

An Integrated Data Compression Using Wavelet and Neural Networks for power quality Disturbances

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Abstract: - This paper introduces a novel data compression technique for the classification of power quality disturbances using wavelet transform and radial basis function neural network. For compression, criterion of maximum wavelet energy coefficient, signal decomposition and reconstruction is been used. The analysis was carried out by simulating power quality disturbance data, such as sag, swell, momentary interruptions and harmonics using MATLAB. Daubechies and Symlet functions were used to select wavelet function and scale to decompose the signals. Radial basis function neural network is been used to compress and classify various power quality disturbance for different orientations. The simulation results shows that the proposed technique compresses and classifies the signals very well when compared to conventional data compression techniques.

Key-Words: - Power quality disturbances, Wavelet Transform, Multi-resolution analysis, Data Compression. Radial basis function neural networks.

1 Introduction

In recent years power quality (PQ) and its related issues have captured attention from both utility and customers. After deregulation, the power quality problems and its entire information has become valuable mainly for pricing, ownership and negotiation. Based on the severity and duration of the power quality disturbances, the disturbances are categorized as shorter and longer duration which frequently affects the entire power system. The power quality disturbance such as voltage sag may be caused in a system while switching on of a heavy loads, whereas swell may be caused by switching off of a heavy loads. Harmonics and its various levels caused using electronics equipment in the distribution end which may degrades the quality of power as well as the performances of the equipment. Most probably the momentary interruption occurs due to short circuits only. In power system, these disturbances need to be identified in order to improve quality. PQ event identification is difficult because it involves wide range of disturbance categories. Therefore, the decision boundaries of disturbance features may overlap. For these reasons, the need of power quality analysis has been strongly increasing [1-3]. The above mentioned disturbances usually will occur in the order of milli and micro

seconds. A single captured disturbance were recorded using recording and monitoring instruments may produce megabytes of data, which results in significant increase in the volume of recorded data[4].

The situation made the researchers to develop an effective data compression technique, which must have the potential to reduce the volume of recorded data. Compression is necessary to speed up the data transmission particularly for remote monitoring, identification and classification of various power quality disturbances, mainly to design mitigating devices to improve power quality in the power system. Many kinds of compression techniques and methods are available, which all have been effectively used in various applications such as satellite communication, commercial telephony...etc. Most of the compression technique will highlights the principle of encoding applied in the data, such a schemes are called as prediction coding schemes. The two major part of the predictive coding algorithms are predictive and quantizer. In this, in quantization the error must be reduced which can be done in the prediction, mainly to improve the compression performance. This reduction process is a time consuming one which is

undesirable for compression and event classification [5].

Wrap around scheme were mostly used in power distribution monitors for reduction techniques. In this, the recycling process takes place in the existing memory to increase the memory capacity level by writing over in the oldest data. This takes place only to represent the group of similar waveforms as a single input. This technique probably will conserve more memory space, but will not compress data as it supposed to do. [6]. Representing a signals as a projection of an orthogonal sine and cosine function is been frequently done in Discrete Fourier transforms, which normally comes under frequency coefficients. This will work well if the signal taken in to consideration is sinusoidal, stationary and periodic. But in real situation, disturbances are subject to transient and non-periodic in nature, so for data compression, the Discrete Fourier transform has become inadequate.

To localize transition, particularly sharp transition the Short Time Fourier Transform uses time frequency window. This time frequency window comes under fixed window types. This kind of fixed window are not a generalized one, it is restricted to certain events, such as for shorter and sharp duration events [7]. The discrete cosine transform has orthogonal property, which is been mostly used in a conventional data compression. This technique provides piece wise smooth nature to almost all signals which are taken in to consideration for denoising and compression. In this the process is normally carried out by filters. In this, there are chances for sparse representation for different signals, which normally connected with transform basis function. This discrete cosine transform will not yield a discrete time basis on time-localization. So this technique will not be appropriate for any type of data compression.

Length of the discrete time and their moment are used as a vehicle in Slantlet Transform. The reason for using the length is to have both time-localization and smoothness properties for performing data compression. The compression ratio and energy retained in terms of percentage were not up to level for classifying the signals [8].

Minimum description length is used to improve the efficiency of data compression. This minimum description length worked well to achieve compromise between the numbers of

retained coefficients. The main drawback in introducing minimum description length in data compression is, the generation of error while signal reconstruction. The error is not in acceptable level which leads to improper solution in filtering process [9].

Splines base compression technique has been used in image processing mainly to interpolate equally spaced samples. This spline has a special property which made to stand apart in the field of wavelet transform. The major issue which will occur frequently in the construction part is the iterative filter bank constructions. So all together by using this technique the compression result is not an effective result, as it has few amounts of unwanted data which must be compressed. The data present mostly as a white noise in the main filtered sequence [10]. To prove the storage capacity of the monitor and its bit rate an enhanced disturbance compression method is used mainly in data transmission in the power quality analysis. This enhances disturbance compression method normally carried out with the past data of the signals taken in to consideration that can be subtracted to reveal a non-stationary type or to slow the difference present in the signals [11]

A hybrid scheme data compression is been introduced to improve the compression further. In this scheme wavelet transform and radial basis function neural network is been used for both data compression as well as for power quality disturbances classification. Recently wavelet transform has become as a powerful tool for almost all engineering applications particularly application related with time-frequency analysis. The redundancy in the signals is been exploited by the wavelet transform to carry out data compression process. The major part lies in wavelet transform for data compression is, its concentrating nature of a large energy from the signals, considering few coefficients. So from this, the related coefficients were alone used, non-related coefficient were discarded without affecting the information been available in the coefficients. Within the wavelet transform multi-resolution analysis is been used to solve compression and classification issues with many computing techniques [12]. The major added advantage of using wavelet transform is the capability of depressing the white noise in the compressed data. The depression is done in the pre-processing of the data in the measuring device itself [13]. By this technique, nevertheless without loss of

important information, the approach is capable enough to compress any type of signal to a time series format which can be used to identify and classify power quality disturbances present in the power system.

By hybrid method, at first power quality disturbances coefficient are obtained by using wavelet transforms. From the obtained coefficients the low energy coefficient are set to zero as it will not have much information to proceed further. In the next step, the compression is carried out in which each coefficient are enclosed to reduce the bits count compared to its conventional coded bits by using radial basis function neural networks [14]. The overall compression performance of this hybrid technique is nothing but the product of each stage compression ratio. Finally with the wavelet transform and RBFNN the data extraction, identification and classification of power quality disturbance was carried out.

The paper organized as follows, in section II wavelet Transform based MRA were briefly discussed. In section III, for data compression the selection of best wavelet function and scales are identified, next in section IV radial basis function neural network were detailed and finally in section V results and discussion were made in which data compression and identification and classification of power quality disturbances are discussed.

2 Wavelet Transforms

Wavelet transformation has the ability to analyze different power quality disturbances in both time and frequency domain. The wavelet transform is useful in extracting features of various power quality disturbances. Wavelet analysis deals with expansion of function in terms of a set of basis function. However, wavelet analysis expands functions not in terms of trigonometric polynomials but in terms of wavelets. Moreover, another important property that the wavelet possesses is perfect reconstruction, which is the process of reassembling a decomposed signal or image into its original form without loss of information.

2.1 Multi-resolution Analysis

Scaling and wavelet functions are most important function in multi-resolution analysis (MRA) to decompose and construct the signals taken in to

consideration in to different resolution levels. MRA's main role is representation of signals at various resolution level which is been done with low pass and high pass filters. The detailed information present in the signals is measured through the resolution levels. This resolution level is changed according to the need by filtering operation, and scales are changed by up and down sampling operation. Reduction and rising of sampling rate are carried out by down and up sampling in the MRA filtering process. Decomposition and reconstruction are shown in Figure 1a and 1b [1].

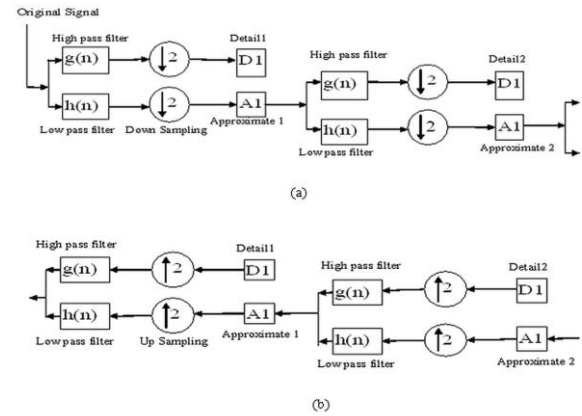


Fig.1 Multiresolution Analysis (a) Decomposition (b) Reconstruction

Consider a signal $x[n]$ which is a discrete signal distributed in level 2. This signal is filtered in to high frequency component and low frequency component in level 2 by high and low pass filters that is by $g(n)$ which is a high pass filter and $h(n)$ which is a low pass filter. The initial signals are components present in the level 1. The signals are passed through these two filters for filtering, the output of these filters are mathematically expressed as in Eq.(1) and (2) as follows

$$y1[k] = \sum_n x[n] \cdot g[2k - n] \quad (1)$$

$$y2[k] = \sum_n x[n] \cdot h[2k - n] \quad (2)$$

As mentioned earlier $h(n)$ is low pass filter and $g(n)$ is high pass filter, $y1[k]$ and $y2[k]$ are the outputs of filters

3 Selection of Wavelets and Decomposition Scale

In this section, the selection of wavelet function and

scale were determined to have effective compression and classification of power quality disturbance. In general within wavelet transform there are number of basis function, which can be used to process wavelet transformation, for the selected signals. Mostly translation and scaling are the two function used in the wavelet transformation, which determines the exact characteristics of the transformed signals. For any application to have an effective usage of wavelet transform, the details of particular task and its parameters are important. The selection of wavelet is done based on shape and the problems handling capability of the signal in an application. So selection of appropriate wavelet function and scale are important to proceed the compression and classification. Energy present in the signal is been extracted by the wavelet, as a wavelet energy, which is the index to the energy concentration on certain scales. This energy normally reflects the information present in various signals taken in to consideration for the analysis .In order to have more information from the signals. Larger wavelet energy must be preserved after decomposition.

Total energy and average power for a signal $x(n)$ is shown in eq.(3) and (4)

$$E = \sum_{n=-\infty}^{\infty} x^2[n] \quad (3)$$

And the average power is

$$P = \lim_{N \rightarrow \infty} \frac{1}{2N} \sum_{n=-N}^N x^n[n] \quad (4)$$

As discussed earlier many wavelet functions are available among them Daubechies and Symlets have been chosen to perform initial phase.

3.1 Daubechies Wavelet Transform

Daubechies wavelet defines discrete wavelet transform which comes under family of orthogonal wavelet. This transforms mostly characterized by more number of vanishing moments. The scaling function present in Daubechies wavelet transform generate an multi-resolution analysis which is orthogonal in nature [7].

Table 1

Results of selection of wavelet function

3.2 Symlet Wavelet Transform

Symlets are proposed as a modification to Daubechies family which is nearly symmetrical. Both Daubechies and Symlets will have similar set of properties. As these wavelets gives best performance in analyzing disturbance signals particularly in compression and classification. Among these two functions, the function which gives highest wavelet energy is chosen as best function and used for faster analysis in compression and classification. In same way optimal decomposition scales are chosen based on the highest energy.

Voltage sag, swell, momentary interruption and harmonics were taken as a signals for performing compression and event classification using hybrid techniques. The results for selection of wavelet function and scale are shown in table 1 and table 2. The highest wavelet energy for a signal corresponding to a certain wavelet is highlighted in yellow in both table 1 and table 2. From table 1 and table 2 db2 and sym2 has the highest wavelet energy. Among db2 and sym2 either one can be chosen for next stage analysis. In this work db2 is been chosen to perform multi-resolution analysis. In table 2 the selection of scale is been carried out, here signals are decomposed by db2 into scales and from table 2 it is clear that wavelet energy at scale 5 has the highest energy and chosen to be a best optimal decomposition scale for performing multi-resolution analysis.

4 Radial Basis Function Neural Network

Radial basis function neural network consists of a network similar to back propagation network as shown in Figure 2 with a single hidden layer. RBFNN proves to be best for classification task from the investigation result presented .

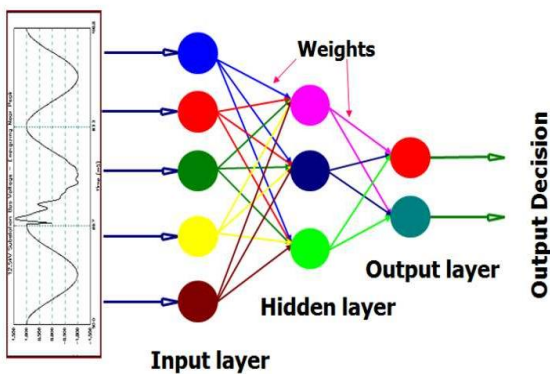
Each hidden layer consists of smoothing factor and centroids. The distance between the input and the centroid are normally computed by the neurons.

The outputs are a radial symmetrical function of the distance .

EVENTS	DAUBECHIES				SYMLETS			
	LEVEL				LEVEL			
	2	3	4	5	2	3	4	5
Sag	0.9748	0.9601	0.9863	0.9726	0.8915	0.9256	0.9793	0.9614
Swell	0.8417	0.8462	0.8917	0.8733	0.8367	0.8511	0.8845	0.8815
Interruption	0.8342	0.8172	0.8915	0.8678	0.7942	0.8173	0.8591	0.8498
Harmonics	0.8569	0.8701	0.8724	0.8655	0.8602	0.8643	0.8597	0.8613

Table 2
Results for selection of Scale

Events	DAUBECHIES					
	SCALE					
	1	2	3	4	5	6
Sag	0.3911	0.3948	0.4794	0.5217	0.5737	0.4955
Swell	0.3841	0.3979	0.4288	0.4812	0.4919	0.4871
Interruption	0.04681	0.0517	0.0594	0.0634	0.0678	0.0646
Harmonics	0.0724	0.0842	0.0849	0.1917	0.1981	0.1895



.Fig.2.Architecture of NN

When it is close to value the output will be a strong one. The real mapping function f_m in general form is

expressed in equation (5).

$$f_m(x) = \sum_{i=1}^M w_i k[(x_i - c_i) / \sigma_i] \quad (5)$$

The function k is a radial symmetrical kernel function computed by M kernel units.

The Gaussian exponential function used in RBF is expressed in equation (6).

$$f(x) = \beta \exp(-\sum_i [(x_i - c_i) / \sigma_i]^2) \quad (6)$$

According to the training data set, centroid and constant have to be chosen.

5 Result and Discussion

5.1 Data Compression

In this work, hard thresholdings are used for compression. To select thresholding there are two techniques based on the compression level. One is based on keeping larger absolute values of the wavelet coefficient. In this only one parameter is enough to set a global threshold. The next technique is the application of level-dependent threshold. In this method one threshold is necessary for each scale level. Here hard thresholding and daubechies 4 are used to compress the power quality disturbance signals. The data needed for compression is been extracted from the signals simulated from MATLAB for various orientation which is likely to occur in the power system. Before applying wavelet transform, the signal taken for the analysis must be dyadic number .As discussed earlier Db4 is used to decompose signals, which is been shown in figure 3 and figure 4.This decomposition is done at level 5.

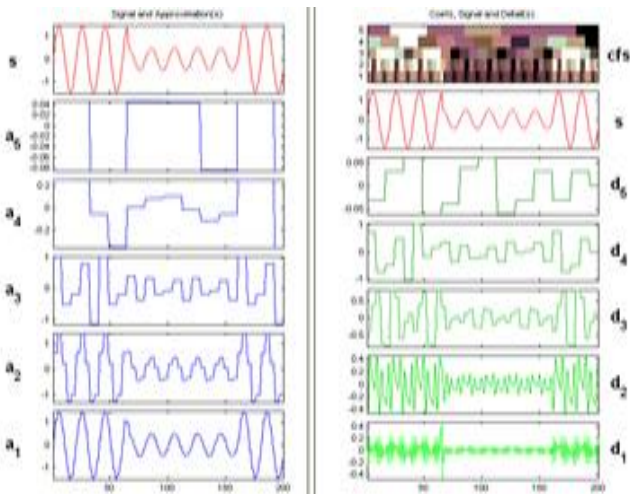


Fig.3 Wavelet decomposition at level 5 for sag

From the figure 3 and 4 at level 5, approximate (a5) and detail (d5) shape and their characteristics are very clear as that of the original signals. By the filter, from level 1 to level 4 all the detail coefficients are filtered, which are mostly high frequencies. At level 5 a smooth version of the original signals are obtained through summation of approximate and detailed coefficients. Determination of threshold values is very important to have subsequent data compression after decomposition process at each level. Here global threshold is

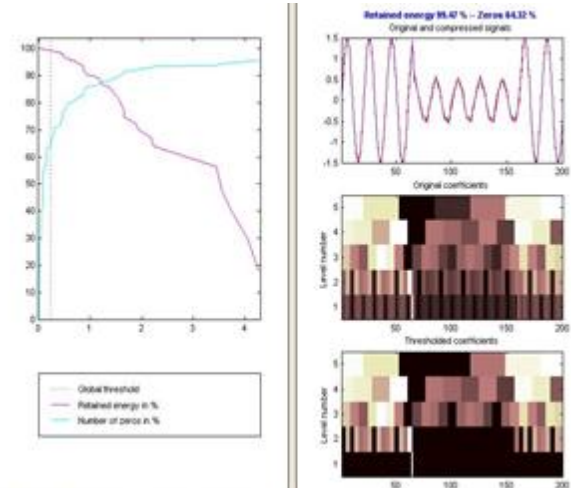


Fig. 4 Compression result for sag

been used which is been calculated only one time at time of processing. From table 3 it is clear that signals which all are compressed are almost perfect. The value of (0.8242) was chosen as a hard threshold value for compressing data in support with Db4 wavelet function and level 5. While carrying out the compression process, raw input data were given as input to wavelet function, to perform decomposition process. As discussed earlier the wavelet function chosen

Table 3
Retained Energy for Compression by Db2

Disturbances	Retained Energy %
Voltage sag	94.47
Voltage swell	95.55
Momentary Interruption	94.31
Harmonics	93.46

has time-frequency localization property, more energetic coefficients are localized which has become sparse in nature. By this, with the wavelet, compact support from the wavelet is been achieved which laid the foundation for proposed hybrid data compression. On applying hybrid threshold criterion the insignificant

wavelet are set to zero by selecting absolute maximum value of the wavelet coefficient in association with selected scale. Due to this the number of retained wavelet coefficient will become smaller than the original input data. In the subsequent stage RBFNN is proposed to compress further. As per the requirement number of input and output are kept same in the input layer of the RBFNN architecture. But in the encoding stage to compress data, the hidden layers are assigned with only less number of neurons mainly to achieve compressed data. For compression, input and hidden nodes are used, whereas out layers were used for expansion which is shown in figure 5.

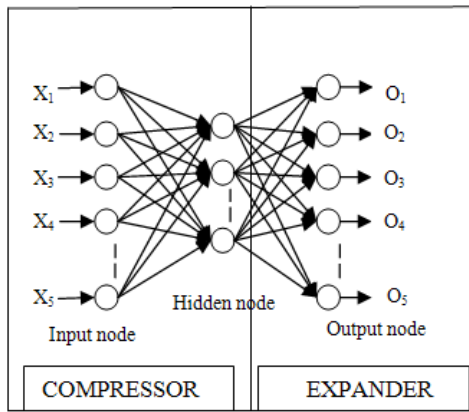


Fig. 5

Hybrid Network

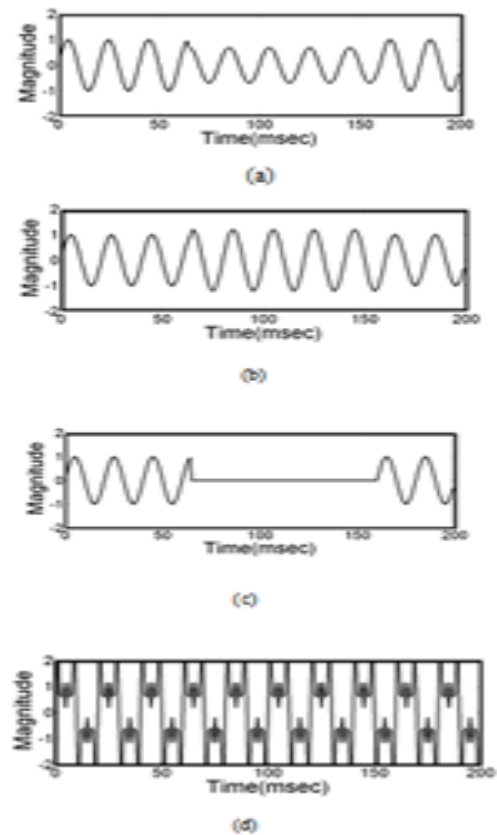
Back propagation algorithm is used for training the network, the training continued until the error reaches possible minimum value. The training is mostly carried out simultaneously both at the input and output layer, in which the portion that have trained from input to hidden nodes perform compression, whereas the other portion used for reconstructing the network. The entire reconstruction was done in reverse order. The entire analysis particularly training phase carried out with random binary pattern, mainly to have generality in nature. This made the network suitable for all kind of signals.

5.2 Detection and Classification of power quality disturbances

5.2.1 Data Generation

Among several typical PQ events, voltage sag is taken for consideration to show the training, validation and testing of RBFNN. Using MATLAB, the most commonly occurring disturbance is initially simulated which is been shown in figure 6. The categories that are simulated are voltage sag, swell, momentary interruption and harmonics. For simplicity here voltage sag alone was discussed. Further the voltage sag is categorized as momentary, temporary and long term sag. This problem occurs due to a fault, switching of heavy loads or starting of large motors.

Fig.6 (a) Sag (b) Swell (c) Interruption (d)



Harmonics

5.2.2 Data Extraction

A distorted signal can be mapped in to wavelet domine and represented by a set of wavelet coefficients using WT. Here, the Daubechies "Db4" wavelet function is used to decompose the signal.

The parameters of the voltage waveforms during

Table 4
Data for training

Sag	Amplitude	Mean	Standard deviation	Median absolute deviation	Mean absolute deviation	Energy
A1	1	0.0132	0.805	1.397	1.263	1
A2	1	0.0106	0.840	0.6657	0.706	0.97
A3	1	0.0132	0.805	0.4755	0.646	0.97
A4	1	0.0132	0.974	0.8817	0.835	0.96
A5	1	-0.01828	0.705	0.4635	0.551	0.98
A6	1	0.00664	0.910	0.8817	0.796	0.96
A7	0.133	0.172	0.772	0.2	0.555	0.99
A8	0.866	0.0026	0.997	0.9667	0.886	0.95
A9	0.866	-0.0036	0.976	0.9667	0.868	0.95
A10	0.866	0.00265	1.039	0.9667	0.9247	0.95

PQ events are statistically different from those that are calculated during an event free time period. The statistical difference is used for effective detection of PQ events. Various numerical indices are found for different orientation of sag for A1 to A10 as given in Table .4.The distribution of data for various events were shown in figure 7 and 8

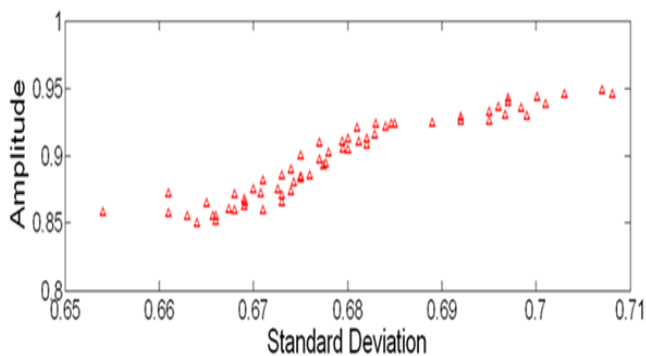


Fig.7 Data obtained for sag in voltage signal

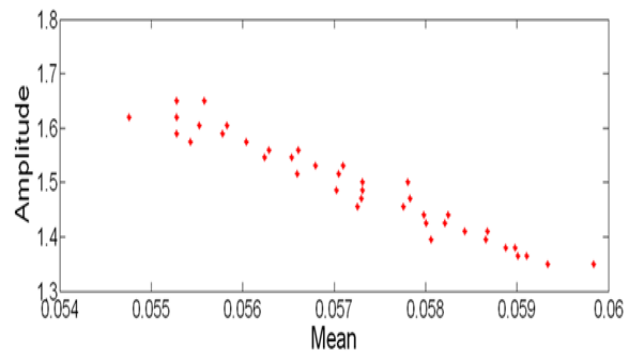


Fig. 8 Data obtained for swell in voltage signal

5.2.3 Network Training

For the training purpose, the learning rate of the RBFNN is chosen as 0.1 and the center and the weight are updated in every iteration . Here amplitude, mean, standard deviation, mean absolute deviation, median absolute deviation and energies are used as inputs to the RBFNN. Hence the RBFNN is trained with 10 different orientation of sag alone which is given in the

table 3. For example, 10 orientation of sag with different indices are generated for training and another 3 cases are generated for testing. Whereas 100 orientations for each event are taken which will be discussed in the next section, since 10 number of orientation may not be adequate in real cases. Daubechies “*Db4*” wavelets with four levels of decomposition are used for analysis. Based on the feature extraction, the total size of training data and testing data set is 10x6 sizes, where 60 comes from 10 cases per class. The RBFNN performance is tested by an existing input to check the level of training. Then the network is tested by a novel input with the help of their features. The RBFNN model is investigated and tested whether it is capable of producing the best performance with higher degree of prediction accuracy even with new interpolate and extrapolate ranges of trained values. The numerically best detected data for training and validation and the testing shown in figure 9. The simulation was carried out combining wavelet transformation with RBFNN for classification for 4 types of power quality problems.

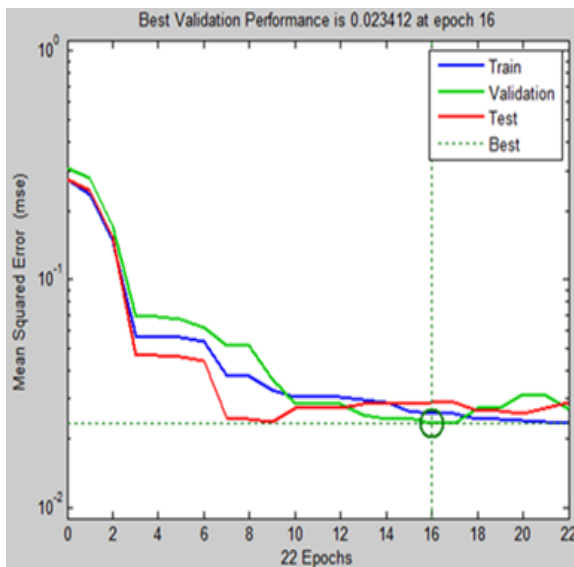


Fig.9 Train ,validation and test performance

0.001. The RBFNN network is trained with 30 input data of each class and 100 data of each class are considered for testing. Centre and weights are updated in each and every iteration, and then in this way new training input is given to the network and processed till the error reduces to minimum value. The contour plot for the error

is shown in figure 10. The randomly selected signal from 100 signals of each power quality problem is used to test RBFNN. The classification result during testing is shown tables 5. The overall accuracy of classification is the ratio of correctly classified events to that of total number of events. These networks are trained and subsequently tested for higher number of classes with the same data. It is identified that RBFNN gives the best classification results for this case.

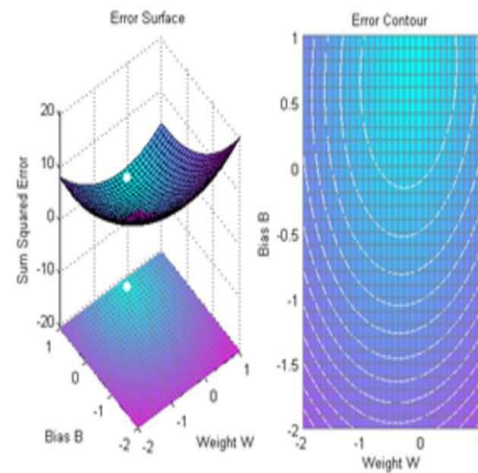


Fig. 10 Contour plot for the error

5.2.4 Comparison of Proposed Work with Real Time Data

To test the proposed work with practical data of (Carlos Leon et al 2007) mainly for ideal signal (230 vrms and 50Hz), sag with (40% and 20ms) and swell (20% and 60ms) were taken and from them the features were extracted and given as input to the proposed trained RBFNN network

[15]. In similar way to test the potential of the proposed network the data of (Martin Valtierra-Rodriguez et al 2014) mainly sag were taken which is an experimental setup composed of a transformer bank in delta- wye of 350VA, a capacitor bank of 77 micro farad and two motors of 1 and 2hp(746W) respectively with data acquisition system with an low pass butterworth antialiasing filter. The results are shown in table 6.

Table 5**Comparison of classification rate**

Events	Comparison of classification rate in %					
	References				Proposed	
	[16] ADALINE AND FFNN	[17] S-Trans. Based L-SVM	[18] S-Tran. PNN	[19] ANN (Field Test)	RBFNN	RBFNN
Sag	100	100	95	90	98	100
Swell	100	97	91	70	93	96
Interruption	--	--	99	--	98	98
Harmonics	--	--	98	80	94	97

Table 6**Comparison of proposed RBFNN with other works practical data**

Test Signals	Disturbances	Overall Classification Accuracy %
		RBFNN
Simulated signals	Sag	98.19
	Swell	98.24
(carls Leon et al 2007)	Sag	98.19
	Swell	98.24
(MartinValtierra-Rodrigues et al 2014)	Sag	98.57

In the previous chapter, less number of events that is voltage sag and swell where considered to check the proposed networks potential with practical data in which 10 orientations of events with different indices are generated for training and tested with practical data. Whereas 10 number of orientation may not be adequate in real cases for detection and classifications of PQ events. Hence 100 orientations for each event are taken in this work.

5.2.5 Results and Discussion based on Features

In any ANN approach, the main difficulty is that, if the number of input variables increases, ANN will take more time to train the network. Hence, selection of features and number of features is necessary to the ANN approach for the practical problems. The performance of the

Table 7 Comparison of proposed RBFNN based on number of features with other

Before Data Compression					
No.of Features	Features	Classifier	Classification rate %	CPU Time(sec) Training	CPU Time(sec) Testing
2	1. Mean 2. Standard Deviation	RBFNN	96.20	2	0.08
3	1. Mean 2. Standard Deviation 3. Energy of the detailed wavelet coefficients	RBFNN	95.17	3.2	0.38
5	1. Mean 2. Standard Deviation 3. Number of peaks of the wavelet coefficients 4. Energy of the detailed wavelet coefficients 5. Energy of the approximate wavelet coefficients	RBFNN	96.01	3.2	1.04
After Data Compression					
No.of Features	Features	Classifier	Classification rate %	CPU Time(sec) Training	CPU Time(sec) Testing
2	1. Mean 2. Standard Deviation	RBFNN	96.20	1.32	0.06
3	1. Mean 2. Standard Deviation 3. Energy of the detailed wavelet coefficients	RBFNN	95.17	3.02	0.27
5	1. Mean 2. Standard Deviation 3. Number of peaks of the wavelet coefficients 4. Energy of the detailed wavelet coefficients 5. Energy of the approximate wavelet coefficients	RBFNN	96.01	2.41	1.01

Table 8**Comparison of proposed RBFNN based on number of features with other technique**

Features	No.of Features	Classifier	Classification rate %
(S. Mishra et al 2008)	4	PNN	97.4
	3	PNN	95.91
(Chung-Yao Lee et al 2011)	5	APNN	96.3
		MLP	98.1
		K-NN	96.0
(PrakashK.Ray et al 2013)	10	MPNN	96.66
		SVM	98.33
(KanirajanPitchai , Suresh kumar, 2015)	2	RBFNN-BP	96.20
Proposed		RBFNN	97.75

Network can be improved in terms of accuracy, time consumption by reducing the number of features. This work proposes Wavelet-MRA based feature selection technique. The input feature are selected based on the values of Mean, Standard deviation, energy of both detail and approximate coefficients of the signals. In different resolution levels, the energy of the wavelet coefficient varies. Energy of the low frequency signals and high frequency signals is distributed in approximation coefficients and in detail coefficients. Since, in real time the waveforms have higher frequency components, it is more desirable to use detail coefficient energies. The performance of the proposed wavelet based on the feature selection method is compared based on the feature and number of features used for various classifier networks. Table 7 shows the percentage of classification rate and CPU time for training

and testing. From the table it is inferred that network trained with less number of features with compressed data gives high classification rate with less CPU time for both training and testing. So it is desirable to use compressed feature to get better classification with less time which is very much need in real time online applications. In table 8 the performance of the proposed wavelet based feature selection method is compared with other works such as from [16] [17] [18] and [19]. From the table 7 and 8 it is inferred that the proposed wavelet based feature selection gives better classification rate with less number of features.

6 Conclusion

This paper proposes an integrated approach of data compression for detection and classification of power quality disturbance using wavelet transform and radial basis function neural network. The

Daubechies 4 and scale 5 were chosen as the best wavelet function based on the maximum wavelet energy present in the wavelet coefficient after multi-resolution analysis decomposition and reconstruction. At first the compression was carried out with wavelet based MRA, which shows performance better than conventional compression techniques. To improve the compression further, a hybrid technique is been introduced just by combining wavelet transform with radial basis function neural network. By this hybrid technique the compression was much better than doing compression separately. Finally the compressed data were used to detect and classify power quality disturbance. The results proved that detection and classification was accurate with minimum data storage, transmission time with faster performance which is very much needed for online real time application

7 References

- [1] P. Kanirajan, V.Suresh Kumar, Power quality disturbances detection and classification using wavelet and RBFNN, *Applied Soft Computing*, Elsevier, Vol.35, pp.470-481, 2015.
- [2] P.Kanirajan,V.Suresh Kumar,Wavelet - based power quality disturbances detection and classification using RBFNN and Fuzzy Logic, *International Journal of Fuzzy Systems*, Springer,Vol.17 ,pp.623-634, 2015.
- [3] P.Kanirajan, V.Suresh Kumar,A wavelet based data compression technique for power quality events classification, *WSEAS Trans, On Power system*, Vol.10 ,pp. 82-88, 2015.
- [4] S.Santoso,E.J.Powers , W.M Grady, Power Quality Disturbance Data Compression using Wavelet Transform Methods, *IEEE Trans.Power Delivery*,Vol.12 ,pp.1250-1257, 1997.
- [5] Ketan Mehta,B.Don Russell,Data Compression for Digital Data from Power Systems Disturbances,Requirements and Technique Evaluation,*IEEE Trans.Power delivery*,Vol.4, pp.1683-1688, 1989. .
- [6] T.B.Littler , D.J.Morrow , wavelets for the Analysis and Compression of Power System Disturbances,*IEEE Trans.Power Delivery*,Vol.14 ,pp. 561-566, 1990.
- [7] Daubechies I,The Wavelet Transform,Time Frequency Localization and signals Analysis,*IEEE Trans.on Info.Theory*,Vol.36, pp.961-1005, 1990.
- [8] G.Panda, P.K.Dash, A.K.Pradhan, S.K. Meher, Data Compression of Power Quality Events Using the Slantlet Transforms, *IEEE Trans.Power delivery*, Vol.17pp.662-667, 1990 .
- [9] EffrinaYantiZen-Ichiro K wasaki,Wavelet-BasedData Compression of Power System Disturbance using the minimum Description Length Criterion, *IEEE Trans.Power Delivery* Vol.17,pp.460-466,2002.
- [10] P.K.Dash, B.K.Panigrahi, D.K.Sahoo, G.Panda, Power Quality Disturbance Data Compression,Detectionand ClassificationUsingIntegratedSpline Wavelet and S- Transforms,*IEEE Trans.Power elivery*, Vol.18 ,pp. 595-600, 2003.
- [11] Moises V,Ribeiro,Joao M.T.Romano , Carlos A.Duque ,An Improved Method for Signal Processing and Compression in Power Quality Evaluation,*IEEE Trans.Power Delivery*,Vol.19 ,pp. 464-471, 2003.
- [12] M.Forghani and S.Afsharnia.” Online Wavelet Transform-Based Control Strategy for UPQC Control System,” *IEEE Trans.Power Delivery*, Vol.22 ,pp. 481-491,2007.
- [13] Jiaxin Ning,Jianhui Wang,Wenzhong Gao and Cong Liu, A Wavelet-Based Data Compression Technique for Smart gril,*IEEE Trans on Smart Grid*,Vol.2,1- 10,2011.
- [14] L.Yingwei,N.Sundarrajan,P.Saratchandran, ,Performance evaluation of sequential minimal radial basis function neural

network learning algorithm”,IEEE Trans.Neural Network,vol. 9 ,pp. 308 - 318,1998.

- [15] Inigo Monedero, Carlos Leon, Jorge Ropero, Antonio Garcia, Jose Manuel Elena, Classification of Electrical Disturbances in Real Time using Neural Networks, IEEE Trans. Power Del., Vol.22, pp.1288-1296, 2007.
- [16] M.Valtierra-Rodriguez, R.D.J Romero-Troneoso, R.A.Oscornio- ios, A.Garciaperez, Detection and classification of single and combined power quality disturbance using neural networks, IEEE Trans. Ind. Electronis Vol.5, pp. 2473 – 2482, 2014.
- [17] Prakash K. Ray, Soumya R. Mohanty, Nandkishor, Classification of Power Quality Disturbances Due to Environmental Characteristics in Distributed Generation System, IEEE Trans. on sustainable energy, Vol.4 pp.302-313, 2013.
- [18] S.Mishra, C.N.Bhende B.K.Panigrahi, Detection and Classification of Power Quality Disturbances using S-Transform and Probabilistic Neural Networks, IEEE Trans. Power Del., Vol.23 ,pp.280-286, 2008.
- [19] Inigo Monedero, Carlos Leon, Jorge Ropero, Antonio Garcia, Jose Manuel Elena, , Classification of Electrical Disturbances in Real Time using Neural Networks, IEEE Trans. Power Del., Vol.22 pp. 1288-1296, 2013.

