

Classification of Transients using Wavelet Based Entropy and Radial Basis Neural Networks

T. Jayasree, D. Devaraj, R. Sukanesh

Abstract— This paper presents an Artificial Neural Network (ANN) based approach for power system transient classification. Wavelet transform is applied to extract the features from the raw signal. An entropy based method is proposed to select the input features of the network. The entropy based method reduces the size of the input features without losing the characteristics of the signal. The selected features are given to a Radial Basis Function (RBF) neural network for further classification. The data required to develop the network are generated by simulating various faults in the test system. The simulation results show that the proposed method provides a robust and accurate method for power system transient classification.

Index terms— Artificial Neural Networks, classification, Power system transients, disturbances, Wavelet Transform.

I. INTRODUCTION

Power system transients are fast, short duration events that produce distortions in the A.C waveform. They are caused by sudden changes in the power system. Some of the more common causes of transients are: lightning strikes, switching operations and electrical faults. The effects of transients on equipment are cumulative, with every succeeding transient having a greater effect on the equipment.

Transients are difficult to detect because of their short duration. The instrument for measuring the transient should have high sampling rate to provide greater accuracy in describing transient events in terms of their amplitude and frequency content. These attributes are essential for performing transient analysis. The amplitude of the waveform provides information about the potential for damage to the affected equipment. The frequency content informs us how the events may couple to other circuits and how they might be mitigated.

The processing of disturbance waveform requires some form of signal analysis in the frequency domain. Traditionally Fourier Transform [1] has been used in the power engineering field to obtain the spectral content of the time domain signal. The wavelet transform (WT) [2]

provides a fast and effective way of analyzing non-stationary voltage and current waveforms. As in the Fourier Transform, the WT decomposes a signal into its frequency components. Unlike the Fourier Transform, 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. In this paper, wavelet multi-resolution analysis is used to extract the relevant features from the disturbance waveform. The dimensionality of the feature vector is reduced by applying an entropy-based feature selection technique.

Artificial Neural Network (ANN) have been proposed in the literature [4] for automatic disturbance waveform recognition. The most important and useful property of ANN is the ability to interpolate unforeseen patterns. Once trained with sufficient number of example patterns that covers a wide range of input variables ANNs can interpolate any new pattern that falls in the domain of its input features. Gouda et al.[2] proposed the wavelet multi-resolution analysis technique to detect, localize and classify different power quality problems. A new feature extraction method based on the standard deviation at different resolution levels was applied as input to the neural network to classify power quality disturbances type. He and Starzyk [3] proposed a novel approach for PQ disturbance classification based on the wavelet transform and Self Organizing Learning Array (SOLAR). In this paper, energy value at each decomposition level using multi-resolution analysis is applied to SOLAR. Elmitwally et al. [5] proposed a new classifier using neuro fuzzy network. A power quality disturbance recognition system using wavelet statistical features is employed.

Safavian et al.[6] 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. N.P.Subramoniam et al. [7] has presented the classification of high impedance transients based on the energy curve from the wavelet coefficient at each level. Most of the authors have used feed forward neural networks with sigmoidal nonlinearities for model development. The short coming of this network is that it takes long time for training. Also, it has no inherent ability to detect the outliers. In this paper, we propose RBF networks [8] to recognize the

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disturbance waveform. RBF networks takes less time for training and the distance - based activation function used in the hidden nodes gives the ability to detect the outliers during estimation.

II. POWER SYSTEM TRANSIENTS

Transients [7] are momentary changes in voltage or current those occur over a short period of time. This interval is usually described as approximately 1/16th of a voltage cycle or about 1ms. Transients are classified into three categories: impulsive transient, oscillatory transient and transient due to fault. The transient is classified in the impulse category when 77% of the peak-to-peak voltage of the pure component is of one polarity. An oscillatory transient is a sudden, non- power frequency change in the steady state condition of voltage, current or both that includes positive and negative polarity values. The transient due to fault is caused by fault conditions, the energization of large loads which require high starting currents or intermittent loose connections in power wiring. Each category of the transient is sub divided in to three types related to the frequencies contained. Each type of transient can be associated with a group of phenomena occurring on the power system. The three types of transients are depicted in the following figures 2.1 to 2.3

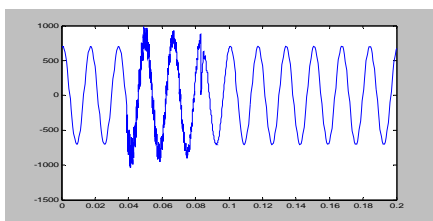


Fig 2.1 Oscillatory Transients

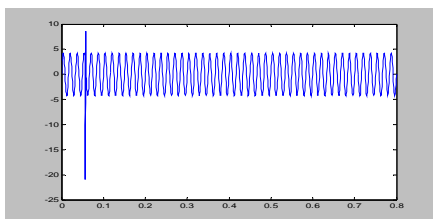


Fig 2.2 Impulsive Transient

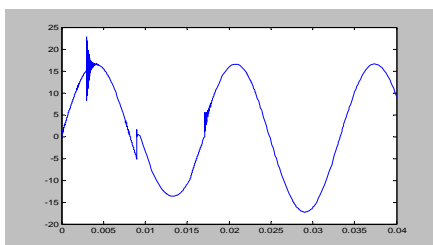


Fig 2.3 Transient due to fault

The impulsive low frequency transient rises in 0.1 ms and lasts more than 1ms. The oscillatory low frequency transient contains frequency components up to 5 kHz. These types are the most common transients recorded on a power system. They are not only propagated but they can also be amplified by a power systems resonance phenomenon. Measurement of these types of transients should be useful for all classes of application. The medium frequency impulsive transient

lasting between 5 ns to 1ms and the oscillatory transient between 5 and 500 kHz are less frequent than the low frequency types but have much higher amplitude. These transients may not propagate as easily as the low frequency types but may cause arcing faults on the power distribution system which result in voltage sag on many user power systems. The high frequency transient types with high amplitude can be observed only near where the phenomenon occurs. The high frequency impulsive transient has duration below 50 ns and the frequency of the high frequency oscillatory type ranges between 0.5 to 5MHz.

III. PROPOSED METHODOLOGY

The proposed methodology for disturbance waveform classification is based on Artificial Neural Network. Artificial Neural Network approach for any application involves two stages: network development and actual usage of the network. During the network development phase, the neural network is trained to capture the relationship between the input and output. The training and the test data required to develop the ANN are generated through off- line simulation process. After training, the network is tested with the test data to assess the generalization capability of the developed network.

The block diagram representation of the proposed model for power system transient classification is shown in fig 3.1

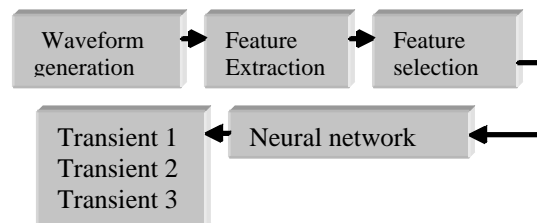


Fig 3.1 Proposed model for power system transient classification

Generation of the appropriate training data is an important step in the development of ANN models. A large number of training data is generated through off-line simulation process. Three types of power quality transients namely, impulse transient, oscillatory transient and transient due to fault are generated by simulating various events in the test system.

Feature extraction is the key for pattern recognition so that it is the most important component of designing the intelligent system based on pattern recognition since even the best classifier will perform poorly if the features are not chosen well. A feature extractor should reduce the pattern (i.e., the original waveform) to a lower dimension which contains most of the useful information from the original vector. The disturbance signal in time domain is transformed into the wavelet domain before applying the input to the neural network. The wavelet coefficients such as approximation and detail coefficients are obtained by finding the wavelet transform of the disturbance signals using Multi Resolution Analysis (MRA) technique.

Most useful features must be first selected from these coefficients to reduce the dimension of feature vectors, in order to more effectively recognize the type of power

quality disturbances. A feature selection algorithm based on Shannon (non normalized) entropy is applied to select the input features of the network. The entropy [9] is a measure of irregularities of states such as imbalance and uncertainty. Since power quality disturbance signals have the imbalance, the non stationary, the different frequency component and the different energy distribution, the Shannon entropy is proposed to extract the features from different power system transient.

The selected features are presented to the Radial Basis Function (RBF) neural network. The RBF network used here has an input layer, a hidden layer consisting of Gaussian function, a set of weights to connect hidden layer and output layer. The attractive feature of RBFNN lies in the linear dependence in the parameters which greatly simplifies the design and analysis of such networks. It also has an advantage of easy and effective learning algorithm compared to the back propagation neural network. After training, the network is tested with the test data to assess the generalization ability of the network.

IV. FEATURE EXTRACTION USING WAVELET TRANSFORM

The wavelet transform [12] can be interpreted as the inner product of the complex conjugate of wavelet function $h_{a,\tau}^*(t)$ and the input signal $s(t)$

$$WT(a,\tau) = \int h_{a,\tau}^*(t) \cdot s(t) dt \quad (1)$$

Where the wavelet function $h_{a,\tau}(t)$ is defined as

$$h_{a,\tau}(t) = a^{-1/2}h(t-\tau/a) \quad (2)$$

The variable a is the scale parameter of the wavelet function and is proportional to the reciprocal of the frequency, τ is the translation parameter and h is called the mother wavelet. A mother wavelet [14] is a function that oscillates, has finite energy and zero mean value. Normally, the mother wavelet that resembles the analyzed signal is the best choice, as this would reduce the number of non-zero Wavelet coefficients.

Wavelet decomposition enables multi resolution analysis as a single signal can be broken down into multiple frequency bands. The goal of MRA is to develop representation of a signal at various levels of resolution. Figure 4.1 shows the two level decomposition of a signal $x(n)$

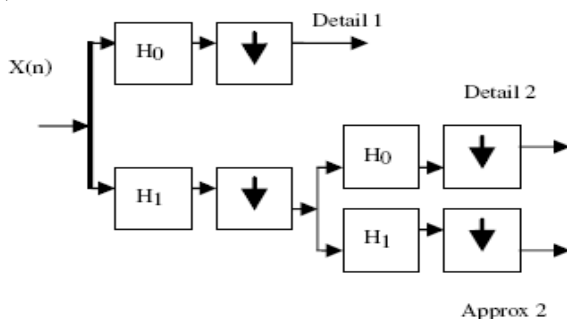


Fig 4.1 Two level multiresolution decomposition of a signal $x(n)$

MRA is composed of 2 filters in each level, which are low pass filter and high pass filter. The scaling function is associated with the low pass Filter with the filter

coefficients $h(n)$ and the wavelet function is associated with the high pass filter with the filter coefficients $g(n)$. The high pass filter coefficients are called as the approximations and the low pass filter coefficients are called as the details. The approximation coefficients and the detail coefficients are given by the following equations.

$$CA_j(k) = \sum_k f(n)h_d(-k+2n) \quad (3)$$

$$CD_j(k) = \sum_k f(n)g_d(-k+2n) \quad (4)$$

Where $f(n)$ is the input signal and j is the resolution level.

Wavelet transformation [13] has the ability to analyze different power quality problems simultaneously in both time and frequency domains. The wavelet transform is useful in detecting and extracting disturbance features of various types of electric power quality disturbances because it is sensitive to signal irregularities but insensitive to the regular-like signal behavior.

V. FEATURE SELECTION USING ENTROPY

In the neural network approach, by selecting only the relevant attributes of the data as input features and excluding the redundant ones, higher performance is expected with smaller computational effort. In this work, the input features of the network are selected based on entropy.

Entropy [10] is a common concept in many fields, mainly in signal processing. In thermodynamics, entropy is a measure of quantifying the imbalance degree of thermo-state. In mathematics, entropy is used to measure the uncertainty of problems. While in information science, entropy is the average uncertainty of information source. In other word, entropy is a measure of irregularity of states such as imbalance, uncertainty. A method for measuring the entropy appears as an ideal tool for quantifying the ordering of non-stationary signals.

Various wavelet entropy measures were defined in [10]. In this paper, the non normalized Shannon entropy is used. Since the power quality signals have the imbalance, the non-stationary, the different frequency component and the different energy distribution, Shannon entropy is used to extract the features from different power quality disturbance signals as a measurement of these irregularities.

Let the disturbance signal be $U = \{U_j, j=1,2,\dots,N\}$. The Shannon (non normalized) entropy of the j^{th} point is represented as

$$SE_j = \sum_{k=1}^N E_{jk} \log E_{jk} \quad (5)$$

where E_{jk} is the wavelet energy spectrum at scale j and instant k and is defined as follows.

The wavelet energy spectrum for detail and approximation coefficients in each decomposition level is obtained from the wavelet multi-resolution analysis of different disturbances and can be calculated as follows:

$$ED_{jk} = |D_j(k)|^2 \quad (6)$$

$$EA_{jk} = |A_j(k)|^2 \quad (7)$$

Where $j=1,2,\dots,J$

ED_{jk} and EA_{jk} are the energy spectrum for detail and approximation coefficients respectively. $D_j(k)$ is the detailed coefficients and $A_j(k)$ is the approximation coefficients.

Where J represents the total number of resolution levels. The extracted features help to distinguish a disturbance signal from another.

The frequency bands with higher entropy values, which contain useful information are selected from the entropy distribution of the wavelet detailed coefficients and the remaining frequency bands with zero entropy values are rejected.

VI. RADIAL BASIS NEURAL NETWORKS

The schematic diagram of RBF neural network is shown in figure 6.1. The RBF network [9] has an input layer, a hidden layer consisting of Gaussian node function, a set of weights W , to connect the hidden layer and output layer. The transfer functions in the nodes are similar to the multivariate Gaussian density function,

$$\Phi_j(x) = \exp(-\|x - \mu_j\|^2 / 2\sigma_j^2) \quad (8)$$

Where x is the input vector, μ_j and σ_j are the center and spread of the corresponding Gaussian function. Each RBF unit has a significant activation over a specific region determined by μ_j and σ_j . Thus each RBF represents a unique local neighborhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units. The value of k^{th} output node y_k is given by

$$y_k(x) = \sum_{j=1}^h w_{kj} \phi_j(x) + w_{k0} \quad (9)$$

where w_{kj} is the connection weight between the k^{th} output and the j^{th} hidden node and w_{k0} is the basis term.

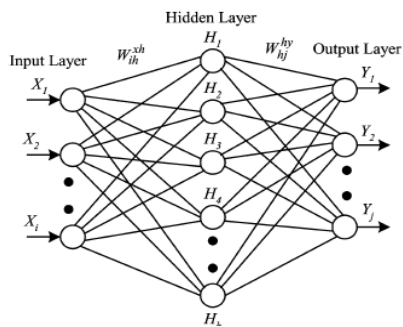


Fig 6.1 Schematic diagram of RBF neural network

The training of RBF is done in three sequential stages. The first stage of the learning consists of determining the unit centers μ_j by the k -means clustering algorithm. Next, the unit widths σ_j are determined using a heuristic approach that ensures the smoothness and the continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least squares objective function.

RBF Neural Networks (RBFNN) [11] can be viewed as alternative tool for learning in neural networks. While, RBFNN exhibit the same properties as back propagation networks such as generalization ability and robustness, they also have the additional advantage of fast learning and ability to detect outliers during estimation.

VII. SIMULATION RESULTS

This section presents the details of the simulation carried out on a sample power system to classify the transient waveforms. The model network shown in the fig 7.1 has been used to simulate the various disturbances in the system. The system was modeled using power system block set in Matlab/Simulink software.

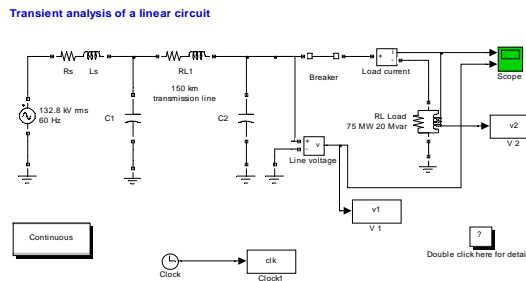


Fig 7.1 Test system for generation of power system transients

The different types of transients were generated by creating various faults such as single line to ground faults, double line to ground faults and using capacitor switching circuits at different points. The signals generated in this way are found to be very close to the real situation. Training samples were obtained from different locations in the system in an attempt to simulate a variety of possible monitoring locations. This provides a wide range of variety of disturbances, since samples were taken from different locations. Totally 600 samples for each class were generated, out of which 300 was used for training and the remaining 300 for testing.

Both the training and testing signals are sampled at 256 points/cycle and the normal frequency of 50 Hz. The features are extracted from these disturbance signals by finding the wavelet transform of the signal and applying MRA technique. The approximations and the detailed coefficients are obtained from the wavelet transform of the signal using 'db4' mother wavelet. From these features, the desired features are selected by using Shannon entropy method. Figures 7.2 to 7.4 show the entropy distribution pattern for the different types of transients. It is observed from fig 7.2 that, the oscillatory transient shows more entropy being distributed among the lower frequency bands (levels 5,6 and 7) whereas the entropy value for levels 1,2,3,4 and 8 is approximately zero.

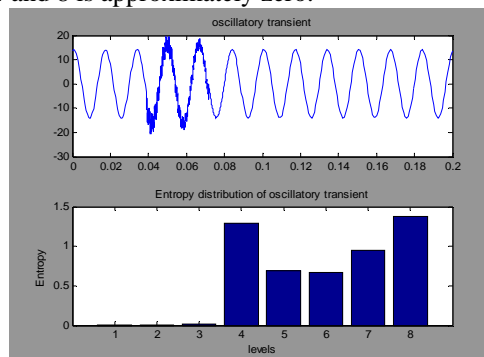


Fig 7.2 Oscillatory transient and its entropy distribution

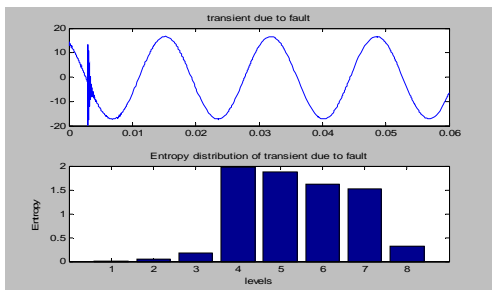


Fig 7.3 Transient due to fault and its entropy distribution

From fig 7.3 it is seen that the maximum value of entropy for transient due to fault is concentrated in level 4.

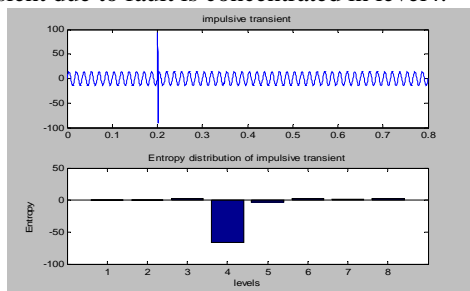


Figure 7.4 impulse transient and its entropy distribution

As shown in fig 7.4, for impulsive transient, the minimum entropy is confined to the mid frequency band (level 4).

The Shannon entropy for the detailed coefficients for the set of three types of transients analyzed with the db4 wavelet for 8 levels are shown in figures 7.5 to 7.7.

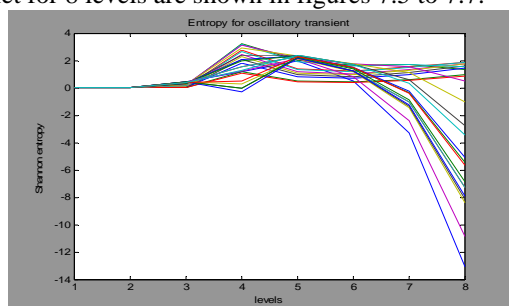


Fig 7.5 entropy for a set of oscillatory transients

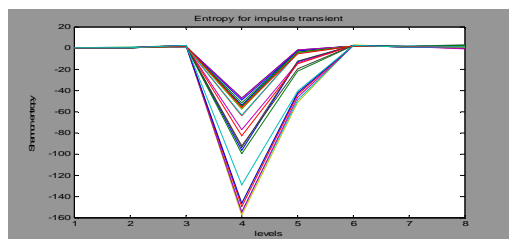


Fig 7.6 entropy for a set of impulse transients

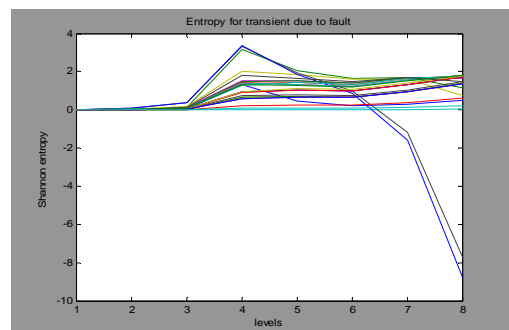


Fig 7.7 entropy for a set of transients due to fault

It is seen from figures 6.5 to 7.7 that, maximum entropy for oscillatory transient is 3.5, the minimum entropy for impulse transient is -60, where as for transient due to fault, it is -9 which clearly distinguishes the different transients. Similarly, the entropy values for each resolution level of each transient signal vary accordingly. It is also observed from the figures 7.5 to 7.7 that, the entropy values for the resolution levels 1, 2 and 3 is approximately zero. Hence the remaining levels (i.e., level 4,5,6,7 and 8) contain useful information and are selected as input features of the neural network. The selected features are given to the RBF network for training. After training, the networks are tested with the test data.

The classification results during training and testing are shown in the table I and table II.

TABLE I RESULTS USING WAVELET ENTROPY BASED RBFNN AND BPNN

ANN type	Training error	Testing error	Training Time (sec)	Accuracy
RBFNN	0.0095	0.1950	4.2	99.3%
BPNN	0.2009	0.2155	16.5	95%

TABLE II RESULTS USING WAVELET BASED RBFNN AND BPNN

ANN type	Training error	Testing error	Training Time (sec)	Accuracy
RBFNN	13.28	0.7839	7.31	78%
BPNN	0.1556	2.1574	17.2	70.7%

A comparison in terms of classification accuracy between the results of entropy based RBF network and the results of classification using wavelet based neural classifier is made. Similarly, the results using RBFNN classifier and Back Propagation Feed forward Neural Network (BPFFNN) classifier are compared. It is observed from table I and II that, the entropy based RBFNN classifier provides best performance with the accuracy of 99.3%.

TABLE III RESULTS OF RBFNN BEFORE AND AFTER APPLYING FEATURE SELECTION

RPF NN	No.Of featur	Training Error	Testing error	Trainig Time (sec)	Accuracy
After Feature Select-ion	5	0.0095	0.1950	4.2	99.3%
before Feature Select-ion	8	0.1295	0.20	5.8	96.2%

Using RBFNN, the computation time is also reduced. It is clear from the table 1 that, the training time required for RBFNN classifier is one fourth of the training time required for Back Propagation neural Networks (BPNN) classifier and the generalization capability of the RBFNN is also better than BPNN. The comparison between the results of the RBFNN with and without feature selection is shown in table III.

From table 3, it is evident that, using the wavelet entropy

based feature selection technique, the feature size is reduced as well as the training time; training and testing error are also less compared to the RBFNN without feature selection. Similarly, the accuracy of the RBFNN with feature selection is 99.3%, while for the other case, it is less.

The feature vectors before and after applying feature selection scheme is shown in figures 7.8 and 7.9.

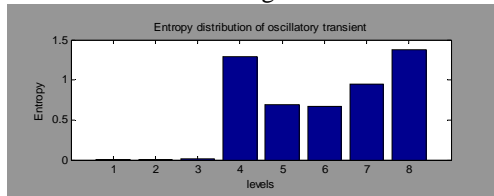


Fig 7.8 Distribution of input features before applying feature selection

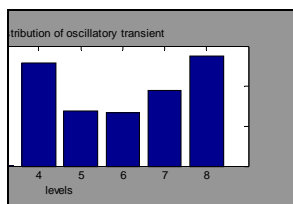


Fig 7.9 Distribution of input features after applying feature selection

From fig 7.8, it is seen that the number of feature vectors is 8. i.e., the information present in levels 1 to 8. But there is no information present in levels 1, 2 and 3. That is, the entropy value for levels 1, 2 and 3 is zero. Thus it is not necessary to give all the 8 features to the input of the neural network. The levels with only non zero entropy values are selected as input features. Hence, after applying feature selection technique, the number of features is reduced to 5 (i.e., levels 4 to 8) which is shown in fig 7.9. which reduces the memory space and increases the computation speed.

VIII. CONCLUSION

In this paper, a neural network based method is proposed for automatic power system transient classification. The input features of the neural network are extracted using wavelet transform and Shannon entropy method is used to select the relevant features. Radial Basis Function neural network is used for classification. Simulation has been carried out on a sample power system to demonstrate the effectiveness of the proposed approach for transient waveform classification. The most important advantage of the proposed method is the reduction of data size as well as indicating the main characteristics of signal without losing its distinguishing characteristics. Further, it reduces the memory requirement and increases computation speed.

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