Combined Approach of PNN and Time-Frequency as the Classifier for Power System Transient Problems

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ABSTRACT

The transients in power system cause serious disturbances in the reliability, safety and economy of the system. The transient signals possess the nonstationary characteristics in which the frequency as well as varying time information is compulsory for the analysis. Hence, it is vital, first to detect and classify the type of transient fault and then to mitigate them.

This article proposes time-frequency and FFNN (Feedforward Neural Network) approach for the classification of power system transients problems. In this work it is suggested that all the major categories of transients are simulated, de-noised, and decomposed with DWT (Discrete Wavelet) and MRA (Multiresolution Analysis) algorithm and then distinctive features are extracted to get optimal vector as input for training of PNN (Probabilistic Neural Network) classifier.

The simulation results of proposed approach prove their simplicity, accurateness and effectiveness for the automatic detection and classification of PST (Power System Transient) types.

Key Words: **Power System Transients, Detection, Classification, Wavelet Transform and Probabilistic Neural Network.**

1. INTRODUCTION

Nowadays, the prime focus of industries is in the field of control engineering. It concerns mainly to monitor a system, detect the occurrence of fault in the system and identify the type of fault. This is mainly done to protect the system and avert any possible damages borne out of the fault. Fault detection is an integral part of the diagnostic system to ensure the reliability and safety of the system under study [1].

Transients in power system cause serious disturbances in the reliability, safety and economy of the system. The transients occur due to switching, lighting strikes, various types of faults and other intended or unintended causes. They become the harmful reasons of power system components which suffer from huge amount of currents and voltages [2].

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1.1 Power System Transient

Transients are momentary changes in voltage or current that occur over a short period of time. Transients are also known as voltage disturbances less than sag or swell and caused by sudden variations in electrical power system.

Transients are classified as: (i) impulse transients which occur due to capacitor switching and tripping of ASDs (Adjustable Speed Drives) systems. Their main impacts are magnification of voltage at customer capacitors. (ii) Oscillatory transients, the most common type of power system transient and are caused due to the switching on secondary systems, radiated noise, lighting induced ringing and electronic equipment. Their main impacts are high rate of oscillations which cause low voltage power supplies failure and short duration voltage variations [3-5].

1.2 Literature Review

It is imperative to remove the impact of faulty system with huge current or voltage and to restore the system to reliable position as quickly as possible [6].

Various types of transients indicate various behaviours and various measurements are taken to maintain the system. From this, it is vital, first to identify and classify the type of fault and then to mitigate it.

Most power quality problems are transitory (short term duration). The disturbances occur in such signals for few cycles, which are difficult to be identified or classified by recording instruments. It is also difficult to analyze and classify transients on line because of huge amount of data storage from the recording instruments.

Digital measuring instrumentations have been in focus to record the transient data for information. These recording instruments do not provide accurate classification of transient events data. Traditionally for event data of transient signals, fast FFT (Fast Fourier Transform) is utilized, which only translates the signal information from time to frequency domain [7-8].

In DSP (Digital Signal Processing), it is well known that the FFT is a powerful tool for the analysis of periodic signals. This technique does not contain the time information of the signal and shows only frequency domain information. Hence, the time information of transient signals is completely lost. Transients possess the nonstationary characteristics of not only time but also of frequency. Simply, FFT algorithm is not suitable for the detection and classification of transient signals which vary with time. Hence such transient analysis demands for time-frequency techniques to decompose and to classify them in an efficient and simple way [7-10]. The processing of waveform distortion requires some form of signal analysis in the frequency domain and traditionally FT (Fourier Transform) is utilized in electrical power engineering to achieve the spectral content of the time-domain signal [11]. The WT (Wavelet Transform) provides a fast and effective way of analyzing nonstationary voltage/current waveform distortion [12]. The WT decomposes a signal into its frequency components and unlike the FT, the wavelet can tailor the frequency resolution, a useful property in the categorization of the source of a transient. The ability of wavelets to focus on short time intervals for high-frequency components and long intervals for low- frequency components improves the analysis of signals with localized impulses and oscillations.

ANN (Artificial Neural Network) has been suggested in the literature for automatic disturbance waveform recognition [13]. The most important and useful property of ANN is the ability to interpolate unforeseen patterns. Once trained with sufficient number of example patterns that cover a wide range of input variables ANNs can interpolate any new pattern that falls in the domain of its input features.

In [2] the wavelet MRA technique has been proposed to detect, localize and classify different power quality problems. In this process new feature extraction method based on the standard deviation at different resolution levels was applied as input to the neural network to classify EPQD types. A proposed novel approach for EPQD classification based on the wavelet transform and SOLAR (Self Organizing Learning Array) was presented where the energy value at each decomposition level using MRA is applied to SOLAR [14]. A new classifier using neuro fuzzy network concept was introduced in [15] in which EPQD recognition system using wavelet statistical features is employed.

Safavian, et. al. [16] proposed a variance fractal trajectory method to categorize the power system transients and to extract the features. Based on these extracted features, classification of transients is carried out using a statistical maximum likelihood classifier, which discriminates between three classes of voltage disturbances such as faults, breaker operations and capacitor switching. The classification of high impedance transients based on the energy curve from the wavelet coefficient at each level has been discussed in [17].

Mostly FFNN with sigmoidal nonlinearities for model development have been focused. But FFNN has no fixed boundary conditions of spread constant and error goals, takes a long time for training and has no natural capability to detect the outliers.

It is proposed that such transient signals can be analysed with the help of discrete wavelet transformation (time-frequency) technique with MRA algorithm. The features of the input data are extracted with the help of DWT (Discrete Wavelet Transform) and MRA of the signal by applying standard statistical techniques and energy distribution of the transformed signal. These feature vectors will be introduced as input to PNN for training, which can have the ability to identify and classify various types of transient waveforms.

2. THE TRANSFORMS THEORY

Original signal is considered as a function of f(t) expressed as linear decomposition in order to process in a better way and is given as:

$$f(t) = \sum c_i \psi_i(t) \tag{1}$$

where i as integer index, c_i is the real coefficient and $\psi_i(t)$ is a set of orthogonal functions.

The important features in DSP field are the selection of an appropriate basis funtions to approximate the original signal.

The basis functions like sine or cosine are considered by FT to analyze and reconstruct a function. In case of nonstationary signals WT technique is more suitable than Fourier transform approach [18].

2.1 Wavelet Transform

Building a model for nonstationary signals with mathematical theory using a family of wavelets, in scaled and shifted versions of the mother wavelet is called wavelet transformation technique of time-frequency domain conversion of the signal.

Wavelet means small waves, and analysis involves process of signal with short duration and finite energy functions. WT can be manipulated in 2 stages: scaling and translation. It can be expressed mathematically as:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\frac{x-b}{a}, \quad a \angle 0 \tag{2}$$

Where a is a scalling parameter, and b is parameter of location.

Diverse frequency components decomposition functionality is performed with wavelet transformation. This transformation is processed at different locations and different scales of the signal. If this process is required in smooth and continuous manner, then the process will be CWT (Continuous Wavelet Transformation). If these locations and scales are converted into discretized fashion, the process will be DWT [19].

2.2 Discrete Wavelet Transform

The DWT belongs to one of the 3 types (Continuous CWT, Packet WPT and Discrete DWT) of WT, which converts a discretized time domain signal into its matching wavelet domain. Such process is done through digital filtration and is known as sub-band codification. This is achieved by a method known in DSP theory, as convolution process of f(t) signal. The signal f(t) passes through high-pass and low-pass digital filters eliminating half of the samples of the signal. Basically the DWT evaluation has two stages: (i) wavelet coefficients determination, which represent the signal f(t) in wavelet domain and (ii) the calculations of the coefficients in time domain resolutions. At the end this gives all the approximation and detail values along with wavelet spectrum [20].

3. METHODOLOGY

The power system transient problems are generally time variant or short-time issues. Hence for the detection or classifying these transient signals, a simple technique of time-frequency domain analysis is suggested and preferred. This work tests DWT for the power system transient disturbances. For computer implementations DWT will be utilized as:

$$W_{\psi}(m,n) = \frac{1}{\sqrt{a_0{}^m}} \sum_{k=-\infty}^{+\infty} x(k)\left(\frac{k - a_0{}^m nb_0}{a_0{}^m}\right) \tag{3}$$

Where $a = a_0{}^m$, $b = a_0{}^m nb_0$, m and n are the integer numbers provided that $a_0 > 1$ and $b_0 \neq 0$ [19].

Due to this process redundancy of continuous form must be eliminated hence should be selected to from orthogonal basis by satisfying the condition $a_0=2$ and $b_0=1$. This requirement invites us to use MRA, which is also known as MWM (Multiresolution Wavelet Method). In this method original signal is decomposed into different scales resolutions and the mother wavelet function $\psi(t) = 2\sum_{n=-\infty}^{+\infty} d_n\varphi(2t-n)$ is chosen with function $\varphi(t) = 2\sum_{n=-\infty}^{+\infty} c_n\varphi(2t-n)$ known as scaling function, where d_n and c_n are squared summable sequences [20].

One of the big advantages of WT is the decomposition of signal into the time-frequency information. High frequency transients and sharp changes can easily be detected with MRA techniques [21].

At the lowest scale like Scale 1, the mother wavelet is most localized in time and oscillates most rapidly within a very short period of time. As the wavelet goes to higher scales, the analyzing wavelets become less localized in time and oscillate less due to the dilation nature of the wavelet transform analysis. As a result of higher scale signal decomposition, fast and short transient disturbances will be detected at lower scales, whereas slow and long transient disturbances will be detected at higher scales [22-23].

3.1 Justification of db4 as Mother Wavelet

Selection of mother wavelet acts an important task in detecting and localizing different kind of power signal disturbances. The choice also depends on the nature and kind of application. For detection of low amplitude, short duration, fast decaying and oscillating type of signals one of the most popular wavelets are Daubechies family (Db2, Db3, ….). It has been proved that this family has a good efficiency in EPQ analysis. Wide and smoothness of db wavelets depends on its number. It is more desirable to have higher level of wavelets but due to computational efficiency and practical consideration four to six levels decomposition of Db4 wavelet has been applied for this research work.

The application of DWT with MRA algorithm with db4 (Daubechies) mother wavelet for Denoising and decomposing is applied to get feature vectors which will be the input of PNN as classifier. Power system transient signals will be generated using Matlab/ simulink and feature vectors with the help of wavelet toolbox and PNN training and testing will be investigated in NN toolbox.

3.2 The Proposed Methodology

The proposed methodology for automatic detection and classification of power system transients disturbance is based on the following stages:

(1) Generation of data

(2) Feature extraction

(3) Data normalization

(4) Network training

Data Generation: The equations for the PQDs signals are available and the parameters were varied within the ranges specified by the IEEE 1159 [5].

Data Normalization: The higher raw input data can suppress the influence of smaller ones; hence to avoid this, the raw data is normalized before the application to the PNN. The data is normalized as:

$$d_n = \frac{\left(d - d_{\min}\right) \times range}{\left(d_{\max} - d_{\min}\right)} + starting\ value \tag{4}$$

Where d_n is the normalized value, d_{max} and d_{min} are the minimum and maximum values of d [24-25].

Feature Extraction: In this article, the features of the input data are extracted with the help of DWT and MRA of the signal and by applying standard statistical techniques and energy distribution of the transformed signal.

In the first step of this research standard statistical techniques are applied to extract the features. Many features such as amplitude, slope of the amplitude, time of occurrence, mean, standard deviation, and energy of the transformed signal are widely used for classification [24, 26]. The following features are considered in this article:

(i) De-noising procedure based on DWT is performed in order to remove the adverse influence of noise.

(ii) To achieve feature vector (characteristic information) the diagnosis procedure called preprocessing of the event is used which consists of: (i) 6-level WT decomposition with Db4 as mother wavelet is sufficient to investigate significant information in different frequency band [27].

(iii) Statistical parameter of DWT coefficients like standard deviation, mean and maximum absolute value of the various scale levels can be a representation of PQD signal energy band to aid in its classification [27].

(iv) For signals sampled at rate of 10 kHz considered in this work first, third and fifth detail and fifth approximate level can reflect this wide range clearly and efficiently [27-29].

(v) The computed feature vector is introduced as the input to a trained PNN classifier for diagnosis.

(vi) To make a decision about the disturbance type and to provide a level of confidence for the decision, a simple threshold level for each events is settled, which depends on size of training data, learning error and reliability of the classifier. The patterns that are out of all thresholds are considered as unknown disturbances [27].

Network Training: PNN is used as the classifier for power system transient:

The PNN model is one among the supervised learning networks, and the Bayesian classifiers. PNN model has been proved as an important net work among the supervised learning networks [25]. It is efficient because of the following reasons:

- ☐ The laborious work of selecting or setting the initial weights of the network is not needed.
- ☐ PNN is always applied with probabilistic model, such as Bayesian classifiers.
- ☐ If it is given the sufficient time to train the PNN is guaranteed to converge to a Bayesian classifier.
- ☐ For the modification of the weights of the network, the tedious process of checking the difference between target vector and the inference vector is not required.
- ☐ Hence, there is no affiliation between learning and recalling processes.

The process produces a closure vector between the input and training and the second layer for each class adjoins all these contributions, in which a vector of probabilities (as output) and exact transfer function is created. Due to these simple and diverse characteristics the learning speed of the PNN model is quicker which makes it suitable in real time for fault diagnosis [30-32].

3.3 Algorithms and Architectures of PNN

Input P is R-by-Q matrix of Q input vectors and Output or target T is S-by-Q matrix of Q target class vectors with spread of radial basis functions having default value of 0.1.

PNN are a kind of radial basis network, appropriate for categorization problems, in which, when an input is offered, the distances are computed by the first layer from the input vector to the training input vectors which creates the vector with the elements indicating how close the input is to the input training. These contributions are added by the second layer for each class of inputs creating the net output known as the vector of probabilities. The maximum of these probabilities on the output of second layer are picked by compete transfer function, which generates one for that class and zero for the further classes.

PNN produces a two-layer network, where first layer has radbas neurons, and computes its weighted inputs with dist and its net input with net product (netprod). Whereas second layer has compet neurons, and computes its weighted input with dot product (dotprod) and its net inputs with net sum (netsum). Only the first layer has biases. PNN sets the first-layer weights to P, and the first-layer biases are all set to specified spread, resulting in radial basis functions. The second-layer weights W2 are set to T [33-34].

4. SIMULATION AND RESULTS

For the efficient computational analysis, decomposition of level 6, with db4 (Daubechies 4) mother wavelet and MRA algorithm of DWT is proposed. The simulation results are investigated in Matlab 7.5, Simulink 7.0, DSP 6.6, and Wavelet toolbox 4.1.

This methodology is applied on original signals which are generated at 10 cycles or 0.2 seconds, and 10 KHz sampling rate. All the major categories of power system transients like oscillatory, impulse, temporary interruptions, line current faults, and transient in linear circuits are developed and analyzed for the useful feature extraction as described in proposed methodology to get optimal feature vector which will be introduced as the input for PNN.

Fig. 1 demonstrates the oscillatory transient signal developed from switching capacitor bank circuit, with 10 cycles at decompositions level of 6. The detail coefficients show higher frequencies from d_1-d_6. These coefficients detect the power system oscillatory transients very quickly at first level. The decomposition of signal gives time-frequency version of signal and accuracy of disturbances with time localization.

Fig. 2 exemplifies clearly the impulse transient signal response at d_1 at once. d_2-d_6 decompose this signal into lower frequency very slowly.

In Fig. 3 d_1 points up temporary interruption of signal very accurately up to d_3, but d_4-d_6 only preserve the information of signal.

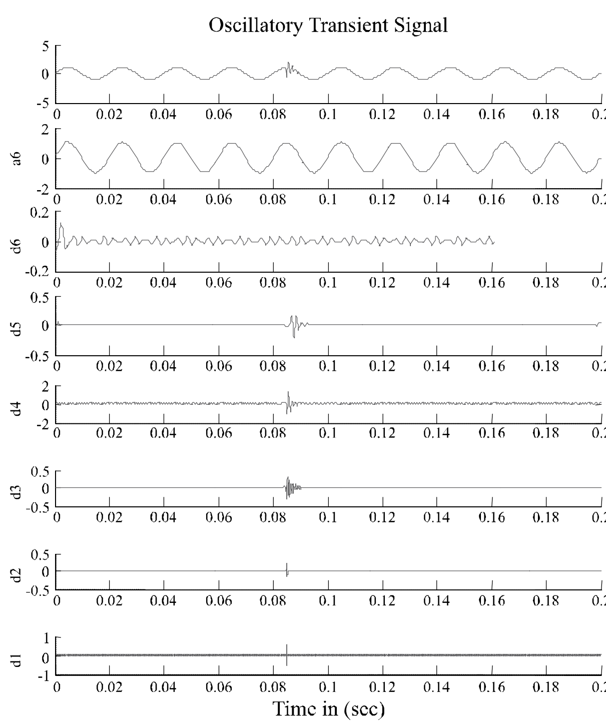

FIG. 1. OSCILLATORY TRANSIENT SIGNAL WITH D_1-D_6 DETAIL AND APPROXIMATION A6 COEFFICIENTS

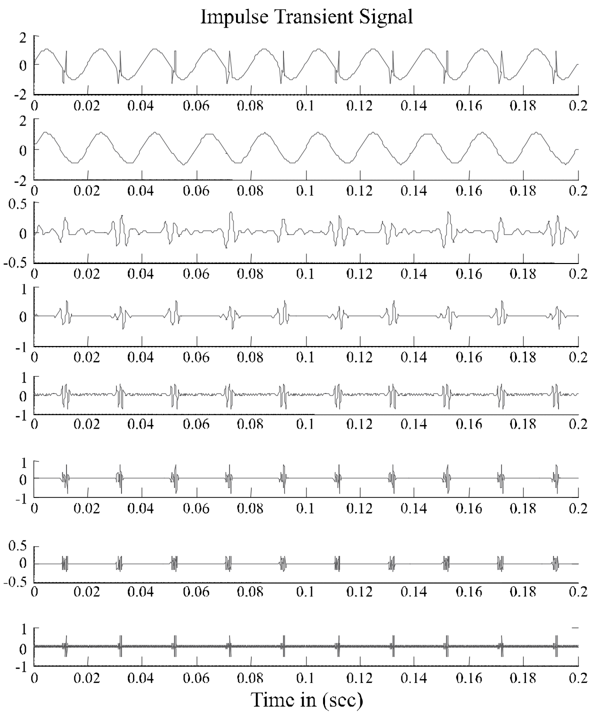

FIG. 2. IMPULSE TRANSIENT SIGNAL WITH D_1-D_6 DETAIL AND APPROXIMATION A_6 COEFFICIENTS

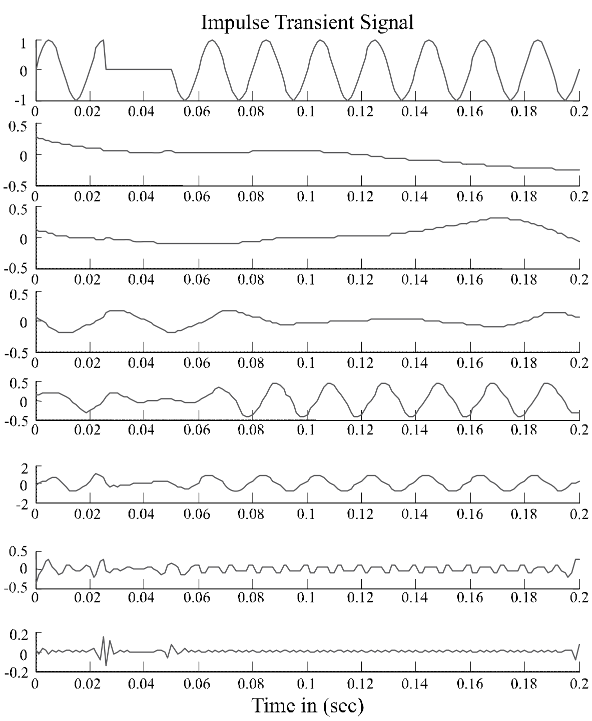

FIG. 3. TEMPORARY INTERRUPTION TRANSIENTSIGNAL WITH D_1-D_6 DETAIL AND APPROXIMATION A_6 COEFFICIENTS

Fig. 4 illustrates the signal of line current faults with 20 cycles (0.4 seconds). d_1 at 0.25 second and after 0.31 up to 0.36 exactly show the impacts of faults of line currents. Same fault current is shown at d_3 and onward with lower frequency decomposition coefficients.

Fig. 5 demonstrates the transient analysis signal of linear circuit which is observed at d_1 level at 0.4 seconds and vanishes at 0.12 seconds. This signal is shown more clearly at levels d_2-d_6.

The demonstrations of the examples with proposed technique, give an idea about magnitude, periods, and time confinement from start to finish of the transient disturbances together with time-frequency information simultaneously.

Due to these accurate time localizations of transient signals, it is easier to detect and classify the transient

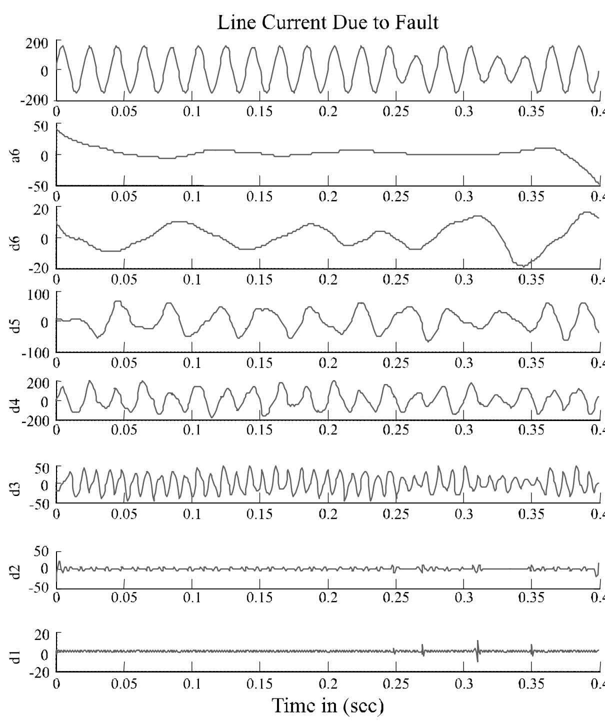

FIG. 4. LINE CURRENT FAULT TRANSIENT SIGNAL WITH D_1-D_6 DETAIL AND APPROXIMATION A_6 COEFFICIENTS

signal and its sources in an efficient way. After this information mitigation methods are easier to be suggested and implemented.

5. PNN TRAINING AS THE CLASSIFIER

We have developed 4 types of power system transient. Each transient types of power signal are sampled at a rate of 10 kHz. In this method over 100 training example are collected and tested. The generated power system models are distributed in duration, frequency and magnitude ranges of studied power system transients types. Table 1 shows the classification results produced by the PNN. The overall classification error rate of first case is 9.0% because only 9 out of 100 samples and in second case it is 4.5% out of 200 samples only 9 samples are not identified.

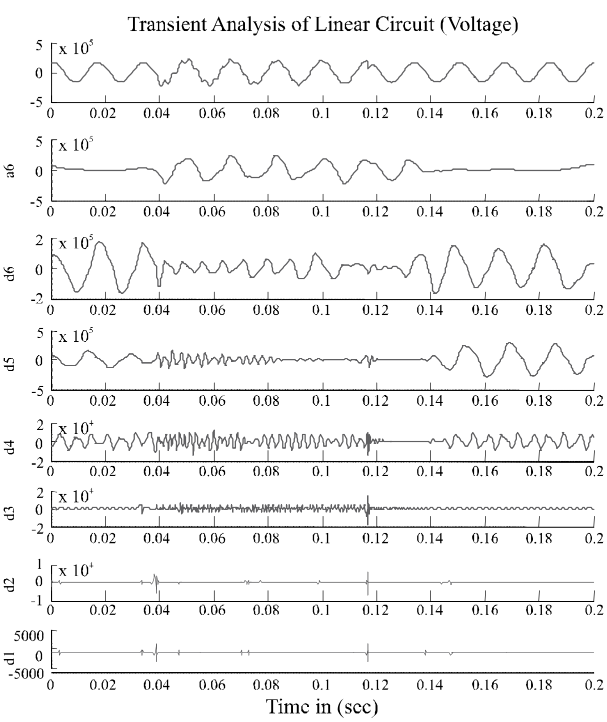

FIG. 5. LINEAR CIRCUIT TRANSIENT SIGNAL WITH D_1-D_6 DETAIL AND APPROXIMATION A_6 COEFFICIENTS

6. CONCLUSIONS

This article presents a combined novel approach for detection and classification of different types of electrical power system transients. This technique proposes DWT with MRA algorithm for decomposition and four statistical parameters for feature vectors which are introduced to train PNN as classifier. The output of the PNN classifier easily diagnosis the type of power system transients. The proposed technique gives a high accuracy in the classification of the PSTs types 91% for small number of samples and more accuracy 95.55% for high number of samples.

This technique has illustrated and proved the appropriateness, potentiality and simplicity for the classification of power system transient disturbances and indicates the simplest method for the power system engineers to deal with the problems of power system transient with just only visualization the signals at decomposition levels.

TABLE 1. SHOWS THE EVALUATIONS PERFORMANCE OF DEVELOPED MODEL OF PNN, WITH ITS CLASSIFICATION RESULTS DURING TESTING

PSTs	Samples	Identified	Unidentified
C1	25	23	2
C2	25	22	3
C3	25	22	3
C4	25	24	1
4	100	91	9
Overall Accuracy 91%			
C1	50	48	2
C2	50	47	3
C3	50	47	3
C4	50	49	1
4	200	191	9
Overall Accuracy 95.55%			

In future this research scheme can be further improved for hybrid EPQ disturbances techniques which can help to develop an automatic EPQDs methodology for detection and classification.

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