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Abstract: Disturbances such as voltage sag, swell, interruption and harmonics are very typical in a power system. Power quality monitoring should be capable of identifying these disturbances to initiate mitigation action and protect sensitive loads. This paper presents wavelet-neural network-based detection and classification of power quality disturbances. Wavelet transform has the ability to analyse signals simultaneously in both time and frequency domains and is used to extract features of the disturbances by decomposing the signal using multi resolution analysis. These features, used to detect and localise the disturbances and are not easily separable, will reduce the performance of multilayer neural network. Improvement in the classification accuracy is suggested by employing modular neural network obtained by dividing a complex task into easier subtasks. The algorithm proposed is tested for classification of various power quality disturbances and it is found that a modular neural network has a higher classification accuracy over traditional multilayer neural network.

Keywords: artificial neural network; classification; harmonics; power quality; voltage sag; voltage swell; wavelet transform.

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1 Introduction

Increasing use of solid state switching devices, non-linear and power electronically switched loads, unbalanced power systems, lighting controls, computer and data processing equipment, industrial plant rectifiers and inverters is resulting to poor power quality. These electronic-type loads cause quasi-static harmonic dynamic voltage distortions, inrush, pulse-type current phenomenon with excessive harmonics, and high distortion. Voltage dips and fluctuations, momentary interruptions, harmonics and oscillatory transients cause failure, or maloperation of the power service equipment.

To improve power quality, it is required to know the sources of power system disturbances and find solution to mitigate them. Short time discrete Fourier transform (STFT) analysis is used particularly for stationary signals where properties of signals do not evolve in time. For non-stationary signals, the STFT does not track the signal dynamics properly due to the limitations of a fixed window width chosen a priori (Robertson et al., 1996). Thus, STFT cannot be used successfully to analyse transient signals comprising both high- and low-frequency components. On the other hand, wavelet analysis provides a unified framework for monitoring power quality problems.

Wavelet analysis is based on the decomposition of a signal according to time-scale, rather than frequency, using basis functions with adaptable scaling properties known as multiresolution analysis (MRA). A wavelet transform expands a signal by wavelets, generated using transition (shift in time) and dilation (compression in time) of a fixed wavelet function (Santoso et al., 1996; Tse, 2006). This gives the wavelet transform much greater compact support for analysis of signals with localised transient components arising in power quality disturbances manifested in voltage, current, or frequency deviations. However, for classifying low-frequency and high-frequency power quality disturbances, artificial neural networks are required along with the features extracted from wavelet MRA (Gouda et al., 1999; Kanitpanyacharoean and

Premrudeepreechacharn, 2004). Neural networks have remarkable ability to derive meaning from complicated or imprecise data and can be used to extract patterns and detect trends that are too complex. Multilayer neural networks (MLNN) with different algorithms are presented in He and Starzyk (2006), Valdomiro et al. (2006), Gouda et al. (2002) and Riaz et al. (2007) for classification of power quality disturbances.

This paper proposes power quality disturbance classifier using modular neural network (MNN) (Auda et al., 1996; R. M. Magalhaes et al., 2008) approach designed by modifying the structure of multilayer neural network. MNN process has been widely used to discriminate direction of faults for transmission line protection (Lahiri et al., 2005), for pattern recognition (Melin et al., 2005), recognition of partial discharge sources (Hong et al., 1996), condition monitoring of industrial machines (Marzi, 2008). Combined wavelet transform and MNN classifier is used for automatic classification of voltage disturbances such as sag, swell, interruption and harmonics. Simulation results are presented showing the classification capability of MNN. Classification accuracy of wavelet-based MNN is found to be higher than wavelet-based MLNN.

2 Power quality event detection

This section discusses the application of wavelet for detection of most severe power quality disturbances such as voltage sag, swell, interruption and harmonics. Wavelet transformation has the ability to analyse different power quality problems simultaneously in both time and frequency domains.

Wavelet analysis expands functions not in terms of trigonometric polynomials but in terms of wavelets, which are generated in the form of translations and dilations of a fixed function called the mother wavelet. Wavelet function is localised in time and frequency yielding wavelet coefficients at different scales (Santoso et al., 1996; Tse, 2006). This gives wavelet transform much greater compact support for analysis of signals with localised transient components arising in power quality disturbances manifested in voltage, current, or frequency deviations.

Wavelet theory is expressed by continuous wavelet transformation (CWT) as

$$CWT_{\psi} x(a,b) = W_x(a,b) = \int_{-\infty}^{\infty} x(t)\psi^*{}_{a,b}(t)dt \tag{1}$$

where $\psi_{a,b}(t) = |a|^{1/2} .\psi\left(\frac{t-b}{a}\right)$, a (scale) and b (translation) are real numbers.

For discrete-time systems, the discretisation process leads to the time discrete wavelet series as

$$DWT_{\psi} x(m,n) = \int_{-\infty}^{\infty} x(t).\psi^*_{m,n}(t).dt \tag{2}$$

where $\psi^*_{m,n}(t) = a_0^{-m/2}.\psi\left(\frac{t-n.b_0.a_0^m}{a}\right)$, $a = a_0^m$ and $b = n.b_0.a_0^m$.

Compared with Fourier transform, wavelet can obtain both time and frequency information of signal, while only frequency information can be obtained by Fourier transform. The signal can be represented in terms of both the scaling and wavelet function (A. M. Gouda et al., 1999) as follows:

$$x(t) = \sum_n c_J(n).\varphi(t-n) + \sum_n \sum_{j=0}^{J-1} d_j(n).2^{j/2}.\psi\left(2^j.t-n\right) \quad (3)$$

where c_J is the J level scaling coefficient, d_j is the j level wavelet coefficient, $\Phi(t)$ is scaling function, $\Psi(t)$ is wavelet function, J is the highest level of wavelet transform, and t is time. Each wavelet is created by scaling and translation operations of mother wavelet.

Using the discrete wavelet transformation (DWT) power quality problems can be classified with the features obtained from MRA. Goal of MRA is to develop representations of a signal at various levels of resolution.

3 Feature extraction of disturbance signals

Wavelet transform has found its applications in various areas and it is gaining importance in particular to power quality problem classification. Wavelet analysis is used to extract features of analysed signal and classify based on information obtained. Features that are commonly used for further power quality analysis are squared coefficients (Santoso et al., 1996), energy (Gouda et al., 1999; He and Starzyk, 2006), deviation of energy (Valdomiro et al., 2006; Gouda et al., 2002) and delta-standard deviation (delta-STD) (Kanitpanyacharoean and Premrudeepreechacharn, 2004).

Standard deviation (*STD*) given by (4) is used to represent data in each level of MRA.

$$STD = \sqrt{\frac{\sum_{i=1}^{N}\left(X_i\right)^2}{N} - \left(\overline{X}\right)^2} \quad (4)$$

where X_i are non-distributed frequency data, $\overline{X}$ is mean of data and N is the number of data.

In power quality problem, the graph of STD of MRA is very similar for various power quality disturbances (Gouda et al., 1999). In order to extract feature of these signals, STD of power quality problem signals (STD_d) are subtracted from STD of pure sinusoidal waveform (STD_p) to get *delta-STD*.

$$\left(delta\text{-}STD\right)_j = \left(STD_p\right)_j - \left(STD_d\right)_j \quad (5)$$

where j is the level of MRA.

delta-STD of the disturbances obtained from MRA analysis is considered as the index for power quality disturbance classification. Disturbances are generated using MATLAB programme with different percentages, durations and instants of disturbances as shown in Figure 1. Patterns of harmonics are generated with random selection of order and magnitude of harmonics. Sampling frequency of 5 kHz is selected with 100 samples per cycle of fundamental time period (fundamental frequency is 50 Hz). Simulation results obtained from *delta-STD* MRA technique in Figure 2 shows that, *delta-STD* is unique to individual disturbance and it is easy to classify various power quality problems. Wavelet coefficients contain information of original signal as shown in Table 1.

Simulation is performed for various percentages of disturbances and is observed that d*elta-STD* index changes with change in percentage of sag, swell, interruption and harmonics. Figure 3 shows the effect of change in *delta-STD* with change voltage sag magnitude from 10% to 90% for voltage of 1-cycle. Level-6 *delta-STD* value (frequency band containing fundamental component information), increases with increase in percentage of sag and is used for identifying level of sag. Similar effect is also found for other disturbance cases.

Figure 1 Voltage signals with disturbances, (a) sag, (b) swell, (c) interruption and (d) harmonics

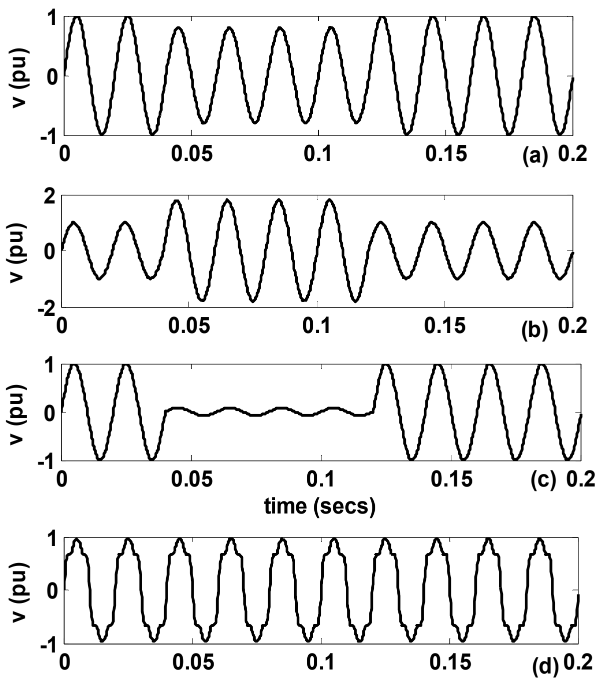


Figure 2 Delta STD MRA (ΔStd_MRA) curves of voltage disturbances

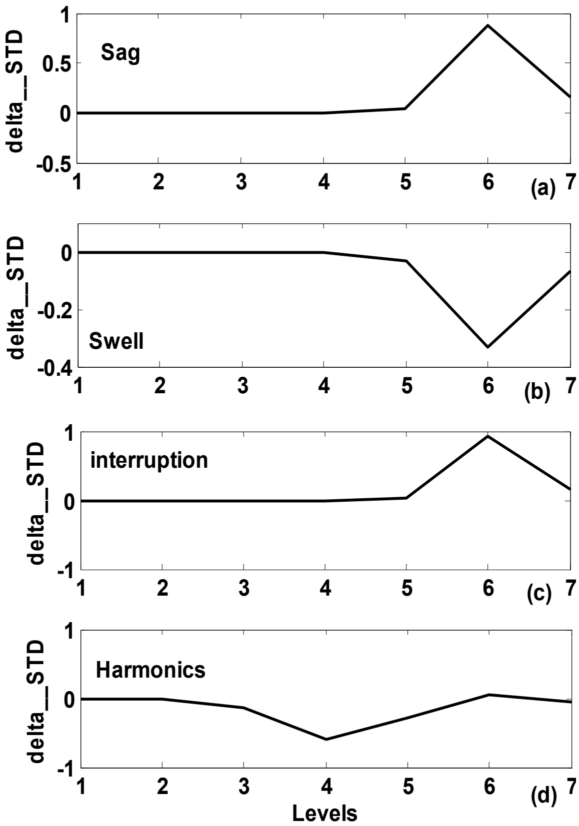
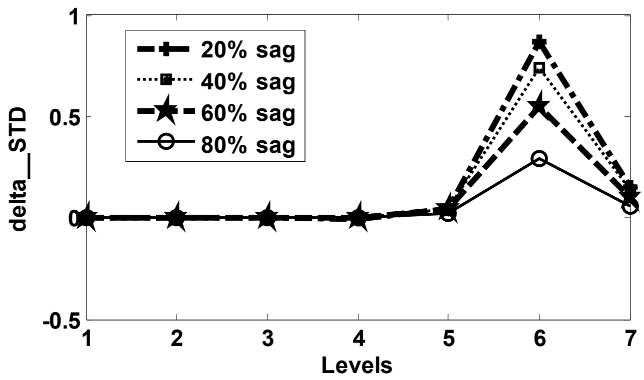


Table 1 Subbands of wavelet transform coefficients

Level	*Wavelet coefficients*	*Frequency range*
1	CD1	1250–2,500 Hz
2	CD2	625–1,250 Hz
3	CD3	312.5–625 Hz
4	CD4	156.25–312.5 Hz
5	CD5	78.125–156.25 Hz
6	CD6	39.0625–78.125 Hz
7	CD7	19.53125–39.0625 Hz
7	AD7	0–19.53125 Hz

Figure 3 Variation of delta-STD values for various percentage of voltage sag of duration 1-cycle



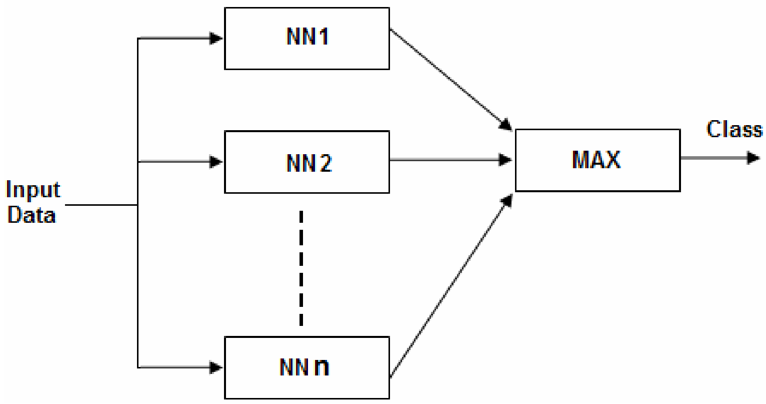
4 Classification technique

Artificial neural networks are parallel distributed information processing units with different connection structures and processing mechanism. They are particularly suitable to link different variables of a physical system where the relationship between independent and dependent variables are not easily separable.

4.1 Modular neural network

To improve the accuracy of neural network in classifying power quality disturbances, the complex task is divided into subtasks to obtain MNN. MNN consists of more than one neural network, called as modules, to handle each subtask. Each module is independent, domain specific and respond to a particular set of data input it is intended for (Magalhaes et al., 2008). Structure of MNN is shown in Figure 4. Solution of the overall task is achieved by combining the result of each module.

Figure 4 Model of MNN technique

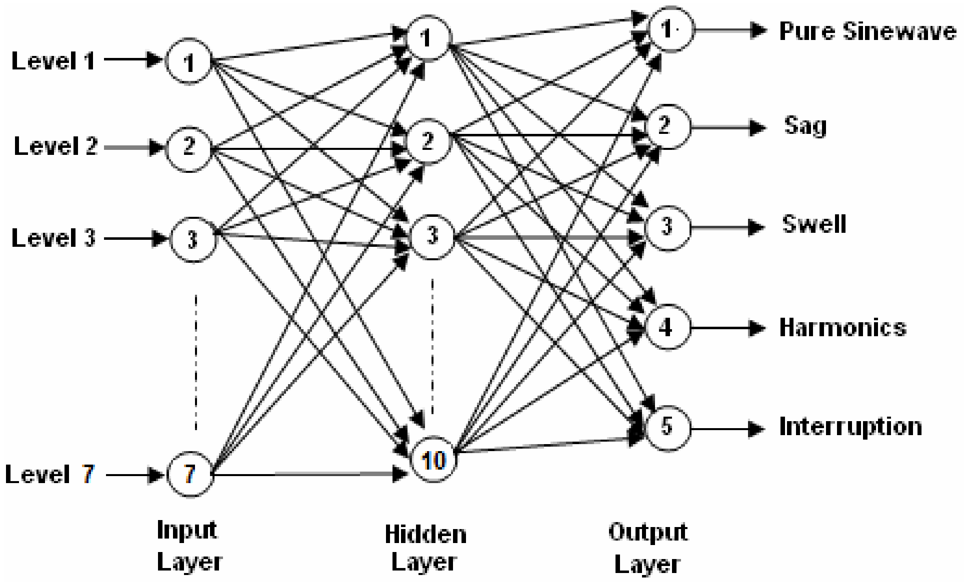


Advantage of modular structure is that individual model responds to a given input faster than a complex monolithic system. Such a modular structure can be imbibed in different types of neural network, including the multilayered neural network. In this paper, an approach of modular neural is exploited to classify power quality disturbance signals. Simulation results are presented and performances of the modular and multilayer networks are compared.

4.2 Implementation of MNN

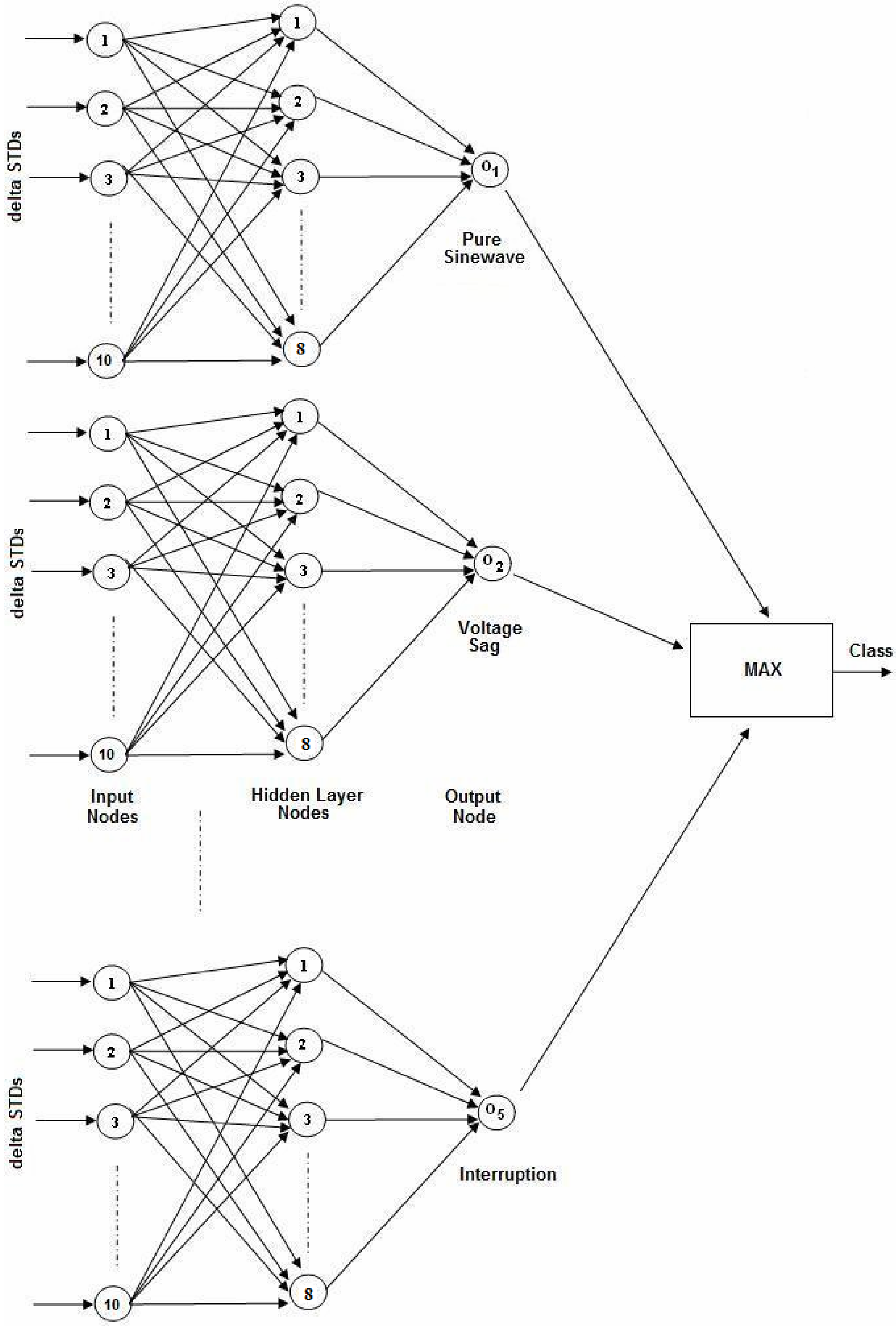
Multi-layer neural network structure shown in Figure 5 with three layers – input, hidden and output layers is implemented. The input layer has seven nodes represented by delta-STD features extracted by wavelet transform; hidden layer has ten nodes, while output layer has five nodes representing normal sine wave and four classes of disturbances: voltage sag, voltage swell, interruption and harmonic distortion. This structure is called WT-MLNN.

Figure 5 Wavelet-based multilayer neural network structure used for power quality classification



Reduction in training time and improvement in classification accuracy is obtained by modifying the structure of MLNN to implement MNN for power quality disturbance classification with five modules for identification of pure sinewave and four disturbances as shown in Figure 6. This structure is called WT-MNN – has seven input nodes, eight hidden nodes and one output node in each module. Hence each module is a multilayer network.

Figure 6 Implementation of wavelet feature-based MNN for power quality classification



5 Simulation results

Disturbances such as sag, swell and interruption are generated by MATLAB programme with different percentages, durations and instants of disturbances. Patterns of harmonics are generated with random selection of harmonic magnitudes and phase compared to fundamental component. Signal generation models and their control parameters are given in Table 2. Here V_m is taken as 230 volts, fundamental frequency $\omega = 2\pi f_0$, $f_0 = 50$ Hz and $T = 1/f_0$. Totally a set of 651 patterns are generated with 200 patterns of sag, swell and harmonics each, 50 patterns of interruption and one pure sine wave. In this work 5 kHz sampling frequency (100 samples/cycle) is selected. Training of MNN is performed with a dataset of 491 patterns consisting of 150 patterns of sag, swell and harmonics disturbances, 40 patterns of interruption and one pattern of pure sine wave signal. Remaining dataset of 160 disturbance patterns and one pattern of the normal sine wave are used for testing.

Table 2 Generation of power quality disturbances

Power quality disturbance	*Model*	*Parameters*
Normal	$v(t) = V_m.\sin\omega t$	$0 \le t \le 10T$
Sag	$v(t) = V_m.\sin\omega t$	$0 \le t \le t1$
	$v(t) = V_m(1 - \text{psag})\sin\omega t$	$t1 \le t \le t2$; $0.1 \le \text{psag} \le 0.9$
	$v(t) = V_m.\sin\omega t$	$t2 \le t \le 10T$
		$t1 < t2$; $\text{T} \le (t2 - t1) \le 0.9T$
Swell	$v(t) = V_m.\sin\omega t$	$0 \le t \le t1$
	$v(t) = V_m(1 + \text{pswell})\sin\omega t$	$t1 \le t \le t2$; $0.1 \le \text{pswell} \le 0.8$
	$v(t) = V_m.\sin\omega t$	$t2 \le t \le 10T$
		$t1 < t2$; $\text{T} \le (t2 - t1) \le 0.9T$
Interruption	$v(t) = V_m.\sin\omega t$	$0 \le t \le t1$
	$v(t) = V_m(1 - \text{pintr})\sin\omega t$	$t1 \le t \le t2$; $0.9 \le \text{pintr} \le 1$
	$v(t) = V_m.\sin\omega t$	$t2 \le t \le 10T$
		$t1 < t2$; $\text{T} \le (t2 - t1) \le 0.9T$
Harmonics	$v(t) = V_m.\sin\omega t + a.\sin3\omega t + b.\sin5\omega t + c.\sin7\omega t$	$0 \le t \le 10T$
		$0.1 \le \text{a} \le 0.25$; $0.05 \le \text{b} \le 0.15$;
		$0.05 \le \text{c} \le 0.1$

Training dataset of size 491 × 10 is generated representing ten *delta-STD*s for 491 training patterns. Both multilayer network, WT-MLNN shown in Figure 5 and MNN, WT-MNN shown in Figure 6 are used for classification. In case of WT-MNN, training dataset is applied simultaneously to all the five modules. Output of the module corresponding to disturbance considered is set to '1' and outputs of all other modules are set to '0' during training. Outputs of all the modules are then combined by maximum operation. The largest of all output nodes is considered as the output of WT-MNN and determines the disturbance class.

Training results are shown in Table 3 for different hidden layer nodes (m) and learning rate. WT-MLNN required 1,443 and 1,660 iterations respectively for m equal to 8 and 10. WT-MLNN with $m = 10$ has better classification accuracy during testing and hence hidden layer with ten nodes are considered. Modularity is employed with WT-MNN and eight nodes in hidden layer for each module was found suitable with learning rate 0.5 having less iteration as given by training results in Table 3.

Table 3 Training results for WT-MLNN and WT-MNN

Classifier	*Module*	*Learning rate*	*No. of iterations*		
			m = 6*	*m = 8*	*m = 10*
WT-MLNN	-	0.4	7,425	1,443	1,660
		0.45	10,347	4,164	3,930
		0.5	7,606	3,663	3,320
WT-MNN	Sag	0.4	564	417	499
		0.45	453	338	430
		0.5	254	199	430
	Swell	0.4	15	11	14
		0.45	15	11	14
		0.5	16	11	15
	Interruption	0.4	988	892	874
		0.45	976	888	865
		0.5	981	859	812
	Harmonics	0.4	14	12	13
		0.45	14	12	13
		0.5	14	13	14

Note: *m – Number of nodes in hidden layer.

Training time of MNN is reduced as each module is trained for its corresponding disturbance class. Architecture with FPGA can be realised (Huang et al., 2002; Choong et al., 2005) with parallel data processing for detection and classification. WT-MNN modules are parallel trained and maximum learning time of network is dependent on module requiring more number of iterations.

Classification performance of WT-MLNN and WT-MNN are tested with 161 patterns (test data size of 161 × 4). Simulation results with WT-MLNN for classification of power quality problems are given in Table 3. In case of sag classification, out of 50 patterns, five patterns are misclassified resulting to 90% accuracy of sag classification. The model presented is capable of classifying the dataset but the classification accuracy is less. The overall accuracy of WT-MLNN is calculated by taking average of diagonal elements of Table 4 given by (6) and it is found to be 90.06%.

$$\begin{aligned}&\%\text{Overall accuracy}\\&= (\text{Total correct classified disturbance events}) / (\text{Total disturbance events}).\end{aligned} \tag{6}$$

Testing performed with WT-MNN for classification of disturbances has shown improvement in the classification accuracy for individual disturbance classification and also in overall performance as compared to WT-MLNN. Classification results for WT-MNN are given in Table 5. The performance accuracy is 98.14%. This improvement is due to the fact that MNN is divided into modules consisting of individual neural network for each disturbance. Testing time of MNN and MLNN is same as the input is applied simultaneously to all the modules where the input is processed in parallel.

Table 4 Testing results of classification with WT-MLNN

Signal	*Test set*	*Classification result*				
		Sine wave	*Sag*	*Swell*	*Interruption*	*Harmonics*
Sine wave	1	*1*	0	0	0	0
Sag	50	0	*45*	0	3	2
Swell	50	0	1	*46*	0	3
Interruption	10	0	2	0	**7**	1
Harmonics	50	0	3	1	0	*46*
Overall classification accuracy: *90.06%*						

Table 5 Testing results of disturbance classification with WT-MNN

Signal	*Test set*	*Classification result*				
		Sine wave	*Sag*	*Swell*	*Interruption*	*Harmonics*
Sine wave	1	*1*	0	0	0	0
Sag	50	0	*48*	0	2	0
Swell	50	1	0	*50*	0	1
Interruption	10	0	2	0	*9*	0
Harmonics	50	0	2	1	0	*50*
Overall classification accuracy: *98.14%*						

Training and testing results of both types of classification techniques shows that modularity in WT-MNN has better performance compared to WT-MLNN.

6 Conclusions

A new approach of classification of voltage disturbances such as sag, swell, interruption and harmonics has been proposed with MNN. Wavelet transform is used to extract the features of disturbance signals and are fed to neural network. MNN designed by having modules for each disturbance has shown less training time and reduction in complexity at the cost of memory compared to multilayer neural network. Simulation results verify that with wavelet-based MNN better classification accuracy is achieved.

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