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A Novel Approach to Measure Harmonic Distortion using Adaptive Morlet Wavelet Neural Network

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ABSTRACT

Background: The recent developments of power electronic based non linear loads introduce more harmonic pollution in power system. The harmonic distortion can cause increased losses in the equipment used in distribution system and interference with communication systems. Objective: The aim of the paper is to measure the harmonic distortion with reduced computational time. The harmonic distortion monitoring is one among the most important processes in active filter design for harmonic reduction. Wavelet Neural Networks (WNNs) has been recently proposed for the effective harmonic distortion measurement with complete accuracy and precision. The WNN is a new kind of neural networks, which combine Feed Forward Neural Network (FFNN) with wavelet theory. WNN also has a higher ability of generalization and fast convergence for learning than FFNN. In this research, the Morlet wavelet has been chosen for activation function in the hidden layer of the network. Results: The results of this proposed method are compared with the conventional Feed Forward Back Propagation Network (FFBPN), and it clearly shows its supremacy in better prediction by accurate discrimination, fast learning, fine adaptability and lesser processing time. Conclusion: The proposed method has been proved that the improved estimation accuracy and low computational time, which makes it suitable for real time application in power quality metering equipment.

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INTRODUCTION

The extensive use of nonlinear loads based on power electronic controlled equipment, such as variable speed drives, automated production lines, personal computers and non linear electronic devices in power systems has contribute current and voltage waveform distortion. Harmonic disturbances come generally from equipment with nonlinear load characteristics, which inevitably change the sinusoidal nature of the AC current, resulting in the flow of the harmonic current in the power system. The major adverse effects are equipment heating, increased losses, loss of life, and overloading of neutrals (G.K. Singh, 2009). The total harmonic distortion is the main parameter, which is used for harmonic distortion measurement. The THD is a measure of the effective value of the harmonic components of a distorted waveform. This index can be calculated for either voltage or current. Fast Fourier transform (FFT) is the conventional method followed for measuring the defined indices began to be considered. It has been reported that the accuracy of FFT measurement is only depends on the power system frequency variations. The FFT has certain drawbacks for the harmonic analysis of a signal such as spectral leakage and the picket fence effect may lead to inaccurate signal measurement

In recent works, Artificial Neural Network (ANN) is the alternative methods to FFT analysis, which is applied to harmonic content determination in three-phase systems and also in single-phase systems (D.O. Abdeslam *et al*., 2007; C.F. Nascimento *et al*., 2013). The ANN based techniques are able to comprise nonlinearity in the system and are immune to noise present in the signal, they often settle in local minima or slow convergence due to their multilayered structure (C.I. Chen *et al*., 2010; C.I. Chen, *et al*. 2012, G.W. Chang *et al*., 2010). To solve these defects, wavelet theory is combined with the advantages of ANN and form a wavelet neural network. WNN has been accepted as a novel universal tool and successfully applied in wider

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Australian Journal of Basic and Applied Sciences, 9(1) January 2015, Pages: 231-237

applications such as functional approximation (Q. Zhang and A Benveniste, 1992; G.G. Zhang *et al*., 1995) and nonlinear system identification (S. A. Billings and H. L. Wei, 2005).

This work proposes an adaptive wavelet neural network for harmonic content measurement in three phase power systems. For this neural network, Morlet wavelet (Z. Bashir and E.I. Hawary, 2000; Z. Zainuddin and O. Pauline, 2011) has been selected as wavelons. The learning ability of the proposed method provides faster and accurate estimates with less number of computations.

The rest of the paper is structured as follows. Section 2.0 depicts the problem of harmonic distortion measurement for three phase supply systems. The performance of the proposed scheme is demonstrated with the simulated model in section 3.0. Section 4.0 presents the results and discussions of the work. Finally, section 5.0 summarizes the conclusion.

2.0 Problem Formulation:

The proposed method is applied in the test circuit to measure the harmonic distortion for determining the compensation characteristics of active power filter

Table 1: Test circuit parameters.

Items	Name of the load	Specifications
Load 1	Thyristor D.C Drive	5 HP, 500 V, 1750 RPM, Field 300 V
Load 2	Thyristor D.C Drive	20 HP,500 V, 1750 RPM, Field 300 V
Load 3	Nonlinear load (converter with resistive load)	1500 ohms
Load 4	Induction motor	5.4 HP,400 V,50 Hz, 1430 RPM
Load 5	Induction motor	10 HP,400 V,50 Hz, 1430 RPM

The performance of the MWNN is demonstrated with the help of a simple three phase test circuit is shown in Fig. 1. The test circuit consists of three non linear loads (two DC drives and one converter with resistive load) and two linear loads (two induction motors) are fed by a purely sinusoidal power supply. Table 1 shows the details of the connected loads with a 400 V, 50 Hz, 3 phase AC source.

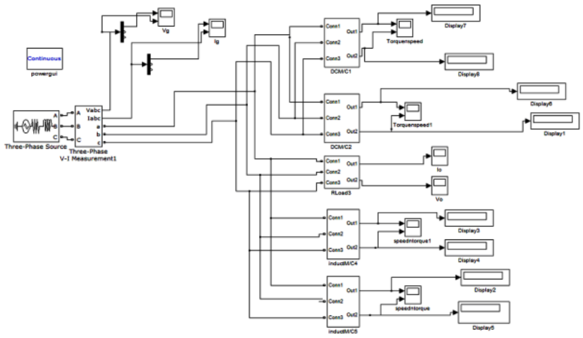

Fig. 1: Simulation circuit.

The time domain representation of current waveform in supply side is shown in Fig. 2 and Fig. 2(a) represents the frequency spectrum of Fig. 2.

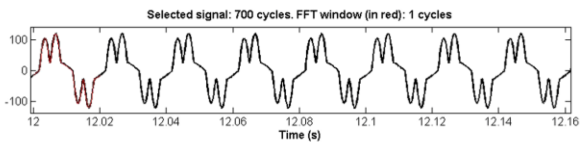

Fig. 2: Source side current waveform.

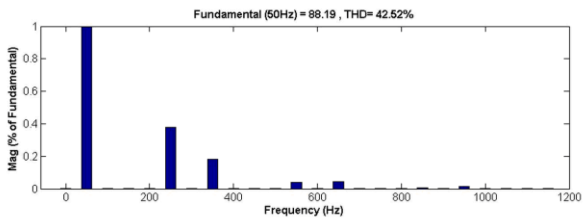

Fig. 2(a): FFT spectrum of Fig, 2.

2.1 Total harmonic distortion (THD):

The Total harmonic distortion (THD) is a significant index commonly used to measure the harmonic content of a waveform with a single number (Francisco C. De La Rosa, 2006, Doron Shmilovitz, 2005). THD

Australian Journal of Basic and Applied Sciences, 9(1) January 2015, Pages: 231-237

can be considered for the contribution of every individual harmonic component on the distorted signal. The THD value can be calculated for either voltage or current signals, respectively, as follows:

$$THD_V = \frac{\sqrt{\sum_{h=2}^{\infty} V_h^2}}{V_1} \quad (1)$$

$$THD_I = \frac{\sqrt{\sum_{h=2}^{\infty} I_h^2}}{I_1} \quad (2)$$

3.0 Wavelet Neural Networks:

3.1 Architecture of Morlet wavelet neural network:

Morlet wavelet neural network is a multilayer feed forward neural network having hidden layer neurons with morlet wavelet function as an activation function instead of sigmoid activation function. It is an alternative approach to the feed forward neural networks for approximating functions. Fig. 3 shows the morlet wavelet function. The MWNN employed in this work are designed as a three layer configuration with an input layer, central hidden layer (wavelet layer) and output layer.

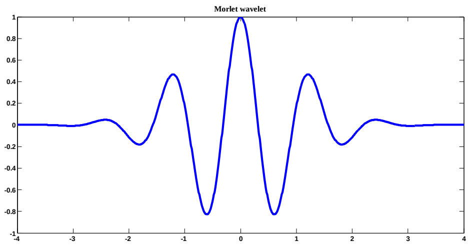

Fig. 3: Morlet wavelet.

Figure 4 shows the typical structural design of an MWNN. The input layer receives the input variable x = [x_1, x_2, . . ., x_n], where 'n' is the number of dimensions and conveys the accepted input to the hidden layer. The neurons in the hidden layer can also be called as wavelons, which constitutes wavelet function. The approximation of the target values are estimated in the output layer. The direct weighted connection helps to achieve input to output mapping. Due to the simple explicit expression, Morlet wavelet has been considered in most of the WNNs. (Z. Bashir and E.I. Hawary, 2000)

$$\psi(x) = \cos(5x) \times \exp\left(\frac{-x^2}{2}\right) \quad (3)$$

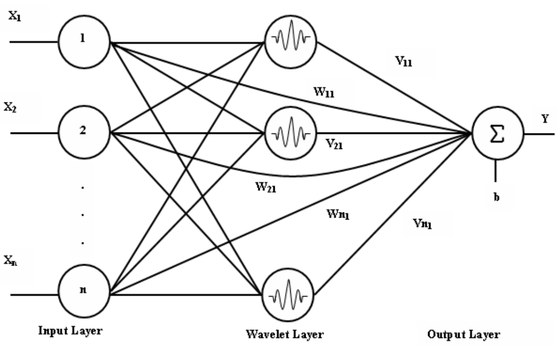

Fig. 4: Typical architecture of a MWNN.

3.2. Training of MWNN:

The process of adjusting the weights in the links between the network layers with the objective of achieving the expected output is called training a network. The efficient training depends on the suitable initialization of the network. The learning is the internal process that takes place when a network is trained. Furthermore, training is done to enable the update of the parameters used in the network. In this work, the standard gradient decent based back propagation algorithm is used due to its simplicity and the ability to update each parameter simultaneously. Adaptive learning rate is used in the training for faster learning process. The training objective function of an adaptive wavelet neural network is derived from the instantaneous total mean square error can be expressed as

Australian Journal of Basic and Applied Sciences, 9(1) January 2015, Pages: 231-237

$$E = \frac{1}{2}\sum_{k=1}^{K}(y_k' - y_k)^2 \tag{4}$$

Where y_k' and y_k are the desired and actual output of the k^{th} output neuron of the network, respectively. Whereas, k is the number of output neurons. The minimization of the above function is carried out during training of the proposed network.

The MWNN parameters are updated at each iteration using the following generalized expression.

$$\beta(m+1) = \beta(m) + (\eta_\beta \times \Delta\beta(m) + (\alpha_\beta \times \Delta\beta(m-1)) \tag{5}$$

Where m is the iteration count, α_β and η_β represent the momentum coefficient and the learning rate. Here, β represents a free parameter (w, v, b, λ or δ).

The free parameters are updated and the output of the MWNN for k^{th} pattern can be computed using the following equation (N. M. Pindoriya *et al*., 2008)

$$y_k = b_k + \sum_{p=1}^{P} w_{pk} x_p + \sum_{q=1}^{Q} v_{qk}\psi_q \tag{6}$$

Where w and v represent the weights of the links connected between the input and output layers and weights of the links connected between the wavelet layers and output layers. ψ_q is the output of the q^{th} hidden neuron and b_k is the bias of the k^{th} output neuron.

3.3 Initialization of network parameters:

The effective training process of the network depends on the suitable initialization of the free parameters. The appropriate parameter initialization would result to less iteration in the training phase of the network. The network initialization signifies the selection of initial parameter values of the WNN parameters, learning rate, number of hidden units, weights and bias are initialized randomly within the constraints. The minimum number of wavelons is implemented in the network such that it does not affect both the computational burden and the output accuracy. A moderate value of learning rate and momentum coefficient are chosen initially to enhance convergence speed and the numerical stability of the learning phase.

Table 2: Training parameter values of the MWNN.

Network Parameters	
Number of wavelons	3
Wavelet function	Morlet
Training Parameters	
Learning rate for translation η_λ	0.2
Learning rate for dilation η_δ	0.2
Learning rate for IO weights η_w	0.01
Learning rate for HO weights η_v	0.4
Learning rate for bias η_b	0.01
Threshold cost function value ε_{th}	0.005

A compromised value of threshold ε_{th} is chosen based on the minimum desired accuracy. Table 2 provides the training parameter values of the MWNN. In this work, the configuration of the BPN and MWNN uses 99 input neurons (only a half cycle of the distorted signal) and the network produces one output neuron that represents the current harmonic distortion level in the supply side. From the results, it is to be noted that the current harmonic distortions are easily estimated without disconnecting any loads from the power system. The results obtained were compared with the back propagation neural network.

RESULTS AND DISCUSSIONS:

The performance of the proposed technique for harmonic distortion measurement can be confirmed by using target and estimated THD values. Fig. 5 shows the measured current waveform in the supply side. Fig. 5(a) represents the frequency spectrum of Fig. 5 .

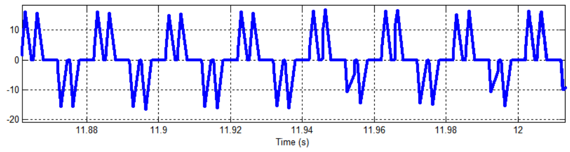

Fig. 5: Source side current waveform.

From Fig. 5(a), it is to be noted that the total harmonic distortion in supply side is 77.37% in phase A. however the target THD is 77.37 %, BPN estimates 76.5968 % and the proposed MWNN method estimates 77.3626 %. The error value also calculated between the actual THD value and its estimated THD values. The

Australian Journal of Basic and Applied Sciences, 9(1) January 2015, Pages: 231-237

calculated error values of BPN and MWNN are 0.7732 and 0.0074. Therefore, the proposed morlet wavelet with ANN method is also capable to predict the system performance correctly, validating its accuracy. Table 3 shows the comparison of THD values and its corresponding error values for the phases A, B and C. From Table 3, it is much obvious that MWNN is more effective than BPN in all the phases A, B and C.

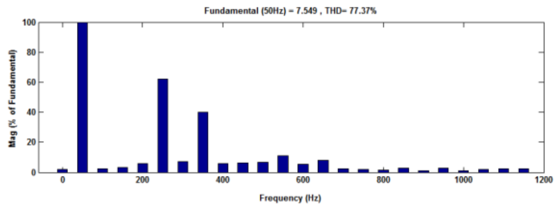

Fig. 5(a): FFT spectrum of Fig. 5.

Table 3: Comparison of THD measurement and Error value.

Phases	Actual current value (in THD)	Predicted current value (in THD)		Error value (in THD)	
		BPN	MWNN	BPN	MWNN
Phase A	77.37	76.5968	77.3626	0.7732	0.0074
Phase B	83	82.1705	82.9944	0.8295	0.0056
Phase C	87.52	86.645	87.5134	0.875	0.0066

Fig. 6 represents the error plot for the phases A, B and C. Fig. 6 shows the comparison of error value between the simulated THD values and the actual THD values in phases A, B and C. In Fig. 6, the morlet wavelet neural network provides the very least amount of error with reduced training time compared with BPN.

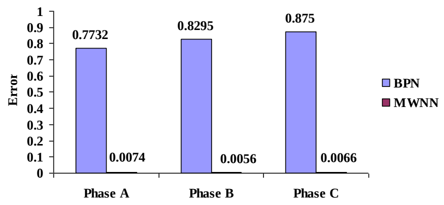

Fig. 6: Error plot for the phases A, B and C.

Table 4 shows the comparison of computational time and training epochs. From Table 4, It can be observed that, the computational time of the proposed method is lower than that of the BPN. The computational times for BPN are 22.013897, 20.365533 and 21.764103 seconds for the phases A, B and C. The computational times for MWNN are 0.149413, 0.153773 and 0.124626 seconds for the phases A, B and C. Table 4 also represents the comparison of training epochs between BPN network and MWNN network.

Table 4: Comparison of computational time and training epochs.

Phases	Computational time (in seconds)		Training Epochs	
	BPN	MWNN	BPN	MWNN
Phase A	22.013897	0.149413	2311	54
Phase B	20.365533	0.153773	2309	55
Phase C	21.764103	0.124626	2305	50

Fig. 7 represents the comparison of computational time plot. From Fig. 7, the computational time for MWNN is very low values compared with the computational time of BPN. The low computational time makes the proposed method is suitable for real time applications.

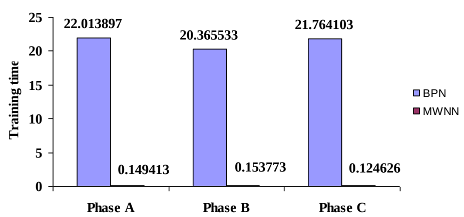

Fig. 7: Computational time for phases A, B and C.

Fig. 8 shows the training epochs plot obtained in phases A, B and C. The BPN network takes 2311, 2309 and 2305 iterations and also MWNN takes the training epochs are 54, 55 and 50. From Fig. 8, the MWNN takes very low training iterations compared with BPN.

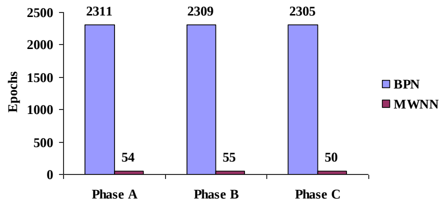

Fig. 8: Training epochs for the phases A, B and C.

Table 5 shows the comparison of relative error between MWNN and other experimental results (Joy Mazumdar *et al*., 2007). The resultant error (e_{rm}) is the new parameter, which is used for the purpose of comparison between the different methods.

Table 5: Comparison of Proposed MWNN with Other works Practical Data.

RNN Method (Joy Mazumdar *et al*., 2007)				Proposed MWNN Method					
Experimental results	Actual current value (in THD)	Predicted current value (in THD)	e_{rm}	Simulation Results	Actual current value (in THD)	Predicted current value (in THD)		e_{rm}	
	FFT	BPN			FFT	BPN	MWNN	BPN	MWNN
Triac with 0° Firing angle	6.11%	4.18%	-46.17%	Phase A	77.37	76.5968	77.3626	0.99935 %	0.00956 %
Triac with 30° Firing angle	29.25%	30.58%	4.35%	Phase B	83	82.1705	82.9944	0.99940%	0.00681%
Phase A of Variable Speed Drive (VSD)	74.27%	66.69%	-11.37%	Phase C	87.52	86.645	87.5134	0.99977%	0.0066%

The resultant error (e_{rm}) is defined as

$$\text{Resultant error in measurement } e_{rm} = \left(\frac{THD_A - THD_P}{THD_A}\right)\%$$

Where THD_A is the actual current THD value measured at the point of common coupling (PCC) and THD_P is the predicted current THD value. The resultant error is calculated for the proposed MWNN method and compared with the Back Propagation Neural network (BPN) and Recurrent Neural Network. The accuracy of the proposed MWNN method is determined based on the resultant error in measurement (e_{rm}). From Table 5, the estimated resultant error for the proposed MWNN method is very less compared with BPN and RNN methods.

5.0 Conclusion:

This paper demonstrated that the ability of adaptive morlet wavelet neural network is used to estimate true harmonic content of the current caused by the load. The proposed adaptive MWNN is utilized to estimate the true harmonic distortion at the PCC without disconnecting any load. The proposed adaptive morlet wavelet neural network employs wavelet coefficients, therefore, reduces the training time and its estimation accuracy is not affected by local variations in the signal due to practical scenarios. When compared to conventional FFT and back propagation neural network whose activation function is sigmoid, the proposed method provides the improved estimation accuracy in the presence of frequency deviation and noise. The computational time of MWNN is considerably low, which makes it suitable for real time application in power quality metering equipment.

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