IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 8, May 2025
Impact Factor: 7.67

Detection and Classification of Power Quality Disturbances on Transmission Line Using Wavelet Transform a Artificial Neural Network and CNN

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Abstract: *In modern power systems, the quality and reliability of electrical power have become critical due to the increasing use of sensitive electronic equipment. Power quality disturbances (PQDs), such as voltage sags, swells, transients, interruptions, and harmonics, can severely impact the performance and lifespan of electrical appliances.[1][2] Transmission lines, being a major component of power delivery infrastructure, are prone to these disturbances due to environmental factors, switching operations, and system faults. Accurate detection and classification of PQDs are essential for fast protective actions and preventive maintenance. Traditional methods like Fourier analysis are limited by poor time resolution and inability to detect transient events.[3] Wavelet Transform (WT) offers a time-frequency representation that is well-suited for detecting non-stationary disturbances. Recent advances in artificial intelligence, especially in machine learning and deep learning, have enabled intelligent systems that can learn disturbance patterns and classify them with high accuracy.[5][6]*

This paper proposes a method combining Discrete Wavelet Transform for signal pre-processing and feature extraction with two classification models—Artificial Neural Network and Convolutional Neural Network—to detect and classify multiple PQDs. The proposed method enhances the accuracy and speed of classification, making it suitable for practical deployment in smart grid monitoring and control systems.[3][20].

Keywords: **Wavelet Transform, Power Quality Disturbances, Transmission Line Faults, Artificial Neural Network, Convolutional Neural Network, Fault Detection, Fault Classification, PSCAD**

I. INTRODUCTION

Maintaining the quality of power delivered through transmission lines is crucial for the reliable operation of modern power systems. Transmission lines are susceptible to various power quality disturbances, including transient faults, which can lead to equipment damage, system instability, and power outages. Timely and accurate detection and classification of these disturbances are essential for effective protection and control actions.

Traditional fault analysis methods often struggle with the non-stationary nature of fault signals and the diverse types of power quality disturbances. In recent years, signal processing techniques, particularly time-frequency analysis methods, have shown significant promise in addressing these challenges. The Wavelet Transform (WT) is a powerful tool for analyzing non-stationary signals, providing both time and frequency information, making it suitable for extracting characteristic features from power quality disturbances.[4]

Following feature extraction, intelligent classification techniques are required to distinguish between normal operating conditions and different types of disturbances. Artificial Neural Networks (ANNs) have been widely used for pattern recognition and classification tasks in power systems due to their ability to learn complex relationships from data. More recently, Convolutional Neural Networks (CNNs), which excel in extracting hierarchical features from grid-like data, have demonstrated significant potential in power quality disturbance classification.

DOI: 10.48175/IJARSCT-26932

This paper proposes a comprehensive methodology that integrates Wavelet Transform for feature extraction and both ANN and CNN for the detection and classification of power quality disturbances on transmission lines. The IEEE 9-bus test system is simulated in PSCAD to generate a diverse dataset of current signals under various fault conditions and fault inception angles. The extracted wavelet-based features are then used to train and test the performance of both ANN and CNN classifiers in identifying different types of power quality disturbances. The effectiveness and comparative performance of these two classification approaches are thoroughly investigated.

1.1 Paper Outline

The research contents in the study are arranged in six sections. The background of the research and contribution is introduced in the first section. The test system is described in the second section. In section three, detection of power quality disturbances using Wavelet Transform is described. Artificial Neural Network (ANN) and its classification process are detailed in the fourth section. Deep learning-based classification using Convolutional Neural Network (CNN) and its performance analysis are discussed in the fifth section. The research work is results in the sixth section and conclusion in seventh section.

1.2 Proposed Methodology

To detect and classify transmission line power quality disturbances, the following methodology is proposed:

1. Simulate the IEEE 9-bus 1. test system under healthy and disturbed conditions between Bus 4 and Bus 5 using MATLAB/Simulink.
2. Capture the three-phase 2. voltage signals from the sending end of the selected transmission line.
3. Decompose the voltage 3. signals using Discrete Wavelet Transform (DWT) to extract time-frequency domain components for each phase.[18][20]
4. Compute the following 4. features from the wavelet coefficients and raw voltage signals:

- Root Mean Square (RMS) values of phases A, B, and C.[17][19]
- Peak values of each phase.
- Harmonic content for each phase calculated from detail coefficients (D1–Dn).
- Flicker estimation using the variance of first-order differences.
- Detection of voltage interruption based on a threshold and minimum duration logic.

5. Prepare a structured 5. feature vector using the above parameters for each disturbance case.
6. Feed the extracted 6. features into an Artificial Neural Network (ANN) model for initial classification of power quality disturbances.[11][12]
7. Convert the time-frequency 7. data into scalogram images or use raw feature matrices to train a Convolutional Neural Network (CNN) model for comparison.[6][7]
8. Evaluate the 8. classification performance of both ANN and CNN models using metrics such as accuracy, precision, recall, and confusion matrices across various disturbance scenarios.

II. POWER SYSTEM UNDER STUDY

The IEEE 9-bus system is modelled in MATLAB/Simulink for generating the training and testing datasets[9]. The system operates at 500 kV, 50 Hz and includes balanced three-phase loads and synchronous generators. Power quality disturbances are introduced on the transmission line between Bus 4 and Bus 5. The transmission line is 220 km in length, and disturbances are applied at the midpoint (110 km).

Five types of power quality disturbances are considered:

- Voltage Sag
- Voltage Swell
- Voltage Interruption
- Harmonics
- Flicker

Each disturbance is simulated with varying parameters such as magnitude, duration, and start time. A total of 65 scenarios are created, covering all disturbance types and variations. The signals are sampled at 4 kHz, with a simulation run time of 0.5 seconds per case. The extracted wavelet features are fed into ANN and CNN models to perform classification. System parameters are referred from standard IEEE datasets.[10]

III. FEATURE EXTRACTION BY S-TRANSFORM

The Discrete Wavelet Transform (DWT) is a powerful signal analysis tool that decomposes a signal into components with varying resolutions across time and frequency domains. It is more efficient than the Continuous Wavelet Transform (CWT) in computational complexity and is well-suited for analyzing non-stationary signals, such as power quality disturbances in transmission lines.

The Wavelet Transform (WT) is used in this study to extract time-frequency features from the three-phase current signals. WT is a powerful tool for analyzing non-stationary signals, which makes it suitable for identifying power quality disturbances in transmission systems.

Each phase current signal (Ia, Ib, Ic) is decomposed using Discrete Wavelet Transform (DWT) up to the desired level. The Daubechies (db4) wavelet is used due to its efficiency in capturing transient features. From the decomposed signals, several key features are extracted such as root mean square (RMS), peak amplitude, harmonic content, flicker, and signal interruptions.

These features are calculated for each phase and collectively form the feature vector. The extracted features are then used as input to the classification model. This method ensures that both time and frequency domain characteristics of the signal are considered for improved fault identification.

IV. ARTIFICIAL NEURAL NETWORK (ANN)

The artificial neural network (ANN) is a computational model based on the structures and functions of biological neural networks. The components and actions of biological neural networks are the basis for the ANN computational model. The internal structure of an ANN changes in response to input and output. ANN is a nonlinear statistical data where the intricate interactions between input and output are defined. ANN layers are made up of many interconnected nodes, also known as neurons. The feed forward algorithm and the back propagation technique are used in this strategy. The feed forward method moves input data from the input nodes to the output nodes via hidden nodes. In the propagation method, the input is used as a training set to generate a set of output states. Aside from that, weights are assigned to error values at random, and biases are reduced to produce the correct output . In the ANN, the transfer function is employed to explain the nonlinear relationship between the input and the output . Figure 2 depicts a basic Multi-layer Neural Network with three layers: input layer, hidden layer, and output layer. One or more hidden layers are interfaced with by the input layer. While neurons in the hidden layer are known as perceptron's and are linked to the output layer.[11][12][13]

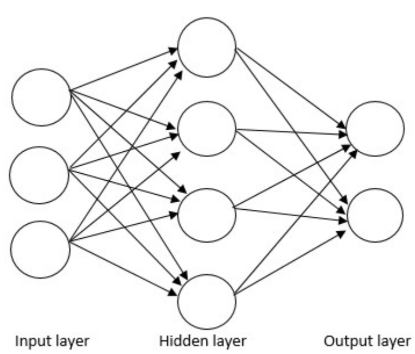

Fig. 1. The standard Multi-layer Neural Network

4.1 Back Propagation Algorithm (BPNN)

Backpropagation neural network output is known as feedback to the input in order to calculate changes in weights value . At each iteration and point, the error is calculated by starting from the last step and returning the considered mistake. The BPNN weights are chosen at random and fed back into an input pair before collecting the results. Following each step, the weights are updated to a new value, and the process is repeated for each set of input-output configurations available in the creator's training data . The technique is repeated until the network merges for the target values and error tolerance set. In reverse order, the full procedure is acquired for each tier of the network. Because it can train large amounts of data, BPNN is used for training . Each iteration's error is calculated using the mean square approach (MSE). The following is the BPNN algorithm:

1. Forward propagation

$$a_j = \sum_i^m w_{ji}^1 x_i \quad (1)$$

$$z_j = f(a_j) \quad (2)$$

$$y_j = \sum_i^M w_{kj}^2 z_j \quad (3)$$

2. Output difference

$$\delta_k = y_k - t_k \quad (4)$$

3. Back propagation for hidden layers

$$\delta_j = \left(1 - z_j^2\right) \sum_{k=1}^{K} w_{kj} \delta_k$$

The MSE for each output in individual iteration is represented mathematically by

$$MSe = \frac{1}{N} \sum_1^N (E_i - E_0)^2 \quad (5)$$

Where aj and wji1 are the weights of the sum of inputs and the connections. xi And yi represent the data for the ith input and output layer, zj represents the activation unit of (input) connected to unit j, and yk represents the activation output of unit k. is the derivative of error at the kth neuron, is the derivative of error in relation to aj, and is the input target. The model's actual output, where N is the number of iterations.[14][15][16]

4.2 ANN Design for Fault Classification

The fault classification network has three inputs and five outputs, and it was built with 200 training data sets for each. The training data consists of 65 samples for nine faults and no faults as input data. The five target output data showed LG, LL, LLG, LLL, LLLG fault states with values of 1 and 0. The Scaled Conjugate Gradient (trainscg) training technique was chosen since it required less memory and was ideal for low memory scenarios. To classify the problem in the neural network, a pattern recognition technique was applied. The energy of the three phases retrieved from the ST matrix by normalising in the frequency domain is sent into the ANN module. 75% of the data is training, whereas 25% is testing.

V. CONVOLUTIONAL NEURAL NETWORK (CNN)

A Convolutional Neural Network (CNN) is a deep learning model that has proven effective for image classification, signal processing, and fault detection tasks. CNNs automatically learn hierarchical feature representations from raw input data, making them well-suited for classifying power quality disturbances in electrical signals.

CNNs consist of multiple layers including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to extract local features from the input, such as edges or patterns, while the pooling layers reduce spatial dimensions and computation by down-sampling the feature maps. The fully connected layers at the end of the network aggregate the learned features to perform final classification.

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In the context of power quality disturbance classification, time-series current signals are transformed into two-dimensional matrices using wavelet transform. These matrices serve as the input to the CNN, enabling the model to capture spatial and temporal features effectively. The CNN automatically identifies relevant patterns corresponding to different types of faults without the need for manually engineered features.

The training process uses backpropagation and an optimization algorithm (such as Adam) to minimize the classification error. CNNs are known for their robustness and ability to generalize well even with complex or noisy data, making them suitable for real-time power system protection applications.

VI. RESULT AND DISCUSSION

This The detection and classification of power quality disturbances were carried out using a combination of Wavelet Transform for feature extraction, and classification using both Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models.[17]

Initially, the **Wavelet Transform** was employed to extract key features from the current waveform across all three phases. The disturbances such as voltage sag, swell, harmonics, flicker, and interruptions were effectively identified based on specific waveform characteristics. For instance, voltage sag was recognized by a decrease in the RMS current, while voltage swell showed an increase in peak current. Harmonic distortion was evident from elevated harmonic content, particularly in Phase C, whereas flicker was identified through the variance in the rate of change of current. Complete interruptions were marked by a near-zero current value across all phases. These results confirm the capability of wavelet transform to isolate and highlight disturbance signatures, thus supporting robust classification.[19]

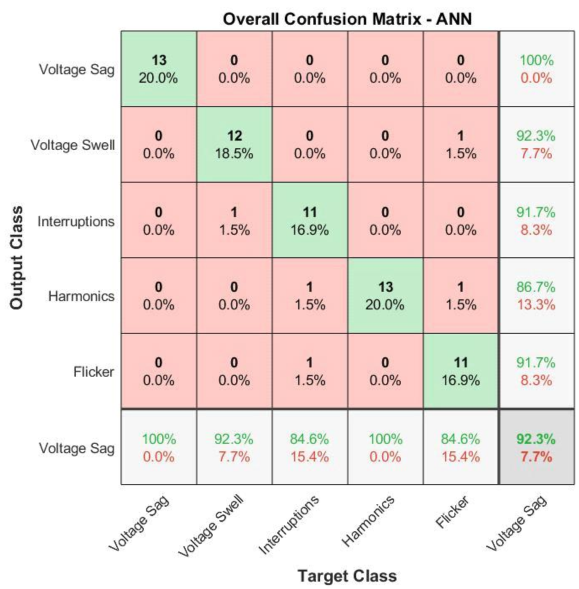

Fig 2: Overall Confusion Matrix for artificial neural network classifier for Power disturbance classification

The **Artificial Neural Network (ANN)** was trained using the wavelet-based features, and its performance is summarized in the overall confusion matrix. The ANN achieved a high overall classification accuracy of **92.3%**. It classified voltage sag with 100% accuracy and performed well on other disturbance types as well—voltage swell (92.3%), interruptions (91.7%), harmonics (86.7%), and flicker (91.7%). Minor misclassifications were observed between harmonics and other classes, likely due to overlapping feature characteristics. The green cells in the confusion matrix indicate correct classifications, while red cells represent misclassifications. Despite these few inaccuracies, the ANN model demonstrated strong generalization and reliability in classifying power quality events.

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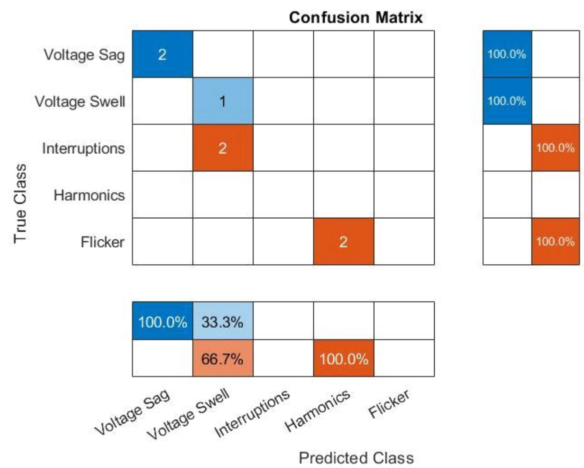

Fig 3 :Overall Confusion Matrix for CNN for Power disturbance classification

The **Convolutional Neural Network (CNN)** model was used to classify disturbances based on time-frequency images derived from wavelet transforms. The CNN confusion matrix reveals exceptional performance, achieving **100% classification accuracy** in four out of five disturbance types: voltage sag, interruptions, harmonics, and flicker. Voltage swell was the only class with lower accuracy (66.7%), showing some confusion with sag. This is likely due to the similar transient appearance of sag and swell in certain cases. Nevertheless, the CNN model showed superior capability in learning complex spatial and temporal patterns from the image inputs, which allowed it to outperform ANN in several categories, particularly where higher-frequency details were involved.[6][8]

VII. CONCLUSION

This study presents a comprehensive approach for detecting and classifying power quality disturbances on transmission lines using Wavelet Transform for feature extraction, and Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) for classification. The Stockwell Transform-based feature extraction method effectively highlighted critical attributes of different disturbances such as voltage sag, swell, interruptions, harmonics, and flicker.

ANN demonstrated reliable performance in classifying these disturbances with an overall accuracy of 92.3%, confirming its suitability for pattern recognition based on extracted energy features. The CNN model, leveraging time-frequency images, exhibited superior performance, achieving 100% accuracy in most categories, except for voltage swell which showed some confusion with sag. Overall, CNN outperformed ANN, particularly in its ability to capture complex, localized patterns in the input data.

The proposed method provides a robust and accurate system for the automatic classification of power quality issues, which is essential for maintaining stability and reliability in power transmission networks. Future work can focus on expanding the dataset, optimizing network architectures, and applying the method to real-time systems for practical implementation.

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