DISCRETE WAVELET TRANSFORM AND MULTIRESOLUTION ANALYSIS ALGORITHM WITH APPROPRIATE FEEDFORWARD NEURAL NETWORK CLASSIFIER FOR POWER SYSTEM TRANSIENT DISTURBANCES


1. INTRODUCTION

Power System Transient (PST) disturbances occur for few cycles, which are very difficult to be identified and classified by digital measuring and recording instrumentation. They cause serious disturbances in the reliability, safety and economy of power system. The transient signals possess the non-stationary characteristics in which the frequency as well as varying time information is compulsory for the analysis. Hence, it is essential, first to detect and classify the type of transient fault and then to mitigate them in an efficient way.

This article recommends the methodology of discrete wavelet transform (DWT) a time-frequency technique with multiresolution analysis (MRA) algorithm as detection and feature extractions and three types of feedforward neural network (FFNN) namely multilayer perceptron (MLP), radial basis function (RBF) and probabilistic neural networks (PNN) as classifier for power system transient problems. Different models of almost all major categories of transient disturbances are developed in Matlab, denoised, and decomposed with the help of DWT-MRA algorithm and then selecting distinctive features to get optimal vector as input for training of three types of FFNN (MLP-RBF-PNN) as classifiers. The simulation results with proposed methodology using Matlab/Simulink/Wavelet Toolbox/Neural network prove their simplicity, accuracy and efficiency for the automatic classification of power system transient signal disturbances and propose PNN as the most suitable classifier.

Key Words: Power System Transient Disturbance, Discrete Wavelet Transform, Multiresolution Analysis and Feedforward Neural Network.

Digital measuring instrumentations have been in focus to record the transient data for information. These recording instrumentations do not provide accurate classifications of transient events data. Traditionally for event data of transient signals, fast fourier transformation (FFT) technique is utilized, which only translates the signal information from time to frequency domain [3-6].

In digital signal processing (DSP), 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. The transient signals possess the non-stationary or time-varying characteristics of time as well as frequency domain. Simply, FFT algorithm is not suitable for the detection and classification of power system transient (PST) signals. Hence such transient signaling demands for time-frequency techniques to decompose and to classify them in an efficient and simple way [4-9]. The wavelet transform (WT) a time-frequency technique provides a fast and effective way of analyzing non-stationary time varying voltage/current transient distortion [7]. 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.

In [3, 11-13] 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 (NN) to classify EPQD types.

The artificial neural network (ANN) has been recommended in the literature for automatic classification of signal disturbance [11-13]. 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. 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. 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 them. 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 [3-7].

It is proposed that such transient signal can be analyzed 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 and MRA of the signal by applying statistical parameter techniques to achieve feature vector. These feature vectors will be introduced as input to PNN-RBF-MLP for training, which can have the ability to identify and classify the various types of PST disturbances.

2. WAVELET TRANSFORM (WT)

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:

$$f(t) = \sum c_i \psi_i(t)$$

(1)

$i = \text{an integer index}$, $c_i = \text{the real coefficient}$ and $\psi_i(t) = \text{is a set of orthogonal functions}$.

The important features in digital signal processing field are the selection of an appropriate basis to represent in simple and an efficient way the nature of considered original signals.

The basis functions like sine or cosine are considered by Fourier transform (FT) to analyze and reconstruct a function. In case of nonstationary signals wavelet transform (WT) technique is more suitable than Fourier transform approach [3-8].

Wavelet Transform (WT)

Building a model for non-stationary 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 02 stages: scaling and translation. Diverse frequency components decomposition functionality is performed with wavelet transformation. This transformation is processed at different locations and different scales of the signal. If the locations and scales are converted into discretized fashion, the process will be discrete wavelet transform (DWT) [3-8].

Discrete Wavelet Transform (DWT)

The discrete wavelet transform belongs to one of the 03 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. The original passes through a 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 represents the original signal in wavelet domain and (ii) the calculations of detail and approximate coefficients in time domain resolutions [3-8, 11, 13-17]

3. METHODOLOGY

3.1 DWT AND MRA

The PST problems are generally time variant, hence for the detection and classifying the transient signals; the time-frequency domain technique analysis is suggested and preferred. For computer implementations discrete wavelet transform is utilized as:

$$W_m(n) = \frac{1}{\sqrt{a_0^m}} \sum_{k=-\infty}^{\infty} x(k) \left( \frac{k-a_0^mnb_0}{a_0^m} \right)$$

(2)

Where $a=a_0^m$, $b=b_0^m$, $m$ and $n$ are the integer numbers provided $a_0^m$1 and $b_0^m0$ [19].

Due to this process redundancy of continuous form must be eliminated hence $a_0$ and $b_0$ be selected as to from orthogonal basis by satisfying the condition as $a_0 = 2$ and $b_0 = 1$. This requirement needs to use multiresolution analysis algorithm. In this method original signal $x(t)$ is decomposed into different scales resolutions and the mother wavelet function

$$\psi(t) = 2 \sum_{n=-\infty}^{\infty} d_n \phi(2t - n)$$

is chosen with function

$$\phi(t) = 2 \sum_{n=-\infty}^{\infty} c_n \phi(2t - n)$$

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

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MRA techniques. 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 dilatation 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 [3-8, 11, 13-17].

3.2 Artificial Neural Networks (ANNs)

The artificial intelligence (AI) with its natural language has demonstrated to be useful in controlling complex and highly non-linear systems which are difficult with conventional control theory. Artificial neural network (ANN) has been chosen from artificial intelligence for this methodology. Literature indicates that ANN is swiftly drawing the attentions and recognition amongst the power system researchers. As ANNs are universal function approximators. They are capable of approximating any continuous nonlinear functions to arbitrary accuracy. They show amazing sturdiness, parallel architecture behavior and fault tolerant capability [26]. The function of neural networks is to produce an output pattern when presented with an input pattern. ANNs can easily handle complicated problems and can identify and learn correlated patterns between sets of input data and corresponding target values. After training, these networks can be used to predict the outcome from new input data [3, 18-22]. This research proposes feedforward neural network (FFNN) with its three types known as radial basis function (RBF), multilayer perceptron (MLP), and probabilistic neural network (PNN) as classifier for PST disturbances.

3.3 Feature Extraction

Power system transient disturbance detection and classification is very tedious problem. Which involves a broad range of disturbance or classes from low frequency dc offsets to high frequency transients or low duration impulse to steady state events. Feature extraction is the key for pattern recognition because it is the most important component for designing the intelligent system. The performance of artificial intelligence can be poor if the features are not chosen well. A feature extractor should reduce the pattern vector to a lower dimension, which contains most of the useful information from the original vector [3-8, 11, 13]. Wavelet Transform is suitable for feature extraction. The properties of WT, like, band pass spectrum, limited effective time duration, orthogonality, and waveform similarity to disturbance allow locating the information in time-frequency domains. It makes possible to obtain high correlation when PST disturbances occur and decompose into different components without energy aliasing. This technique provides the methodology by which the identification of the difference of disturbances and make selection of suitable pattern recognition very easier. The reconstructed signal is almost free of noise and has the same energy content to avoid the adverse influence of noise a denoising procedure based on DWT is performed. For this methodology it consists of, a five level WT decomposition using Db4 which is found sufficient to explore minimum significant information in different frequency band. The statistical parameter of DWT coefficients such as standard deviation, mean and maximum absolute value of the various scale levels can be a representation of event signal energy band to aid in its classification [3-8, 11, 13].

3.4 Model or Data Generation

The mathematical equations within the parameters of PST signals guided and described by the IEEE 1159 [23] have been developed. Table 1 show all categories of PST signals with spectral content, typical duration and voltage magnitude [23]. Almost all the categories of PST signals (impulse, oscillatory, temporary interruptions, line current faults, and transient in linear circuits) are developed in Matlab/Simulink at 10 cycles (0.2 seconds), at 10 KHz sampling rate as specified in [23].

Table. 1: IEEE 1159 (1995) all categories of PST in respect of spectral content, duration, and voltage magnitude.

<table>
<thead>
<tr>
<th>CATEGORY</th>
<th>SPECTRAL CONTENT</th>
<th>DURATION</th>
<th>VOLTAGE MAGNITUDE</th>
</tr>
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<tbody>
<tr>
<td>Impulsive</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nanosecond</td>
<td>5-ns rise</td>
<td>&lt;50 ns</td>
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</tr>
<tr>
<td>Microsecond</td>
<td>1- s rise</td>
<td>50 ns–1 ms</td>
<td>---</td>
</tr>
<tr>
<td>Millisecond</td>
<td>0.1- ms rise</td>
<td>&gt;1 ms</td>
<td>---</td>
</tr>
<tr>
<td>Oscillatory</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>&lt;5 kHz</td>
<td>0.3–50 ms</td>
<td>0–4 pu</td>
</tr>
<tr>
<td>Medium</td>
<td>5–500 kHz</td>
<td>20μs</td>
<td>0–8 pu</td>
</tr>
<tr>
<td>High</td>
<td>0.5–5MHz</td>
<td>5μs</td>
<td>0–4 pu</td>
</tr>
</tbody>
</table>

3.5 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 MLP, RBF and PNN. The data is normalized as:

\[
d_n = \frac{(d - d_{\text{min}}) \times \text{range}}{(d_{\text{max}} - d_{\text{min}})} + \text{starting value}
\]

Where \(d_n\) is the normalized value and \(d_{\text{max}}\) and \(d_{\text{min}}\) are the minimum and maximum values of \(d\) [3, 11, 13].

3.6 Network Training or Classification Algorithm

Training a network by i) selected algorithms of feedforward NN (back-propagation and orthogonal least-squares (OLS) and Bayesian model as the input training pattern, ii) the adjustment of the weights and bias during the learning process, and iii) the ANN weights are adapted in order to create the desired output vectors are the main stages for classification purposes. After training the weights and bias they can be used as classifier data for PST disturbances.

A. Design methodology of MLP network

The weights and biases have been initialized and adapted with a specified learning function. The training is done with specified hyperbolic tangent sigmoid transfer function. In the last the performance is identified according to the specified performance function activities. The iteration type loop uses Levenberg-Marquardt algorithm which is the fastest training algorithm for FF networks of moderate size.
and possesses very simple and an efficient Matlab implementation, occupying very less memory. Mean squared error (mse) is selected as performance function and network is stored with a command “generate simulation net”[3, 11, 13, 18-22].

This MLP methodology of FFNN network architectures creates three-layer structure.
The numbers of layers generated are 03 having 17, 09 and 04 neurons in each layer. Initial weights and biases are random in nature, with tangent sigmoid activation transfer function. Levenberg–Marquardt back-propagation (BP) supervised learning algorithm is proposed as 1e-06 mean square error, 16500 epochs and training parameters with 1.82 as learning rule.

B. Design methodology of RBF network
The RBFs have distinctive properties of simple network structure, efficient learning way, and best approximation applicant, which make RBF more powerful and promising tool than the other architectures of neural networks. The RBF networks consist of three utterly different layers. The input layer or 1st layer consists of a number of units fastened to the input vector. The units constituted by 2nd or hidden layer have an overall response function, mostly a Gaussian function. The function of each class is computed by 3rd layer.
The universal approximator orthogonal least-squares (OLS) algorithm for this research work has been preferred [26-29, 34-40]. The OLS learning algorithm generates RBF, which has a hidden or 2nd layer, smaller than that of RBF with arbitrarily chosen centres.

This RBF methodology proposes two-layer network architectures, with 41 neurons or nodes are chosen in the 1st hidden layer with activation function of radial basis activation function and 07 neurons in the 2nd layer with linear transfer function, spread constant of 1.71 and the error goal is set at 0.000001.

C. Design methodology of PNN network
The PNN model is one amongst the supervised learning networks, and the Bayesian classifiers having the distinct features from those of other networks in the learning processes. The vigorous work of selecting/setting the initial weights of the network is not required. The tedious process of checking the difference between target vector and the inference vector is not required for the modification of the weights of the network.

The process produces a closure vector between the input and training. The second layer for each class adjoins all these contributions, in which a vector of probabilities known as output and exact transfer function is created. Having these simple and diverse characteristics, the learning/training speed of the PNN model is always faster which makes PNN network more suitable for real-time fault diagnosis [3, 24-26].

PNN produces a two-layer network, where 1st layer has radbas neurons, and computes its weighted inputs with dist and its net-input with net product (netprod). Whereas 2nd layer has compet neurons, and computes its weighted input with dot product (dotprod) and its net inputs with net sum (netsum). The 2nd layer weights W2 are set to T output/target. Only the 1st layer possesses the biases. PNN sets the 1st layer weights to P, and the 1st layer biases where all are set to the specified spread, resulting in radial basis functions.

4. SIMULATION AND RESULTS
This methodology proposes six-level decomposition by wavelet with multiresolution analysis algorithm of discrete wavelet transform and daubechies 4 (db4) as mother wavelet function for an efficient computational analysis. The simulation results are investigated with the help of Matlab 7.5/Simulink 7.0, Wavelet toolbox 4.1 and Neural network toolbox 7.02. All the major categories of PST signals (impulse, oscillatory, temporary interruptions, line current faults, and transient in linear circuits) are developed in Matlab/Simulink at 10 cycles (0.2 seconds), and 10 KHz sampling rate as described and specified by in IEEE 1159-1995 [23]. The second step is the selection of useful feature extraction as proposed in the methodology to get optimal feature vector. This optimal feature vector is introduced as the input for MLP-RBF-PNN three types of FFNN. After training the network the most suitable classifier is tested, selected and concluded.

Fig. 01 exemplifies clearly the impulse transient signal response at d1 at once. d2 to d6 decompose this signal into lower frequency very slowly.

Fig. 02 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 d1 to d6. 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.

In Fig. 03, d1 points up temporary interruption of signal very accurately up to d3, but d4 to d6 only preserve the information of signal.

In Fig. 04 illustrates the signal of line current faults with 20 cycles (0.4 seconds). d1 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 d3 and onward with lower frequency decomposition coefficients.

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In Fig. 05 demonstrates the transient analysis signal of linear circuit which is observed at d1 level at 0.4 seconds and vanishes at 0.12 seconds. This signal is shown more clearly at levels d2 to d6.
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 the transient signal. Now for the automatic classification of these signals MLP-RBF-PNN network based classifier is suggested.

MLP-RBF-PNN NETWORKS AS THE CLASSIFIER

Five types of power system transient namely impulse, oscillatory, temporary interruption, line current fault, and linear circuit transient signals are represented by $S_1$, $S_2$, $S_3$, $S_4$, and $S_5$. In this methodology 00 samples for each type have been trained and then tested which are distributed in magnitude ranges, duration and frequency bands. Table 02, describes the percentage of classification accuracy $CA (%) = \frac{N_{\text{correctly identified sample}}}{N_{\text{actual trained sample}}} \times 100$ trained and tested ratios of MLP-RBF-PNN network classifier. The overall classification error and identified rate of MLP classifier is 2.8% and 97.2% respectively. In the second case of RBF as classifier, when 500 samples of all types of PST signals are tested it is 3.0% and 97% unidentified and identified rate of performance evaluations respectively. Whereas in third case of PNN as classifier it improves and becomes 98% identified and 2% as unidentified error rate of assessment performance.

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CONCLUSIONS

This article presents a combined novel approach for detection and classification of different types of electrical power system transients. This technique proposes discrete wavelet transform with multiresolution analysis for decomposition and statistical parameters suitable for feature vectors which are presented as input data to three types of feedforward neural networks namely multilayer perceptron, radial basis function and probabilistic neural networks to train and test as suitable classifier. The classification accuracy of all the classifiers shows very promising results by easily diagnosing the disturbances of power system transient signals. The proposed methodology demonstrates high classification accuracy of 97.2%, 97% and 98% with MLP-RBF-PNN networks for the automatic classification of the PSTs disturbances.

The classification accuracy of MLP is better than RBF but there is no straightforward rule of choosing an appropriate number of hidden layer neurons for an optimal performance, which is a big disadvantage of MLP networks. This number is chosen by trial and error methods, starting with two or three neurons, and then increasing the number gradually, until satisfactory performance is achieved, which makes it as laborious and time-consuming task. To overcome this drawback of MLP the applicability and potentiality of RBF networks for this research is also investigated. The RBFs have distinctive properties of simple network structure, efficient learning way, and best approximation applicant, which make RBF more powerful and promising tool than the MLP architectures of neural networks. But in case of RBF more numbers of neurons are required.

The PNN model is one among the supervised learning networks. The Bayesian classifiers PNN model proves as an important among the supervised learning networks processes having the distinct features from those of other networks in the learning processes. The vigorous work of setting the initial weights of the network and the tedious process of checking the difference between target vector and the inference vector is not required in case of PNN. The classification accuracy also proves PNN as most suitable classifier for this application. Also having these simple and diverse characteristics, the learning/training speed of the PNN model is always faster which makes PNN network more suitable for real-time fault diagnosis.

This software based technique has illustrated and proved the appropriateness, potentiality and simplicity for the automatic classification of power system transient problems for the power system engineers and researchers. This automatic classification methodology will suggest the solutions of mitigation and filtration of transient disturbances very easily. In future this research scheme can further be moderated with the help of hybrid type PST disturbances techniques with neuro-fuzzy as classifiers, changing noise ratios, selecting most suitable mother wavelet function or implementation some other domain transformation like stockwell transform (ST) domain analysis.

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