A New Method for Measurement of Harmonic Distortion Using Adaptive Wavelet Neural Network

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Abstract: - The proliferation of power electronic based nonlinear loads and time varying devices causes harmonic pollution in industrial power system in recent years. The harmonic distortion can cause overheating and increased losses in the equipments used in distribution system and also interference with the communication systems. This paper presents a new soft computing technique based on an adaptive wavelet neural network (AWNN) for harmonic distortion measurement. Wavelet Neural Network (WNN) is a new technique recently proposed for harmonic distortion monitoring. In this work, Mexican hat wavelet has been selected for activation function in the hidden layer of the network. The validation of proposed AWNN is examined with feed forward back propagation network (FFBPN). The proposed method has been verified that the improved estimation accuracy and low computational time, when compared to the FFBPN.

Key-Words: - Adaptive wavelet neural network (AWNN), Back propagation network (BPN), Harmonic distortion, Power quality, Total harmonic distortion

1 Introduction

The increasing use of power semiconductor based electronic devices such as variable frequency drives, inverters and solid state switching devices causes voltage distortions, harmonics, power frequency variations and voltage fluctuation in power system. The power quality problems cause system equipment malfunction, computer data loss and memory malfunction of the sensitive equipment such as, programmable logic devices controls, protection and relaying equipment. Recently, harmonics has become a key issue due to the widespread use of power semiconductor based devices. Harmonic disturbances come generally from equipment with nonlinear voltage/current characteristics. The nonlinear load characteristics inevitably change the sinusoidal nature of the AC current, resulting in the flow of the harmonic current in the power system. The major consequences are the heating of induction motors, transformers, capacitors and the overloading of neutral [1].

In general, total harmonic distortion (THD) is the key factor to be considered and can be measured for the quality of the power system. The term expresses the distortion as a percentage of the fundamental of the voltage and current waveform.

When the issues of measuring the defined indices began to be considered, fast Fourier transform (FFT) is the conventional method accepted for measuring the THD in the power system quality for the past decades. It has been reported that the accuracy of FFT measurement is found that, it is only depends on the power system frequency variations. The disadvantage of FFT is suffered from spectral leakage and the picket fence, which affects the accuracy of measurement. Windowing, Interpolation and synchronization techniques [2-4] were suggested to get over the defects of FFT, but those come at the expense of additional computational burden. Wavelet transform is reported as easy implementation solution for harmonic distortion measurement, but it offers very high computational burden and also faces delays due to inherent filter banks used [5]. To attain better frequency resolution, Prony models and estimation of signal parameters via rotational invariance technique (ESPRIT) [6-7] were proposed. However, these models are sensitive to modeling inaccuracies and demands more computational cost. To achieve faster processing speed, artificial intelligence based techniques, namely, Kalman filtering, adaptive linear neuron (ADALINE), multilayer perceptron neural network (MPNN), radial basis function neural network (RBFNN) were popularly used. Though, artificial neural network (ANN) based techniques are particularly suitable for dealing with the non linear characteristics and are immune to noise present in the signal, also they often settle in local minima or converge slowly due to their multilayered structure [8-10].

This paper introduces an adaptive wavelet neural network (AWNN) technique for harmonic distortion measurement. For this work, Mexican hat wavelet has been chosen for activation function (wavlons) in the hidden layer of the network. The learning ability of the AWNN provides faster and accurate estimates with reduced training time.

This paper is organized as follows. Section 2 of this paper describes the problem formulation of harmonic distortion measurement for three phase supply systems. In section 3, the performance of the proposed scheme is demonstrated with the simulated model. Section 4 describes the comparisons of the various neural networks results and errors are given with the advantages of the proposed scheme. Finally conclusions are drawn in section 5.

2. Problem Formulation

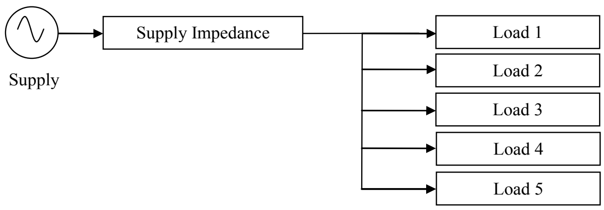

Fig. 1. Block diagram of test circuit.

The performance of the proposed technique is verified with the help of a simple three phase test circuit is shown in Fig. 1. Fig.2 shows the simulation circuit.

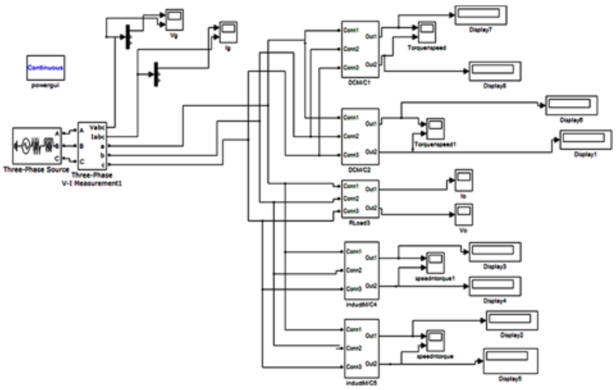

Fig. 2. Simulation circuit.

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.

Table1 Test Circuit Parameters

Items	Load Type	Load Specifications
Load 1	Thyristor D.C Drive	5HP, 500 V, 1750 RPM, Field 300 V
Load 2	Thyristor D.C Drive	20HP, 500 V, 1750 RPM, Field 300 V
Load 3	Thyristor D.C Drive	20HP, 500 V, 1750 RPM, Field 300 V
Load 4	Nonlinear load (converter with resistive load)	5.4 HP,400 V,50 Hz, 1430 RP M
Load 5	Induction Motor	10 HP,400 V,50 Hz, 1430 RPM

A nonsinusoidal periodic voltage or current signal can be decomposed into a sum of sinusoidal components as given below.

$$x_i = \sum_{h=1}^{H} A_h \sin\left(2\pi f_h t + \theta_h\right) \quad (1)$$

Where t is the time, h is the harmonic order, and f_h, A_h and θ_h are the frequency, amplitude and phase angle of the h^{th} component, respectively.

The total harmonic distortion (THD) is the common index employed to find out the quality of current and voltage signal.

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

Where I_h represents the individual harmonics and I_1 is the fundamental component of the signal.

3. Adaptive wavelet neural network

3.1 Structure of an AWNN

An adaptive wavelet neural network (AWNN) is a multilayer feed forward neural network and having three layers such as input layer, hidden layer and output layer. It is a new network combining the ideas of the feed forward neural networks and the wavelet decompositions, Zhang and Benveniste (1992) provide an alternative to the feed forward neural networks for approximating functions. In the input layer, an informative n-dimensional input is given. The neurons in the hidden layer can also be called as wavelons, which constitutes wavelet function. In the output layer the approximation of the target values are estimated. The direct weighted links helps in achieving smooth input to output mapping [11]. Many significant works have been done using adaptive wavelet neural network [12-14]. Hence, in this work, the excellent features of the AWNN [15] is attempted to estimate harmonic distortion. The basic network structure of an adaptive wavelet neural network is shown in Fig. 3.

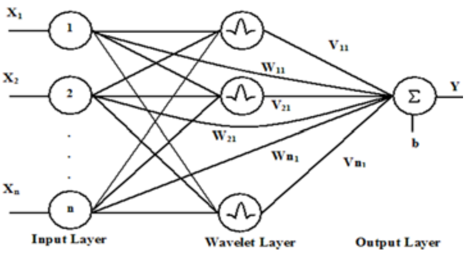

Fig. 3. Basic AWNN structure

In this paper, Mexican hat wavelet is used for activation function in the hidden layer of the network. Out of the various mother wavelets such as Morlet, Meyer, Haar, Gaussian, Mexican hat, B-Spline, Daubechies, the Mexican hat wavelet function is chosen because it is computationally efficient and it has an analytical expression. For a single dimensional input vector x, Mexican hat wavelet function is defined as

$$\psi(t) = (1 - t^2)e^{-0.5t^2} \tag{3}$$

Where t is the norm of vector x, $t = \dfrac{x_p - \lambda_{pq}}{\delta_{pq}}$

Where λ_{pq} and δ_{pq} is the translation and dilation parameter of the q^{th} wavelons for the p^{th} input.

The k^{th} output of the adaptive wavelet neural network can be expressed as

$$y_k = \sum_{i=1}^{n} w_{ik} x_i + \sum_{j=1}^{m} v_{jk} z_j + b_k \tag{4}$$

Where w and v are the weights of the connections between the input and output layers and between the hidden and output layers respectively. b_k is the bias of the k^{th} output neuron. The AWNN has better approximation property as compared to the conventional feed forward back propagation network (FFBPN), due to the adapting the wavelet shape in accordance with training data set.

3.2 Training of an AWNN

The process of modifying the weights in the connections between the network layers with the objective of achieving the expected output is called training a network. The internal process that takes place when a network is trained is termed as learning. Moreover, training is done to enable the iterative update of the parameters used in the network. In this paper, the standard gradient decent based back propagation algorithm is used due to its simplicity and the ability to update each parameter simultaneously. In order to ensure faster learning, adaptive learning rate is used in the training. The training objective function of an adaptive wavelet neural network is derived from the instantaneous total mean square error, expressed as

$$E = \frac{1}{2}\sum_{n=1}^{N}\left(y_n' - y_n\right)^2 \tag{5}$$

Where y_n' and y_n are the desired and actual output of the n^{th} output neuron of the network, respectively. Whereas, N is the number of output neurons. The minimization of the above function is carried out during training of the proposed network. The AWNN parameters are updated in each iteration using the following generalized expression.

$$\beta(n+1) = \beta(n) + (\eta_\beta \times \Delta\beta(n) + (\alpha_\beta \times \Delta\beta(n-1)) \tag{6}$$

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

The AWNN free parameters are updated and the output of the for k^{th} pattern can computed using the following equation [12]

$$y_k = b_k + \sum_{r=1}^{R} w_{rk} x_r + \sum_{q=1}^{Q} v_{sk} \psi_s \tag{7}$$

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_s is the output of the s^{th} hidden neuron and b_k is the bias of the k^{th} output neuron. The process of network learning is stopped when the objective function is converged to a predefined value ε_{th}.

3.3 Network initialization

The proper initialization of the network parameters would considerably increase the efficiency of the training. The effective initialization would result to less iteration in the training phase of the network. The network initialization means the proper selection of initial parameter values of the AWNN parameters such as learning rate and the number of hidden units. The input to output connection weights w, bias b and the hidden to output connection weights are initialized randomly within the constraints. The minimum number of wavelons is adopted in the network such that it does not account to computational burden and output accuracy.

A moderate value of learning rate is chosen initially to improve convergence speed and the numerical stability of the learning phase.

An optimal threshold value ε_{th} is chosen for obtaining lesser computational time and better output accuracy. Table 2 provides the training parameter values of the AWNN.

In the simulations, the configuration of the BPN and AWNN 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 in supply side.

Table 2 Training Parameter Values for the AWNN

Network parameters	
Number of wavelons	3
Wavelet function	Mexican hat
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 bias η_b	0.01
Threshold cost function value ε_{th}	0.005

IO: Input to output layer; HO: Hidden to output layer

From the results, the current harmonic distortions are easily evaluated without disconnecting any loads from the power system. The results obtained were compared with the feed forward back propagation neural network.

The performance of the proposed technique for harmonic distortion measurement can be confirmed by using target and estimated THD values. Fig. 4 shows the measured current waveform in the supply side. Fig. 4(a) represents the frequency spectrum of Fig. 4.

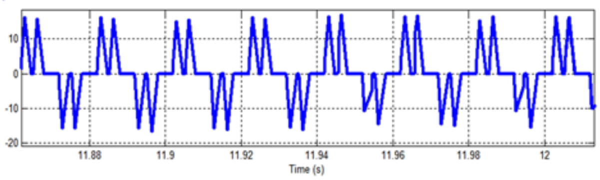

Fig. 4. Input current waveform.

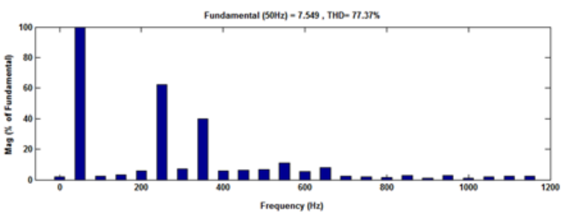

Fig.4(a) FFT spectrum of Fig.4

Table 3 gives the comparison of simulated results with the actual THD values and error for the phases A, B and C. From Table 3, the true harmonic distortions in supply side are easily evaluated without disconnecting any load.

Table 3 Comparison of THD Values.

Phases	Actual value (in THD)	Predicted value (in THD)		Error value (in THD)	
		FFBPN	AWNN	FFBPN	AWNN
Phase A	42.4400	42.6454	42.4394	-0.2054	0.00010
Phase B	42.8500	43.2014	42.8490	-0.3514	0.00100
Phase C	42.3600	43.5754	42.3598	-0.0166	0.00020

From Table 3, it is to be noted that the total harmonic distortion in supply side is 42.44 % in phase A. however the target THD is set as 42.44 %, BPN estimates 42.6454 % and the proposed AWNN method estimates 42.4394 %. The error value also calculated between the actual THD value and its estimated THD values. The calculated error values of FFBPN and AWNN are -0.2054 and 0.00010. Therefore, the proposed Mexican hat wavelet with ANN method is also capable to predict the system performance correctly, validating its accuracy.

Table 4 Comparison of Computational Time and Training Epochs

Phases	Computational time (in seconds)		Training epochs	
	FFBPN	AWNN	FFBPN	AWNN
Phase A	18.147729	0.709005	976	21
Phase B	18.445982	0.794059	945	24
Phase C	17.505242	0.705268	927	19

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 FFBPN. The computational times for FFBPN are 18.147729, 18.445982 and 17.505242 seconds for the phases A, B and C. The computational times for AWNN are 0.709005, 0.794059 and 0.705268 seconds for the phases A, B and C. Table 4 also represents the comparison of training epochs between BPN network and AWNN network. Fig. 5 represents the computational time plot obtained in phases A, B and C.

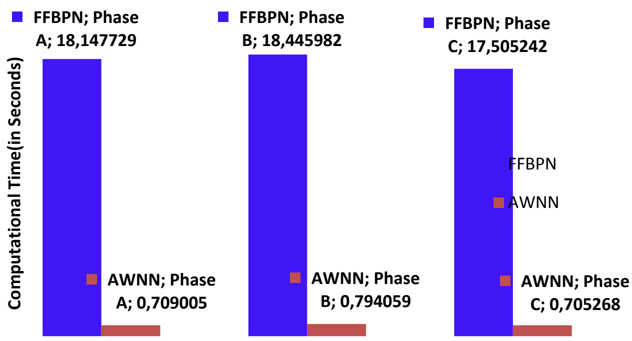

Fig. 5. Computational time for phases A, B and C

Fig. 6 shows the training epochs plot obtained in phases A, B and C. The BPN network takes 976, 945 and 927 iterations and also AWNN takes the training epochs are 21, 24 and 19. From Fig. 6, the

AWNN has very low training iterations compared with BPN.

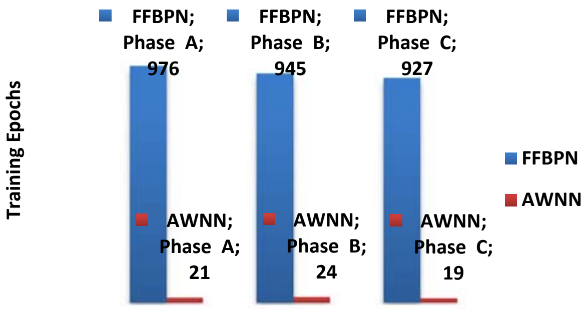

Fig. 6. Training epochs for the phases A, B and C

The proposed technique can also be verified in the practical environment. This is achieved by adding one number of harmonic source at the supply side. Fig.7 shows the test circuit with a harmonic source is connected in the utility side

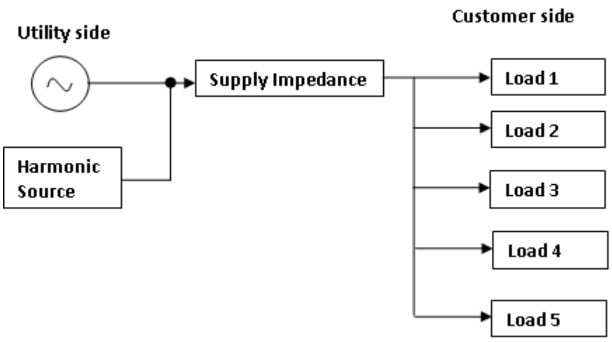

Fig**. 7.** Test circuit with a harmonic source connected in utility.

In this case, the voltage harmonic distortion is increased from 0.59% to 0.91% and the current harmonic distortion is decreased from 42.44% to 42.35% in phase A.

Table 5 Comparison of THD Values

Phases	Actual value (in THD)	Predicted value (in THD)		Error value (in THD)	
		FFBPN	AWNN	FFBPN	AWNN
Phase A	42.3600	42.3916	42.3595	-0.0316	0.0005
Phase B	42.6200	43.7195	42.6199	-1.0995	0.0001
Phase C	42.6700	43.0074	42.6693	-0.3374	0.0007

The proposed neural networks are again utilized and the true current harmonic distortions at supply side are identified. Table 5 indicates the comparison of THD measurement and error between FFBPN and AWNN in practical environment

Table 6 shows the comparison of relative error in measurement between AWNN and other experimental results (Joy Mazumdar et al., 2007). The relative error [16] is the new parameter which is used to examine the performance of the AWNN based harmonic distortion monitoring on the simulated signals.

$$\text{Relative error} = \left(\frac{\text{THD}_P - \text{THD}_T}{\text{THD}_P}\right)\%$$

Where THD_T is the True current THD value measured at the point of common coupling (PCC) and THD_P is the predicted current THD value. The relative error is calculated for the proposed AWNN method and compared with the Back Propagation Neural network (BPN) and Recurrent Neural Network. The accuracy of the proposed AWNN method is determined based on the relative error in measurement (e_r). From Table 6, the estimated relative error for the proposed AWNN method is very less compared with BPN and RNN methods.

4 Conclusion

The effectiveness of an adaptive wavelet neural network in terms of accuracy, robustness and time efficiency is tested on a simulated signal and implemented on MATLAB platform.

The proposed neural network method was able to evaluate the harmonic content of the currents efficiently in the three phase system. The estimation of harmonic distortion in the power system forms the basis in the field of harmonic filter design. The accuracy and computational complexity are the two main features that determine the effectiveness of any harmonic distortion estimation technique. The fast Fourier transform is used widely to obtain the harmonic spectrum. The proposed adaptive wavelet neural network uses 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 fast Fourier transform and back propagation neural network whose activation function is sigmoid, the results confirms the improved estimation accuracy of adaptive wavelet neural network in the presence of frequency deviation and noise. The computational time of AWNN is considerably low, which makes it suitable for online application in power quality metering equipment.

Table 6: Comparison of proposed AWNN with other works (Joy Mazumdar et al., 2007)

RNN Method (Joy Mazumdar et al., 2007)				Proposed AWNN Method					
Experimental results	**Actual current value (in THD)**	**Predicted current value (in THD)**	**Relative Error (e_r)**	**Simulation Results**	**Actual current value (in THD)**	**Predicted current value (in THD)**		**Relative Error (e_r)**	
	FFT	**BPN**			**FFT**	**BPN**	**AWNN**	**BPN**	**AWNN**
Triac with 0° Firing angle	6.11%	4.18%	-46.17%	Phase A	42.4400	42.6454	42.4394	0.4816%	-0.0014 %
Triac with 30° Firing angle	29.25%	30.58%	4.35%	Phase B	42.8500	43.2014	42.8490	0.8133%	-0.00233 %
Phase A of Variable Speed Drive (VSD)	74.27%	66.69%	-11.37%	Phase C	42.3600	43.5754	42.3598	2.7891%	-0.000472%

References:

[1] V. E. Wagner, J.C Balda, D.C.Griffith, A.McEachern. Effects of harmonics on equipment. *IEEE Transactions on Power Delivery*, Vol.8, No.2, 1993, pp. 672-680.

[2] H. Wen, Z. Teng, Y. Wang, and X. Hu. Spectral correction approach based on desirable sidelobe window for harmonic analysis of industrial power system. *IEEE Transactions on Industrial Electronics,* Vol.60, No.3, 2013, pp. 1001-1010.

[3] K. Fu Chen and S. L. Mei. Composite interpolated fast Fourier transform with Hanning window. *IEEE Transactions on Instrumentation and Measurement*, Vol.59, No. 6, 2010, pp. 1571-1579.

[4] Ferrero, R. Ottoboni. High-accuracy Fourier analysis based on synchronous sampling techniques. *IEEE Transactions on Instrumentation and Measurement*, Vol.41, No.6, 1992, 780–785.

[5] J. Barros and R. I. Diego. Analysis of harmonics in power systems using the wavelet packet transform. *IEEE Transactions on Instrumentation and Measurement*,Vol.57, No.1, 2008, pp. 63-69.

[6] Z. Leonowicz, T. Lobos and J. Rezmer. Advanced spectrum estimation methods for signal analysis in power electronics, *IEEE Transactions on Industrial Electronics*, Vol.50, No.3, 2003, pp. 514–519.

[7] Y. H. Gu and M. H. J. Bollen. Estimating interharmonics by using sliding-window ESPRIT, *IEEE Transactions on Power Delivery*, Vol.23, No.1, 2008, pp. 13–23.

[8] C. I. Chen, G. W. Chang, R. C. Hong and H. M. Li. Extended real model of Kalman filter for time varying harmonics estimation. *IEEE Transactions on Power Delivery*, Vol.25, No.1, 2010, pp. 17–26.

[9] C. I. Chen, Virtual multifunction power quality analyzer based on adaptive linear neural network. *IEEE Transactions on Industrial Electronics*, Vol.59, No.8, 2012, pp. 3321–3329.

[10] G. W. Chang, C. I. Chen, and Y. F. Teng, Radial basis function based neural network for harmonic detection. *IEEE Transactions on Industrial Electronics*, Vol.57, No.6, 2010, pp. 2171–2179.

[11] Q. Zhang and A. Benveniste, Wavelet networks. *IEEE Transactions on Neural Network*, Vol.3, No.6, 1992, pp. 889–898.

[12] N. M. Pindoriya, S. N. Singh, and S. K. Singh, An adaptive wavelet neural network based energy price forecasting in electricity markets, *IEEE Transactions on Power Systems*, Vol.23, No.3, 2008, pp. 1423–1432.

[13] S. H. Ling, H. Iu, F. H. F. Leung and K. Y. Chan, Improved hybrid particle swarm optimized wavelet neural network for modeling the development of fluid dispensing for electronic packaging, *IEEE Transactions on Industrial Electronics,* Vol.55, No.9, 2008, pp. 3447–3460.

[14] W. Chen, C. Pan, Y. Yun, and Y. Liu, Wavelet networks in power transformers diagnosis using dissolved gas analysis. IEEE Transactions on Power Delivery, Vol.24, No.1, 2009, pp. 187–194.

[15] S. K. Jain and S. N. Singh, Low Order Dominant harmonic estimation using adaptive wavelet neural network. IEEE Transactions on Industrial Electronics, Vol.61, No.1, 2014, pp. 428–435.

[16] J.Mazumdar, R.G.Harley, F.C.Lambert, G.K.Venayagamoorthy, Neural network method based method for predicting non liner load harmonics, IEEE Transactions on Power Electronics,Vol.22.No.3,2007,pp.1036-1045.