SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I6P111

Volume 12 Issue 6, 136-145, June 2025

Original Article

Faults Identification and Classification in Power Systems Using Integrated Wavelet Transform and RBFNN Approach

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Received: 07 April 2025 Revised: 09 May 2025 Accepted: 08 June 2025 Published: 30 June 2025

Abstract - *This research presents an integrated Wavelet Transform and RBFNN approach for identifying and classifying power system faults. The RBFNN is trained to output values corresponding to specific fault classes based on WT-derived features, where a predicted value near 1 indicates a fault on a particular phase or Ground, and a value near 0 indicates no fault. The novelty of this work lies in the application of RBFNN with these features, aiming for improved performance over common Artificial Neural Network approaches. Various short-circuit faults were simulated on an IEEE 30-bus system using PSCAD. Fault parameters like location and resistance were varied to create 2541 scenarios. Discrete Wavelet Transform extracted features from phase and ground currents, comparing Daubechies 4 (dB4) and Symlet4 (sym4) wavelets at decomposition levels 1, 2, and 3. The RBFNN was trained with 90% of the data and tested on the remaining 10%. The outputs of the RBFNN are continuous values intended to approximate these binary (0 or 1) targets, and their proximity is measured by Mean Squared Error (MSE). Results showed that the dB4 wavelet at decomposition level 3 provided the best performance, achieving MSE values below the 10^{-5} threshold for all phases (Phase A: 4.59621×10^{-8}, Phase C: 2.7304×10^{-8}). These low MSE values indicate high accuracy in the RBFNN's output regressing to the target binary vectors, thereby effectively classifying the fault types. This approach showcases an effective technique for identifying faults and then categorizing them.*

Keywords - *Transmission lines, Radial basis function Neural network, Signal processing, Wavelet transformation, PSCAD.*

1. Introduction

Power transmission is essential for transporting electrical energy from generation sources to consumers. These transmission systems are the pillar of dependable power delivery; however, they are vulnerable to disturbances that can significantly impact consumers and utility providers. Transmission lines are primarily categorized into overhead and underground lines. Overhead lines are often preferred due to their lower maintenance costs and greater ease of fault detection [1]. Faults in transmission systems are often characterized as short or open-circuit. [2, 3]. Short-circuit issues are one of the most severe risks. They indicate direct contact between phases or between a phase and the earth, leading to significant current flows that can interrupt power delivery, damage critical system components, and compromise overall system stability. Power systems may encounter a variety of such faults. One-phase line grounding is the most frequent kind of electrical fault. Line-to-line and line-to-line-to-ground faults are two more prevalent types besides single-line-to-ground faults. The three-phase short circuit is the most severe due to its balanced nature, which often simplifies analysis [4]. Various methods exist to mitigate power system faults, including modifying transients with earth wires, resistance switching, and diverting surges using devices like rod gaps and lightning arresters coordinated by switchgear and protective relays [4]. The critical first step remains the rapid and accurate detection and classification of these faults [5]. Delays or inaccuracies in this initial stage can exacerbate the impact of faults, leading to wider outages and increased repair costs. Methodologies for fault identification and classification have seen significant evolution. Early traditional methods that relied on reactive power measurements were often hampered by propagation delays, which reduced their accuracy [6]. Fourier Transform (FT) techniques were introduced, proving effective for stationary signals. When working with non-stationary signals, whose frequency components fluctuate over time—a common feature of fault transients—their usefulness was constrained. [7]. Although it analyzed signal segments, the Short Time Fourier Transform (STFT) improved; however, its time-frequency resolution was still constrained by its fixed window size. [5]. Consequently, Wavelet Transform (WT) became a more effective instrument praised for its better capacity in time-frequency localization and the study of transient disturbances [8]. Building on WT's strengths, researchers such as Ali and Sinha (2023) and Aryaguna et al. (2021) effectively used WT in conjunction with Artificial Neural Networks (ANNs) and other computational learning systems for fault classification, so proving its efficacy in analyzing transient signals acquired during fault events. [9, 10].

Notwithstanding these developments, more research is needed to examine and validate alternative neural detection and classification methods fully. The authors concluded that network architectures combined with WT for possible methodology could improve power system reliability by improving fault classification performance. While WT-ANN approaches [9, 10] have shown promise, the unique characteristics of other neural networks might offer advantages in terms of training efficiency, generalization capabilities, or accuracy for specific fault signatures.

This research addresses this gap by focusing on how faults in power systems are detected and categorized using a combination of Wavelet Transform and a Radial Basis Function Neural Network (RBFNN). This work's novelty lies in integrating and applying RBFNN with WT-derived features for power system fault analysis. Unlike the more commonly adopted ANN structures explored in [9, 10], RBFNNs possess distinct architectural advantages, such as simpler network structures and potentially faster convergence, which could prove beneficial for the rapid and accurate classification of complex fault patterns. An IEEE 30-bus test system is used in this study to model and simulate various short-circuit faults. Features from the fault signals are extracted using WT, which are then used to train and test an RBFNN. The RBFNN is trained to classify these faults by minimizing the MSE between its continuous output and target vectors representing predefined fault categories (0 and 1). The research addresses key questions about optimal fault identification strategies, effective feature extraction via WT for RBFNN, and robust model training for accurate fault classification.

The scope is focused on the IEEE 30-bus power system simulated using PSCAD software, with WT for feature extraction and RBFNN for the classification task. Classification performance is inferred from the MSE of the RBFNN's continuous outputs against target class vectors, where a low MSE indicates the predicted outputs are close to the ideal binary (0 or 1) values representing the fault state of each phase and Ground. The expected outcomes include contributions to scientific literature through publications and a comprehensive thesis report. This research is anticipated to advance fault detection methodologies by presenting a rigorously evaluated WT-RBFNN framework, demonstrating how low MSE in regression can effectively translate to accurate fault classification, thereby providing a valuable reference and a potentially improved tool for researchers and practitioners in power system analysis, distinct from existing WT-ANN paradigms.

2. Literature Review

2.1. Prior Research

A few researchers have conducted preceding studies to develop fault classification methods in power systems. A prior study by Ali and Sinha (2023) [9] focused on detecting and categorizing faults on transmission lines using Wavelet Transform. They developed a simulation model to analyze various fault types, applying the Wavelet Transform to current signals and extracting features via wavelet packet decomposition. Their findings showed precise fault classification and detection. The authors concluded that real-time implementation of this methodology could improve power system reliability. The method's reliance on threshold values necessitating system-specific determination was one of its main limitations. They recommended using sophisticated computational techniques in future research to get around this restriction, employing technologies such as adaptive neuro-fuzzy inference systems and artificial neural networks.

Aryaguna et al. (2021) [10] studied the simulation of power quality disturbances in distribution lines. Both typical signals and various sag variations were included in the simulated disturbances. The hidden layer of this study's Artificial Neural Network (ANN) used a 5x5 neuron configuration. The outcomes demonstrated that ANN could detect fault signals with 100% accuracy.

By combining Wavelet Transform with a Radial Basis Function Neural Network (RBFNN), Prasanth and Srinivas (2022) [11] proposed a fault identification and classification technique for electrical systems. Seeking to get beyond the restrictions of using wavelet transform alone, such as reliance on threshold values, this work obtained detailed coefficients of various fault types using Discrete Wavelet Transform (DWT), which the RBFNN then used to detect and classify. With RBFNN outputs closely matching the real fault conditions without depending on predefined threshold values, their MATLAB Simulink verification results revealed that this combined approach successfully identified and classified three-phase faults.

Sundararaman and Jain (2023) [12] proposed an intelligent Wavelet Transform (WT)-based method for identifying and categorizing problems in electrical power transmission networks. This work employed a member of the Daubechies wavelet family, the Daubechies 4 (db4) wavelet, To examine phase and ground currents detail coefficients. Its primary focus was to accurately identify and categorize faults by observing significant differences in these maximum detail coefficients when the system fails. It provided a more suitable approach for analyzing fast electromagnetic transients than methods that require extensive training, such as neural networks or fuzzy logic. Tests employing a standard IEEE 5-Bus system (modeled in MATLAB Simulink) verified that detailed wavelet coefficients could detect and identify fault-related signals.

According to the literature review above, power systems have extensively used artificial neural network-based algorithms, Wavelet Transform, and other signal processing methods for classifying and detecting faults. However, there are ways to improve the accuracy and efficiency of these systems by integrating different methodologies and refining the parameters utilized in data processing and fault categorization.

3. Methodology

This study looks into A way to identify and categorize different types of power system faults on the IEEE 30 Bus system that integrates a Radial Basis Function Neural Network (RBFNN) with Wavelet Transform. Phase-to-phase, three-phase, and single-phase-to-ground faults were among the faults examined. RBFNN is trained to provide a vector representing each phase's fault status (a, b, c) and Ground (g), with '1' indicating a fault and '0' indicating no fault on that specific component.

The success of the classification is determined by how closely the RBFNN's continuous output values resemble these binary objectives, with a low Mean Squared Error (MSE) indicating accurate classification, as shown in Figure 1.

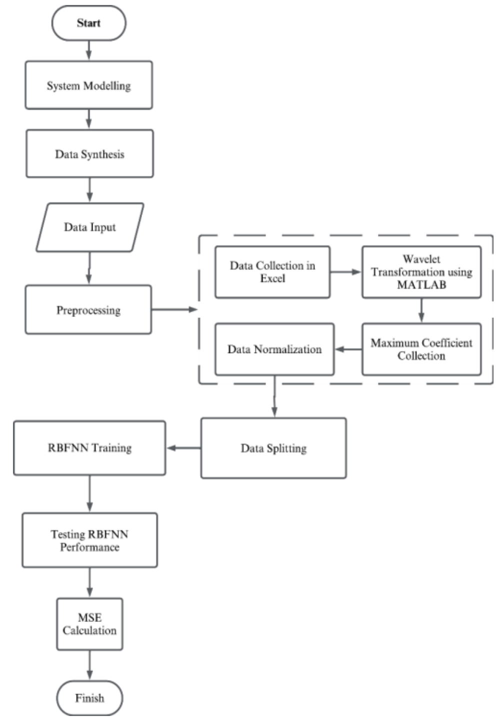

Fig. 1 Research flowchart

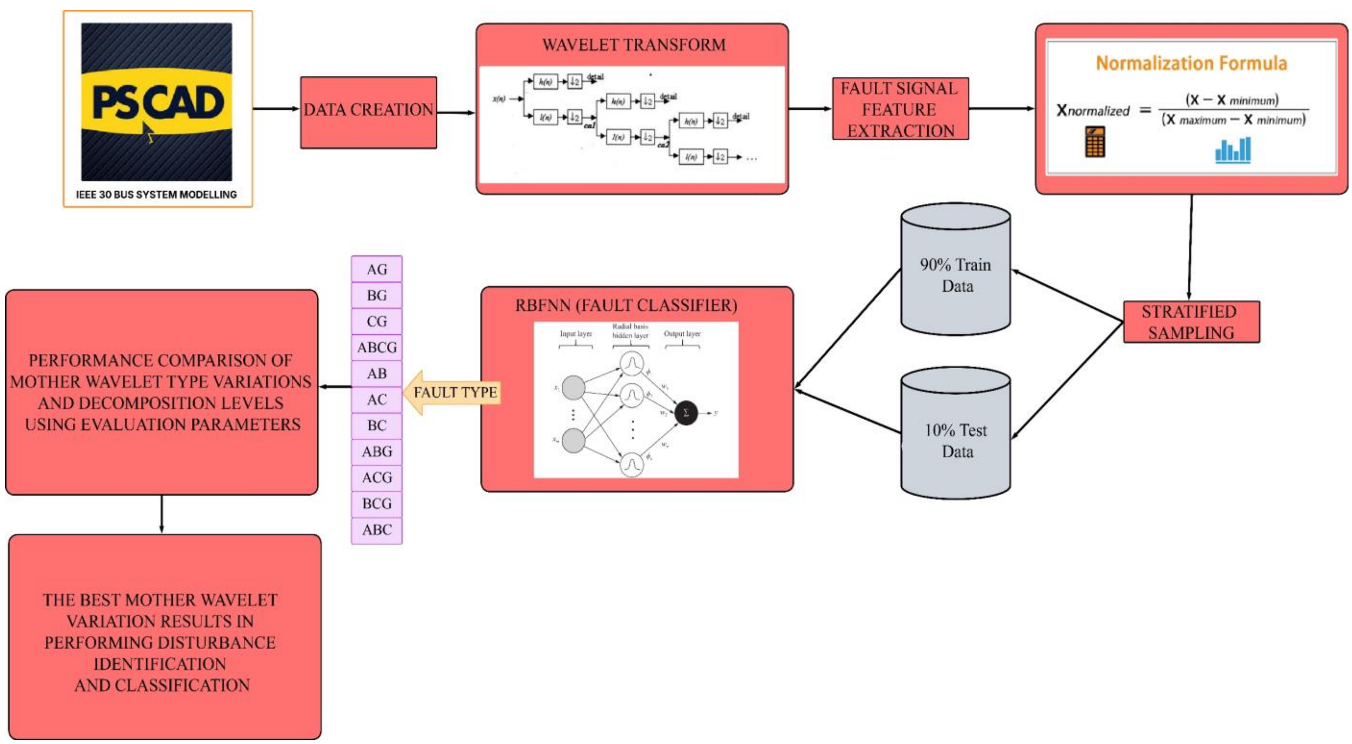

Fig. 2 Identification & classification block diagram

The methodology consists of defined processes that range from data collection and preprocessing to model training and performance evaluation. Figure 2 illustrates the overall block diagram for the identification and classification process. The diagram shows fault types as inputs ultimately classified by the RBFNN. The RBFNN (Fault Classifier) block processes input features to produce output vectors. The target outputs for the RBFNN are structured to represent specific fault types (ag, bg, cg, ab, ac, bc, abc, abcg, which correspond to combinations of 0 and 1 across the phase and ground outputs).

The performance evaluation relies on comparing the RBFNN's predicted output vectors to these binary target vectors using MSE.

3.1. Data Generation and Characteristics

Fault data was generated by modeling the IEEE 30 Bus test system using PSCAD V5.0.2. The simulations were designed to create a comprehensive dataset encompassing a variety of fault conditions. The specific fault types simulated include single-line-to-ground faults (a-g, b-g, c-g), line-to-line faults (ab, ac, bc), and three-line faults, including three-line-to-ground (abc, abc-g), as outlined in the study's aims and represented in the fault type inputs shown in the block diagram.

To ensure a diverse dataset reflective of real-world scenarios, key parameters were varied during the simulations:

- Fault location: Faults were modeled at different locations along the transmission lines 0%, 50% and 100% of each transmission line in the IEEE 30 Bus.
- Fault Resistance: 0.01 □ and 0.1 □□
- Sampling Rate: 50kHz.

This process resulted in 2541 unique fault scenarios, forming the initial raw dataset for feature extraction.

3.2. Feature Extraction using Wavelet Transform

Discrete Wavelet Transform (DWT) extracted features from the generated fault signals. For this study, a comparative analysis of different Mother Wavelets was conducted to identify the most effective one for fault feature extraction. The Daubechies-4 (dB4) and Symlet4 (sym4) Mother Wavelets were specifically investigated. Features were extracted by focusing on the maximum coefficients from the detailed levels of the wavelet transformation for each selected mother wavelet. The study particularly investigated decomposition levels 1, 2, and 3 for these wavelets to determine the optimal level for classification accuracy. The extracted features from phase currents and ground currents served as the input vectors for the RBFNN model. Each fault case was thus represented by a feature vector of dimension maximum detailed coefficient of the phase currents and ground current.

3.3. Dataset Preprocessing and Splitting

Following feature extraction, the dataset of 2541 samples was prepared for the neural network using Radial Basis Functions (RBFNN). Regarding categorization, target output vectors were generated for each fault scenario. These vectors have four elements: phase a, phase b, phase c, and Ground.

Every component has a binary value assigned to it: "1" if the fault involves the corresponding Ground or phase and '0' otherwise. The RBFNN is trained to regress these target vectors, meaning its continuous outputs should ideally be close to these 0 or 1 values.

- Normalization: To optimize the RBFNN training process, the extracted features were normalized using min-max scaling.
- Stratified Sampling: The dataset was separated into training and testing portions using stratified sampling after normalisation. This approach was selected to ensure that every fault type maintained a proportional representation across both subsets, which is vital for developing a dependable model and conducting an impartial evaluation.
- Dataset Composition: The dataset was partitioned such that 90%, amounting to 2287 samples, was used for training the RBFNN, while the other 10%, or 254 samples, was kept for testing the network's performance.

4. Results and Discussion

Mean Squared Error (MSE) is used to assess the effectiveness of RBFNN training and testing. The MSE quantifies how close the RBFNN's continuous predicted outputs (for each phase and Ground) are to the binary (0 or 1) actual target values that define the fault class. A lower MSE indicates a more accurate classification.

4.1. RBFNN Training Results dB4 and Sym4 Level 1

The training results of the RBFN using Mother Wavelet Daubechies 4 (dB4) and Symlet 4 (Sym4) at level 1 are presented in Figure 3 and Figure 4 . The training process was completed with a maximum of 1000 epochs, a spread value of one, and a goal Mean Squared Error (MSE) of 0.0001. The performance of the model was assessed using the training dataset.

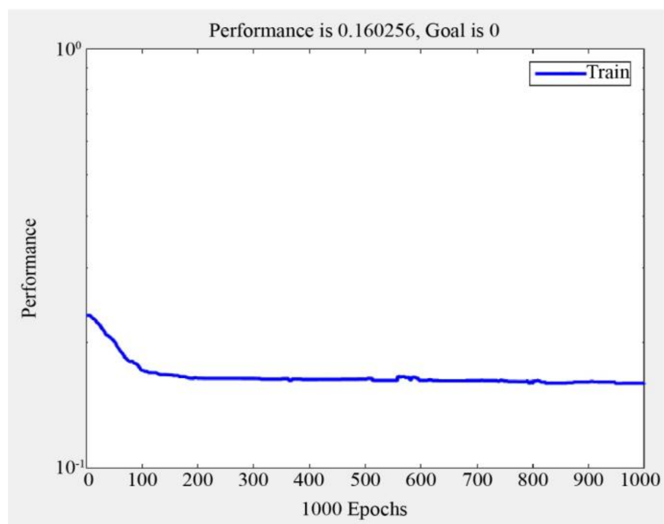

Fig. 3 Training MSE of RBFNN using dB4 Level 1

Figure 3 shows the training results using the dB4 wavelet, illustrating the network's capacity to learn patterns from the training dataset. The convergence behavior and final MSE demonstrate the usefulness of the specified parameters in optimizing the model.

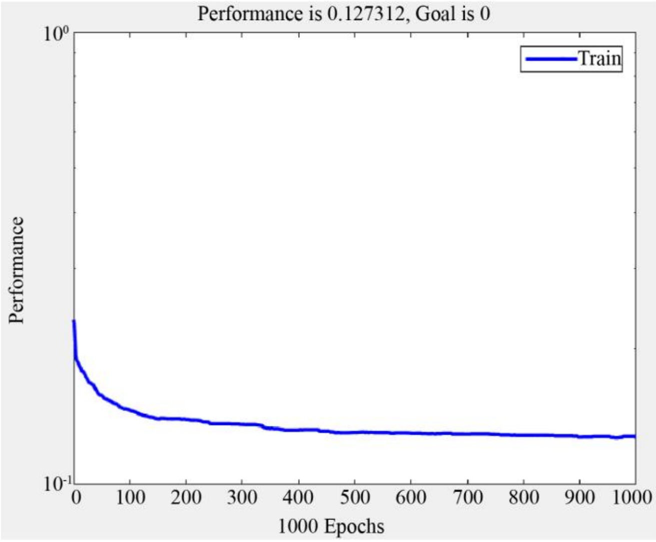

Fig. 4 Training MSE of RBFNN using Sym4 Level 1

Figure 4 shows the training results using the Sym4 wavelet, illustrating the network's capacity to learn patterns from the training dataset. The convergence behavior and final MSE demonstrate the usefulness of the specified parameters in optimizing the model.

4.2. RBFNN Training Results dB4 and Sym4 Level 2

Figure 5 and 6 show the training results of the RBFNN with the Mother Wavelet Daubechies 4 (dB4) and Symlet 4 (Sym4) at level 2. The training process was completed with a maximum of 1000 epochs, a spread value of one, and a goal Mean Squared Error (MSE) of 0.0001. The training dataset was used to evaluate the model's performance.

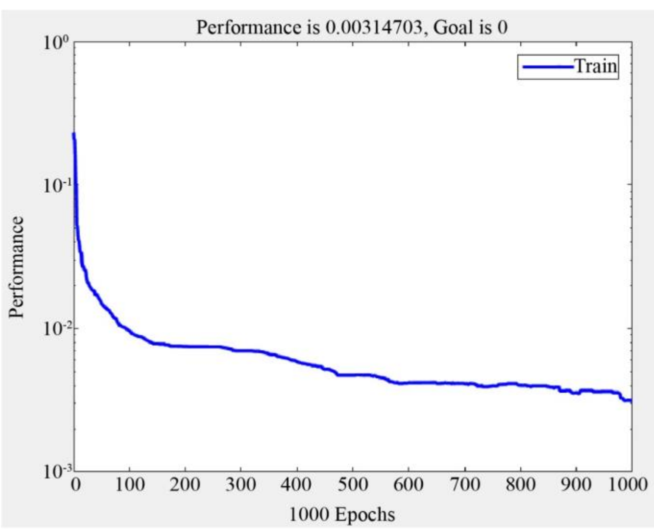

Fig. 5 Training MSE of RBFNN using dB4 Level 2

Figure 5 shows the Mean Squared Error (MSE) values obtained while teaching an RBFNN using Mother Wavelets Daubechies 4 (dB4) at level 2. At epoch 1000, with a spread value of 1, the MSE of the RBFNN was 0.00314703.

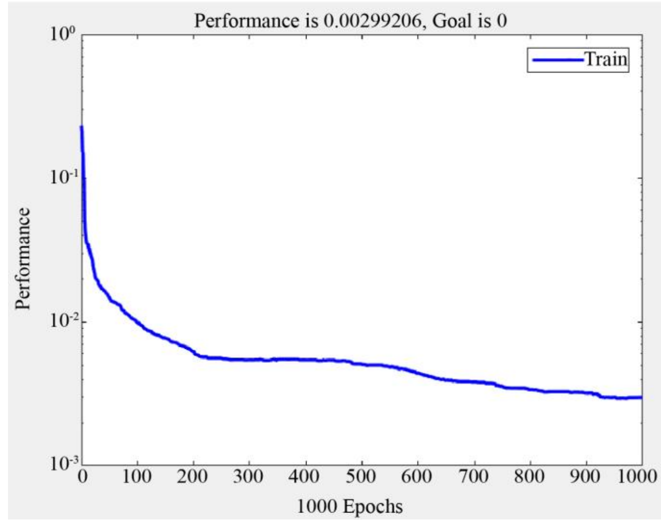

Fig. 6 Training MSE of RBFNN using Sym4 Level 2

Figure 6 shows the Mean Squared Error (MSE) values obtained while teaching an RBFNN using Mother Wavelets Symlet 4 (Sym4) at level 2. At epoch 1000, with a spread value of 1, the MSE of the RBFNN was 0.00299206. The results show that as the epochs increase, the MSE value decreases, proving the network's potential to improve its performance over time. This pattern indicates that further training rounds benefit the model by lowering error and improving accuracy.

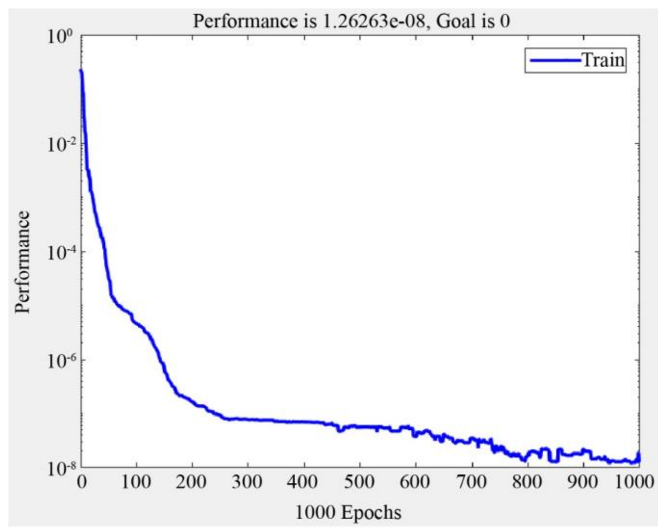

Fig. 7 Training MSE of RBFNN using dB4 Level 3

4.3. RBFNN Training Results dB4 and Sym4 Level 3

The training results of the Radial Basis Function Neural Network (RBFNN) using the Mother Wavelet Daubechies 4 (dB4) and Symlet 4 (Sym4) at level 3 are presented in Figure 7 and Figure 8. The training process was conducted with a maximum of 1000 epochs, a spread value of 1, and a target Mean Squared Error (MSE) of 0.0001. The performance of the model was evaluated using the training dataset. Figure 7 shows the Mean Squared Error (MSE) values produced while teaching an RBFNN using Mother Wavelets Daubechies 4 (dB4) at level 3. At epoch 1000, with a spread value of one, the MSE of the RBFNN was 1.26263e-08.

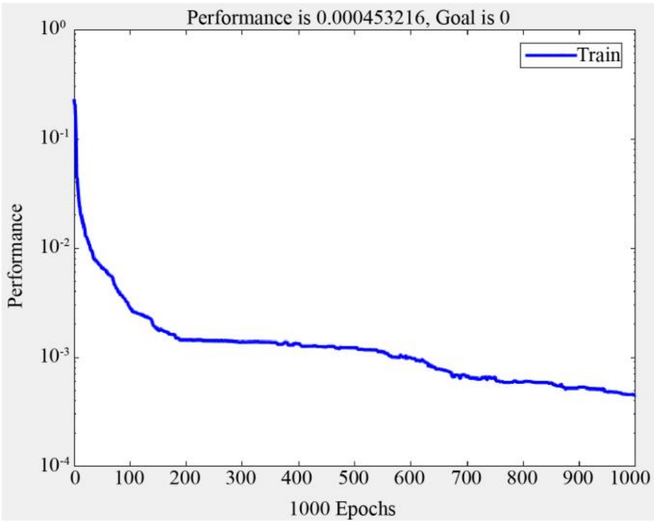

Fig. 8 Training MSE of RBFNN using Sym4 Level 3

Figure 8 shows the Mean Squared Error (MSE) values obtained while teaching an RBFNN using Mother Wavelets Symlet 4 (Sym4) at level 3. At epoch 1000, with a spread value of one, the MSE of the RBFNN was 0.000453216. The results show that as the epochs increase, the MSE value decreases, proving the network's potential to improve its performance over time.

4.4. RBFNN Testing Performance dB4 and Sym4 Level 1

The 'Actual Values' in the following tables represent the target binary outputs (0 for no fault, 1 for fault) for each phase (and Ground), indicating the actual state for a specific fault type. The 'Predicted Values' are the continuous outputs from the RBFNN, which ideally should be close to these binary targets for accurate classification. The Actual vs. predicted values for the Mother Wavelet dB4 and Sym4 at Level 1 in the testing data are presented in Table 1 to Table 2 and Table 4 to Table 5. In these tables, the First two columns after the data set represent the actual (target) values obtained from the testing dataset. Meanwhile, the subsequent 2 columns display the predicted (continuous output) values generated by the pre-trained RBFNN model.

Table 1. RBFNN phase A & B prediction results compared to the actual output values of mother wavelet dB4 level 1

Set	Actual Value Phase A	Actual Value Phase B	Predicted Value Phase A	Predicted Value Phase B
1	0	1	0.807335	0.805473
2	1	1	-0.09262	1.217983
3	0	1	0.399593	0.742409
…	….	….	….	….
253	1	1	0.959038	0.305832
254	1	0	0.627438	0.649929

Table 2. RBFNN phase C & ground prediction results compared to the actual output values of mother wavelet dB4 level 1

Set	Actual Value Phase C	Actual Value Ground	Predicted Value Phase C	Predicted Value Ground
1	1	0	0.744476	0.244047
2	1	0	1.064831	0.462688
3	1	0	0.598675	0.655682
…	….	….	….	….
253	1	1	0.887829	0.562401
254	0	1	0.567593	0.634171

The Actual vs. predicted values for the Mother Wavelet dB4 at Level 1 in the testing data are presented in Table 1. To Table 2. In this table, the first two columns after the data set represent the actual values obtained from the testing dataset. Meanwhile, the subsequent 2 columns display the predicted values generated by the pre-trained RBFNN model. The MSE is first calculated for each phase (Phase A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

Table 3. MSE value for mother wavelet dB4 level 1

Group	Phase A	Phase B	Phase C	Ground
MSE	0.177678	0.187425	0.170585	0.158634

From Table 3, as can be seen, the highest MSE value for Phase A is 0.177678. This value, significantly higher than the predefined threshold of 10−5, suggests that the RBFNN's output for this phase does not consistently align closely with the target binary values, thereby indicating suboptimal classification performance for this configuration.

Table 4. RBFNN phase A & B prediction results compared to the actual output values of mother wavelet Sym4 Level 1

Set	Actual Value Phase A	Actual Value Phase B	Predicted Value Phase A	Predicted Value Phase b
1	1	1	1.023941	6.44E-01
2	1	1	0.836273	0.9687004
3	0	1	0.816162	9.18E-01
…	….	….	….	….
253	1	0	7.76E-01	0.4379959
254	1	1	0.152679	0.9912109

Table 5. RBFNN phase C & ground prediction results compared to the actual output values of mother wavelet Sym4 level 1

Set	Actual Value Phase C	Actual Value ground	Predicted Value Phase C	Predicted Value Ground
1	1	0	0.9750671	7.30E-01
2	0	0	2.30E-01	3.77E-02
3	1	0	0.4433212	2.07E-01
…	….	….	….	….
253	1	1	0.7442474	0.7030029
254	0	1	-0.058441	1.0557251

The Actual vs. predicted values for the Mother Wavelet Sym4 at Level 1 in the testing data are presented in Table 4 - Table 5. In this table, the first two columns after the data set represent the actual values obtained from the testing dataset. Meanwhile, the subsequent 2 columns display the predicted values generated by the pre-trained Radial Basis Function Neural Network (RBFNN) model.

The MSE is first calculated for each phase (phases A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

Table 6. MSE value for mother wavelet Sym4 Level 1

Group	Phase A	Phase B	Phase C	Ground
MSE	0.152682	0.150574	0.138027	0.122615

Table 6 shows that the highest MSE value in phase A is 0.152682, which is still significantly higher than the predefined threshold of 10−5, indicating a less accurate approximation of the target binary fault state.

4.5. RBFNN Testing Performance dB4 and Sym4 Level 2

The Actual vs. predicted values for the Mother Wavelet dB4 and Sym4 at Level 2 in the testing data are presented in Table 7 to Table 8 and Table 10 to Table 11. These tables compare the RBFNN's continuous predicted outputs against the binary (0 or 1) actual target values for each phase and Ground.

Table 7. RBFNN phase A & B prediction results compared to the actual output values of mother wavelet dB4 level 2

Set	Actual Value Phase A	Actual Value Phase B	Predicted Value Phase A	Predicted Value Phase B
1	1	1	0.9911	0.9845
2	1	1	1.0020	1.0027
3	0	1	0.0379	0.9907
…	….	….	….	….
253	1	0	1.0115	0.0585
254	1	1	1.0132	1.0157

Table 8. RBFNN phase C & ground prediction results compared to the actual output values of mother wavelet dB4 level 2

Set	Actual Value Phase C	Actual Value ground	Predicted Value Phase C	Predicted Value Ground
1	1	0	1.0221	-0.0001
2	0	0	-0.0007	0.0000
3	1	0	1.0171	-0.0001
…	….	….	….	….
253	1	1	0.9010	0.9999
254	0	1	-0.0008	1.0000

The MSE is first calculated for each phase (Phase A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

Table 9. MSE value for mother wavelet dB4 level 2

Group	Phase A	Phase B	Phase C	Ground
MSE	0.008949	0.005442	0.005883	0.000000

From Table 9, it can be observed that the highest MSE value in phase A is 0.008949. This is still significantly higher than the predefined threshold of 10−5, suggesting that the classification based on the proximity of predicted values to the binary targets (0 or 1) is not yet optimal.

Table 10. RBFNN phase A & B prediction results compared to the actual output values of mother wavelet Sym4 level 2

Set	Actual Value Phase A	Actual Value Phase B	Predicted Value Phase A	Predicted Value Phase B
1	1	0	1.000067	-1.14E-05
2	1	1	1.005067	1.008451
3	1	0	0.998966	6.06E-03
…	….	….	….	….
253	0	1	-2.1E-02	1.011227
254	0	1	-0.00106	0.985338

Table 11. RBFNN phase C & ground prediction results compared to the actual output values of mother wavelet Sym4 level 2

Set	Actual Value Phase C	Actual Value Ground	Predicted Value Phase C	Predicted Value Ground
1	1	0	1.000053	-2.98E-07
2	0	0	5.71E-01	3.51E-06
3	1	0	0.997959	-1.52E-06
…	….	….	….	….
253	1	1	-2.1E-02	1.011227
254	1	1	-0.00106	0.985338

The Actual vs. predicted values for the Mother Wavelet Sym4 at Level 2 in the testing data are presented in Table 10 - Table 11. The MSE is first calculated for each phase (phases A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

The MSE is first calculated for each phase (phases A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

Table 12. MSE value for mother wavelet Sym4 level 2

Group	Phase A	Phase B	Phase C	Ground
MSE	0.234892	0.051758	0.359282	9.87E-07

Table 12 shows that the highest MSE value in phase C is 0.359282, which is still significantly higher than the predefined threshold of 10−5, indicating a poorer match between predicted outputs and the actual binary fault states.

4.6. RBFNN Testing Performance dB4 and Sym4 Level 3

The Actual vs. predicted values for the Mother Wavelet dB4 and Sym4 at Level 3 in the testing data are presented in

Table 13 to Table 14 and Table 16 to Table 17. A low MSE in these results would mean the RBFNN's continuous outputs are very close to the target '0' or '1' values, signifying accurate fault classification.

Table 13. RBFNN phase A & B prediction results compared to the actual output values of mother wavelet dB4 level 3

Set	Actual Value Phase A	Actual Value Phase B	Predicted Value Phase A	Predicted Value Phase B
1	1	0	1.00020	-0.00007
2	1	1	0.99996	0.99998
3	1	0	0.99985	-0.00002
…	…..	….	….	….
253	0	1	-0.00002	1.00002
254	0	1	-0.00014	0.99999

Table 14. RBFNN phase C & ground prediction results compared to the actual output values of mother wavelet dB4 level 3

Set	Actual Value Phase C	Actual Value Ground	Predicted Value Phase C	Predicted Value Ground
1	1	0	0.99998	0.00000
2	0	0	0.00001	0.00000
3	1	0	1.00001	0.00000
…	….	….	….	….
253	1	1	1.00010	1.00000
254	1	1	1.00013	1.00000

The MSE is first calculated for each phase (Phase A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

Table 15. MSE value for mother wavelet dB4 level 3

Group	Phase A	Phase B	Phase C	Ground
MSE	4.59621E-08	3.86603E-08	2.7304E-08	9.19482E-12

Table 15 shows that the highest MSE value among the phases is for Phase A at 4.59621×10^{-8}. All individual phase and ground MSE values are well below the predefined threshold of 10−5. This extremely low MSE across all outputs signifies that the RBFNN's predicted vectors closely match the target binary vectors representing the true fault classes (i.e., predicted values are very near 0 or 1 as appropriate), indicating a high accuracy in classifying the fault types.

Table 16. RBFNN phase A & B prediction results compared to the actual output values of mother wavelet Sym4 level 3

Set	Actual Value Phase A	Actual Value Phase B	Predicted Value Phase A	Predicted Value Phase B
1	0	1	5.96E-04	1.003412
2	1	0	1.003788	-0.00243
3	1	0	9.98E-01	-1.2E-03
…	….	….	….	….
253	1	0	1.001135	-0.00027
254	1	0	1.001947	0.001321

Table 17. RBFNN phase C & ground prediction results compared to the actual output values of mother wavelet Sym4 level 3

Set	Actual Value Phase C	Actual Value Ground	Predicted Value Phase C	Predicted Value Ground
1	1	0	0.985884	-3.16E-06
2	1	0	9.94E-01	-9.6E-07
3	1	0	1.00E+00	-4.70E-07
…	….	….	….	….
253	0	1	3.81E-05	0.999998
254	0	1	0.014292	0.999986

The Actual vs. predicted values for the Mother Wavelet Sym4 at Level 3 in the testing data are presented in Table 16 to Table 17. The MSE is first calculated for each phase (phases A, B, C, and Ground) before determining the overall MSE, as shown in the following table. The MSE is first calculated for each phase (Phase A, B, C, and Ground) before determining the overall MSE, as shown in the following table.

Table 18. MSE value for mother wavelet Sym4 level 3

Group	Phase A	Phase B	Phase C	Ground
MSE	0.011125	0.004289	0.00409	1.9E-08

From Table 18, it can be observed that the highest MSE value in phase A is 0.011125. This is still significantly higher than the predefined threshold of 10−5, suggesting that this configuration does not classify faults (by predicting values close to the binary targets) as accurately as the dB4 level 3 configuration.

4.7. RBFNN Diagram and MSE Comparison

This section presents the RBFNN diagram and a comparative evaluation of the model's performance across the three defined levels. RBFNN diagram depicted in Figure 9 and the classification accuracy and Mean Squared Error (MSE) for each level are summarized in Table 19.

Figure 9, titled "RBFNN Diagram", illustrates the architecture of the Radial Basis Function Neural Network (RBFNN) used in the study, which processes 4 input features (representing maximum detailed coefficients from phase and ground currents Ia, Ib, Ic, Ig) through a hidden layer and an output layer to produce 4 output values. The hidden layer, or first "Layer" block, contains 1000 neurons, each employing a radial basis activation function (depicted as a Gaussian-like curve) with associated weights (W) and biases (b); the study also mentions a spread value of 1 was used for these neurons.

Following this, the second "Layer" block, the output layer, consists of 4 neurons that sum weighted inputs (W) with biases (b) and apply a linear activation function (depicted as a straight diagonal line). The final 4 outputs from this layer represent the continuous values corresponding to the fault status of each phase (a, b, c) and Ground (g), which are intended to approximate binary targets.

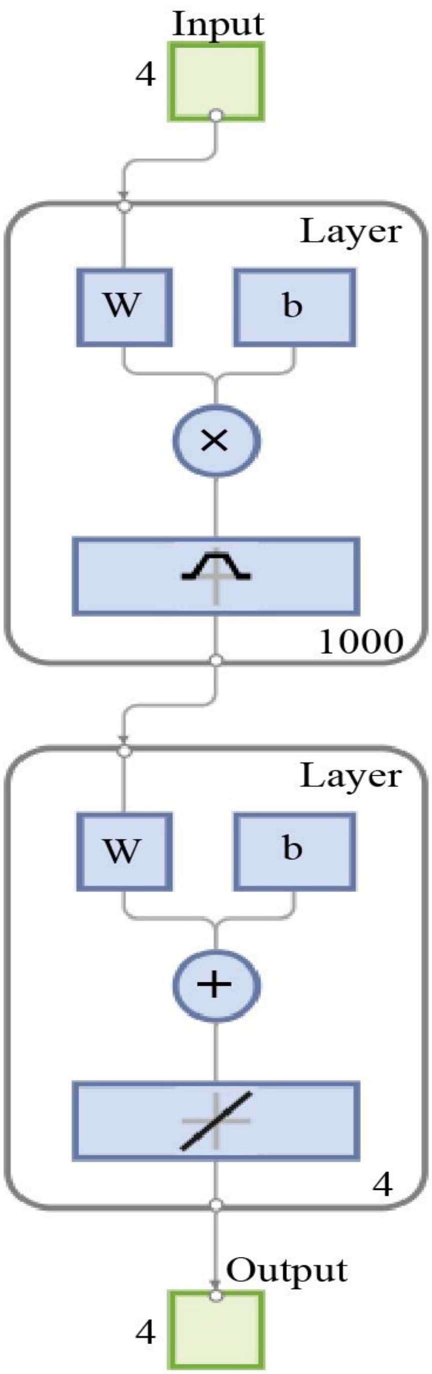

Fig. 9 RBFNN diagram

Table 19. MSE value for mother wavelet and level combination

Mother Wavelet	Level	Highest MSE
dB4	1	0.177678
dB4	2	0.008949
dB4	3	4.59621×10^{-8}
Sym4	1	0.152682
Sym4	2	0.359282
Sym4	3	0.011125

4.8. Comparative Discussion

The methodology and results presented in this research demonstrate notable advancements in identifying and classifying power system faults compared to several existing techniques reported in the literature. The successful combination of Discrete Wavelet Transform (DWT) using Daubechies 4 (dB4) mother wavelet at decomposition level 3 for feature extraction, followed by an RBFNN for classification, yielded exceptionally low Mean Squared Error (MSE) values. The best configuration achieved MSEs well below the predefined $10{-}5$ threshold for all phases and ground (e.g., Phase A: $4.59621 \times 10{-}8$, Phase C: $2.7304 \times 10{-}8$, and Ground: $9.19482 \times 10{-}12$). This high level of precision in mapping fault signatures, represented by binary target vectors (1 for fault, 0 for no fault per phase/Ground), to their respective classes, forms the basis of the improved performance.

5. Conclusion

This research successfully demonstrated the application of an RBFNN combined with Wavelet Transform (WT) for identifying and classifying faults in an IEEE 30-bus power system. The classification of fault types was achieved by training the RBFNN to produce output vectors whose elements (corresponding to phases A, B, C, and Ground) should regress to binary target values (1 for fault, 0 for no fault). Performance was evaluated based on the MSE between the predicted continuous outputs and these binary target vectors. The study systematically evaluated the performance of different mother wavelets (Daubechies 4 - dB4 and Symlet 4 - sym4) at various decomposition levels (1, 2, and 3) for feature extraction. The key findings indicate that the choice of mother wavelet and decomposition level significantly impacts the RBFNN's classification accuracy, as reflected in the MSE values. While level 1 and level 2 decompositions for both dB4 and sym4 wavelets resulted in MSE values that were still considerably higher than the predefined threshold of $10{-}5$ during testing (indicating less precise mapping of the RBFNN outputs to the correct binary fault class representation), the level 3 decomposition proved to be more effective.

Specifically, the RBFNN model utilizing features extracted with the dB4 mother wavelet at decomposition level 3 achieved the best performance. The MSE values for all phases (Phase A: $4.59621 \times 10{-}8$, Phase B: $3.86603 \times 10{-}8$, Phase C: $2.7304 \times 10{-}8$) and Ground (Ground: $9.19482 \times 10{-}12$) were well below the target threshold. This demonstrates the capability of this configuration to accurately predict fault conditions, with the low MSE signifying that the network's outputs closely align with the target binary values (0 or 1) for each fault class, thus effectively classifying them.

In contrast, while the sym4 wavelet at level 3 showed improved performance compared to its lower decomposition levels, its highest MSE in phase A (0.011125) still exceeded the desired threshold, implying less reliable classification for specific conditions with this wavelet, as its outputs did not approximate the binary targets as closely. Therefore, the study concludes that the combination of DWT using the dB4 mother wavelet at decomposition level 3 for feature extraction, followed by an RBFNN for classification, provides a robust and accurate method for identifying and classifying various fault types in power transmission systems. The classification is effectively performed as the RBFNN's continuous outputs, representing the fault state (fault/no-fault) of individual phases and Ground, closely match the actual binary fault conditions, evidenced by the low MSE values. This approach successfully overcame the limitations associated with reliance on predefined threshold values often seen in wavelet-only methods.

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