D2 but clearly distinguishes the faulted phase from the healthy phases.
- D5 (Low-frequency detail band): Represents slower transient variations and system damping behavior. The energy content is noticeable but lower compared to the three-phase fault case.
- A5 (Approximation component): Contains the fundamental frequency (50 Hz) component and steady-state behavior before and after the fault.

Overall, the SLG fault produces localized transient energy mainly concentrated in the first two decomposition levels (D1–D2).

2) Line-to-Line (LL) Fault

Fig. 8. Five-level db5 DWT–MRA decomposition of voltage signals under LL fault conditions.

Fig. 9. Five-level db5 DWT–MRA decomposition of current signals during LL fault conditions.

Fig. 10. Three-phase wavelet decomposition results for LL faults.

Observations:

- Increased disturbance magnitude compared with SLG faults
- Energy distribution across D1–D4 bands
- Strong electromagnetic interaction between the two faulted phases

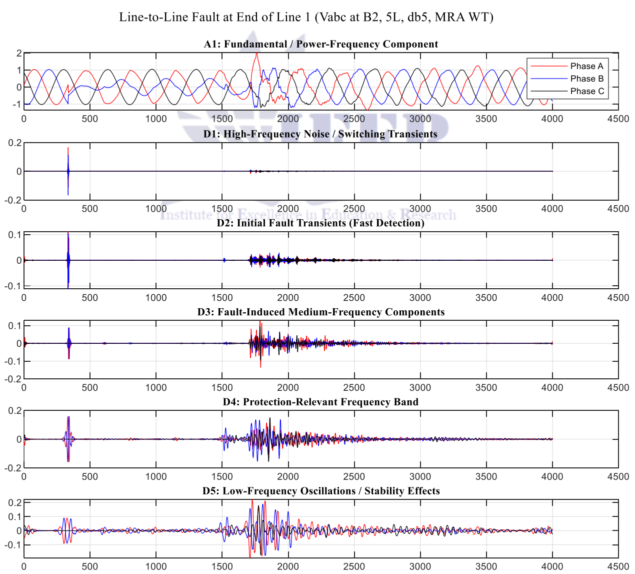

Fig. 8. Five-level db5 DWT–MRA decomposition of phase voltage signals under a four-cycle line-to-line (L–L) fault on Line 1, demonstrating increased transient energy distribution across

5) Decomposed Current Signal – L–L

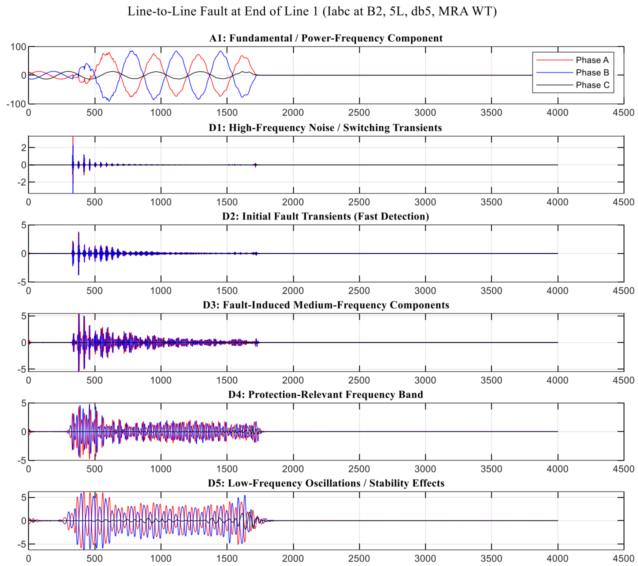

Fig. 9. **Five-level db5 DWT–MRA decomposition of phase current signals during a four-cycle L–L fault, showing pronounced high-frequency components in D1–D2 and enhanced medium-frequency oscillations in D3–D4.**

6) Three-Phase Decomposed Signals – L–L

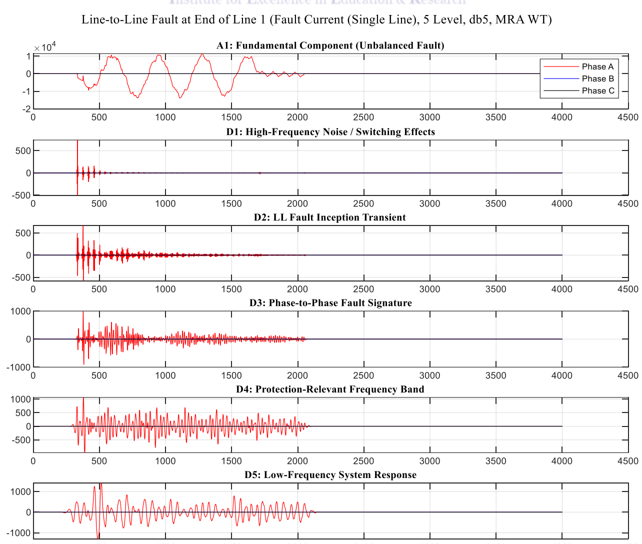

Fig. 10. **Five-level db5 DWT–MRA decomposition of three-phase signals under L–L fault conditions, indicating disturbance in two faulted phases with moderate spectral spread across decomposition levels.**

- D1 and D2:

High-frequency spikes are more pronounced than in SLG due to higher fault current magnitude and phase coupling effects.

- D3 and D4:

These levels show significant oscillatory behavior caused by electromagnetic interaction between the two faulted phases and the series compensation dynamics.

- D5:

Displays increased energy compared to SLG, reflecting enhanced low-frequency transient components.

- A5:

Shows distortion in the fundamental waveform during the fault interval.

The L–L fault exhibits greater distributed energy across D1–D4 compared to SLG, indicating higher transient severity.

3) Three-Phase-to-Ground (LLLG) Fault

Fig. 11. Voltage signal decomposition during LLLG fault.

Fig. 12. Current signal decomposition during LLLG fault.

Fig. 13. Three-phase decomposition signals during LLLG fault.

Observations:

- Highest transient spikes in D1–D2 bands
- Sustained oscillations across D3–D5 bands
- Uniform disturbance across all three phases

These results confirm that the LLLG fault produces the most severe disturbance among the studied fault types.

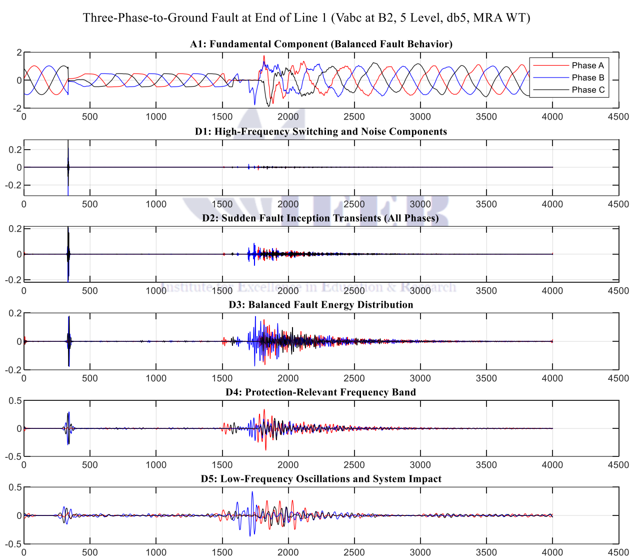

Fig. 11. **Five-level db5 DWT–MRA decomposition of phase voltage signals under a four-cycle three-phase-to-ground (3Φ–G) fault on Line 1, illustrating severe symmetrical disturbance and strong energy concentration across all detail levels.**

8) Decomposed Current Signal – 3Φ–G

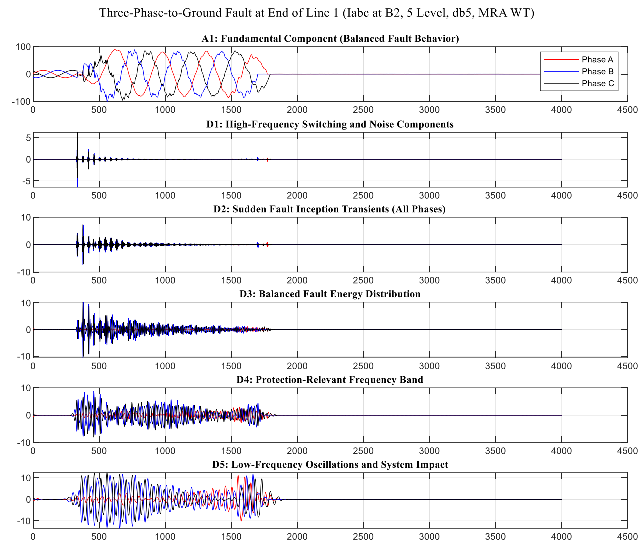

Fig. 12. **Five-level db5 DWT–MRA decomposition of phase current signals during a four-cycle 3Φ–G fault, showing dominant high-frequency spikes in D1–D2 and sustained oscillatory behavior in D3–D5.**

9) Three-Phase Decomposed Signals – 3Φ–G

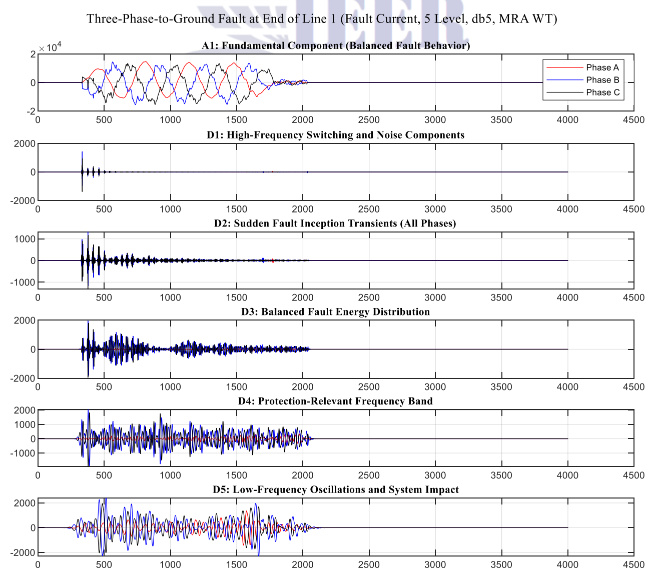

Fig. 13. **Five-level db5 DWT–MRA decomposition of three-phase voltage/current signals under symmetrical 3Φ–G fault conditions, highlighting maximum transient energy distribution and uniform disturbance across all phases.**

- D1 and D2:

These components exhibit the highest magnitude spikes among all fault types. The abrupt symmetrical short-circuit condition generates intense high-frequency components at fault inception.

- D3 and D4:

Significant oscillatory content is observed due to large fault current and system response. These components remain elevated throughout the fault duration.

- D5:

Shows substantial low-frequency transient energy, reflecting strong system-wide disturbance.

- A5:

Displays considerable deviation from steady-state due to symmetrical voltage collapse during the fault.

Compared to SLG and L–L faults, the 3Φ–G fault distributes higher energy across all decomposition levels, particularly D1–D3, confirming its maximum severity.

5.4 Comparative Interpretation of db5 Level-5 Decomposition

The five-level db5 DWT–MRA decomposition clearly differentiates fault types based on transient energy distribution across frequency bands.

The high-frequency detail coefficients (D1–D2) are particularly effective for early fault detection, while D3–D5 provide valuable information for fault classification and severity assessment.

5.5 Interpretation across Wavelet Bands

Table II. Interpretation with D1-D5 phyisical meaning and protection significance

Band	Physical Meaning	Protection Significance
D1	Fault inception transients	Early fault detection
D2	Fast electromagnetic disturbances	Disturbance identification
D3	Dominant oscillatory dynamics	Best classification feature
D4	Sub-synchronous resonance dynamics	Robust discrimination
D5	Low-frequency system response	Pattern consistency
A5	Fundamental system behavior	Severity estimation

5.6 Energy Distribution of Wavelet Coefficients

Table III. Energy distribution across wavelet detail coefficients for different fault types.

Fault Type	D1	D2	D3	D4	D5
SLG	High	Moderate	Low	Low	Minimal
LL	High	High	Moderate	Low	Minimal
LLLG	Very High	High	Moderate	Moderate	Low

The results clearly show that high-frequency coefficients (D1–D2) are most effective for fault detection, while D3–D5 provide useful information for fault classification.

5.7 Feature Extraction from Wavelet Coefficients

To enable machine-learning classification, statistical parameters were extracted from the wavelet coefficients.

Extracted features include:

Energy

Mean

Standard Deviation

RMS

Entropy

These features convert the wavelet coefficients into compact discriminative feature vectors suitable for AI classifiers.

Key observations:

Energy: Highest for three-phase faults.

Standard deviation: Indicates increased dispersion during faults.

Entropy: Reflects nonlinear signal complexity.

5.8 AI-Based Fault Classification Performance

Three neural network models were evaluated:

Table IV. AI characteristics and advantages

Network	Characteristics	Advantages
LP	Feedforward network with backpropagation	Strong nonlinear learning capability
RBF	Radial basis neurons	Fast convergence and transient sensitivity
PNN	Probabilistic classification	Very high accuracy for multi-class problems

Classification Accuracy

Table V. Comparative classification accuracy of AI models

Classifier	Training Accuracy	Testing Accuracy	Convergence Speed
MLP	97.2%	96.8%	Moderate
RBF	95.6%	94.2%	Fast
PNN	99.1%	98.5%	Very Fast

The PNN classifier achieved the highest accuracy, while the RBF network demonstrated faster training performance.

6. DISCUSSION

The simulation and analytical results obtained in this study demonstrate the effectiveness of the proposed Wavelet–AI-based framework for fault detection and classification in series-compensated transmission systems.

The results clearly indicate that series compensation significantly influences the transient response of the transmission system during fault conditions. In particular, the presence of the series capacitor introduces pronounced high-frequency transient components immediately after fault inception, which are difficult to capture using conventional phasor-based protection techniques.

The application of the Discrete Wavelet Transform (DWT) using the Daubechies-5 (db5) wavelet successfully isolates these transient signatures across multiple frequency bands. The multi-resolution decomposition enables clear identification of disturbance characteristics within the detail coefficient bands (D1–D5).

Statistical features extracted from the wavelet coefficients provide strong discriminative information for fault classification. These features effectively capture variations in signal energy, magnitude dispersion, and randomness associated with different fault types.

The comparative evaluation of three neural-network architectures demonstrates that artificial intelligence techniques can reliably classify transmission-line faults based on wavelet-derived features. Among the investigated classifiers, the Probabilistic Neural Network (PNN) achieves the highest classification accuracy, while the Radial Basis Function (RBF) network demonstrates faster convergence behavior during training.

Overall, the results confirm that the integration of wavelet-based signal processing with artificial intelligence classifiers provides a powerful and reliable approach for intelligent protection of series-compensated transmission networks. The proposed Wavelet–AI framework therefore provides a promising intelligent protection solution for modern FACTS-compensated and smart-grid transmission systems.

7. CONCLUSION

This study presented an advanced Wavelet–Artificial Intelligence (AI)-based fault classification framework for improving the protection performance of series-compensated transmission systems. A detailed transmission system model incorporating series capacitor compensation and mid-line fault application was developed in MATLAB Simscape Electrical to investigate the transient behavior of the system under different fault conditions.

The proposed methodology combines multi-resolution signal decomposition using the Daubechies-5 (db5) Discrete Wavelet Transform (DWT) with statistical feature extraction and comparative neural-network-based classification using Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Probabilistic Neural Network (PNN) models.

The main findings of this study can be summarized as follows:

1. Series compensation significantly increases high-frequency transient components during fault initiation, which contain important diagnostic information for fault detection.
2. The db5-based DWT multi-resolution decomposition effectively isolates transient signatures within different frequency bands, particularly within the lower-level detail coefficients.
3. Statistical features extracted from wavelet coefficients provide clear separability between SLG, LL, and LLLG fault conditions.
4. Among the evaluated classifiers, the Probabilistic Neural Network (PNN) achieved the highest classification accuracy (98.5%) and demonstrated superior classification capability compared with MLP and RBF networks.
5. The proposed Wavelet–AI framework provides reliable and robust fault discrimination performance under varying compensation levels and fault resistance conditions.

Overall, the integration of wavelet-based time–frequency signal analysis with intelligent classification techniques offers an effective solution for enhancing protection reliability in series-compensated transmission systems. The developed framework contributes to the advancement of intelligent protection schemes for modern FACTS-integrated and smart-grid transmission networks.

8. REFERENCES

[1] P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares et al., “Definition and classification of power system stability,” IEEE Trans. Power Syst., vol. 19, no. 3, pp. 1387–1401, Aug. 2004.

[2] IEEE Subsynchronous Resonance Working Group,“First benchmark model for computer simulation of subsynchronous resonance,”IEEE Trans. Power App. Syst., vol. PAS-96, no. 5, pp. 1565–1572, Sept. 1977.

[3] A. Ghorbani and M. Joorabian,“Impact of series compensation on the performance of distance protection,” IEEE Trans. Power Del., vol. 27, no. 2, pp. 756–763, Apr. 2012.

[4] A. Ghorbani and M. Joorabian,“Protection challenges in series-compensated transmission lines,”IEEE Trans. Power Del., vol. 35, no. 3, pp. 1456–1464, Jun. 2020.

[5] IEEE Power System Relaying Committee,“Performance of distance relays on series-compensated transmission lines,”IEEE PES Report, 2019.

[6] I. Daubechies,*Ten Lectures on Wavelets*. Philadelphia, PA, USA: SIAM, 1992.

[7] S. Mallat,“A theory for multiresolution signal decomposition: The wavelet representation,”IEEE Trans. Pattern Anal. Mach. Intell., vol. 11, no. 7, pp. 674–693, Jul. 1989.

[8] S. Mallat,*A Wavelet Tour of Signal Processing: The Sparse Way*, 3rd ed.Burlington, MA, USA: Academic Press, 2009.

[9] S. Haykin,*Neural Networks and Learning Machines*, 3rd ed.Upper Saddle River, NJ, USA: Pearson, 2009.

[10] H. Livani and C. Y. Evrenosoglu,“A machine learning and wavelet-based fault classification method for transmission lines,”IEEE Trans. Smart Grid, vol. 6, no. 3, pp. 1231–1239, May 2015.

[11] S. Jamali and A. Bahmanyar,"Wavelet-based fault detection in transmission lines,"Int. J. Electr. Power Energy Syst., vol. 104, pp. 309–318, Jan. 2019.

[12] M. Kezunovic,"Smart fault location for transmission networks,"IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1231–1242, Mar. 2020.

[13] Y. Zhang, J. Li, and H. Wang,"Intelligent fault classification of transmission lines using wavelet transform and neural networks,"IEEE Access, vol. 9, pp. 84521–84533, 2021.

[14] S. Mishra, C. N. Bhende, and B. K. Panigrahi,"Detection and classification of power quality disturbances using signal processing techniques,"IEEE Trans. Power Del., vol. 36, no. 5, pp. 2895–2904, Oct. 2021.

[15] A. R. Moradi and M. H. Vaziri,"Wavelet-based feature extraction for power system fault detection," Electr. Power Syst. Res., vol. 202, 2022.

[16] Y. Zhang, L. Wang, and H. Chen,"Entropy-based analysis of transient disturbances in power systems using wavelet transform,"Int. J. Electr. Power Energy Syst., vol. 140, 2022.

[17] J. Moody and C. J. Darken,"Fast learning in networks of locally tuned processing units,"Neural Comput., vol. 1, no. 2, pp. 281–294, 1989.

[18] D. F. Specht,"Probabilistic neural networks,"Neural Netw., vol. 3, no. 1, pp. 109–118, 1990.

[19] MathWorks,*Simscape Electrical User's Guide*. Natick, MA, USA: MathWorks, 2023.

[20] W. Akram, A. P. Memon, Z. M. Alaas, M. I. Jamali, and M. A. Koondhar,"Optimal coordinative design of SVC and PSS with the application of neural network to improve power system transient stability,"Ain Shams Eng. J., vol. 16, 103790, 2025.

[21] A. P. Memon, G. M. Bhutto, M. Memon, J. Lashari, M. Ibrahim, and J. Aslam,"A robust wavelet–ANN framework for noise-aware detection and classification of power quality disturbances,"Spectrum Eng. Sci., vol. 4, no. 2, 2026.

[22] A. P. Memon, W. Akram, M. M. Shaikh, K. Hussain, M. H. Qureshi, and L. A. Memon,"Adaptive energy entropy weighted feature ranking framework for hybrid power quality disturbance classification using multi-resolution DWT–ANN,"Spectrum Eng. Sci., vol. 4, no. 2, 2026.

[23] B. K. Panigrahi and V. R. Pandi,"Optimal feature selection for classification of power system disturbances using wavelet transform,"IEEE Trans. Power Del., vol. 26, no. 4, pp. 2172–2180, Oct. 2011.

[24] A. Abur and A. G. Expósito,*Power System State Estimation: Theory and Implementation*.New York, NY, USA: CRC Press, 2004.

[25] M. Kezunovic, J. J. Gu, and S. M. McKenna,"Digital protection and data analysis in modern power systems," Proc. IEEE, vol. 99, no. 1, pp. 15–30, Jan. 2011.