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ESTIMATION OF HARMONICS USING ADAPTIVE WAVELET NEURAL NETWORK

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ABSTRACT

Increase in the power electronic devices had leads to the harmonic contamination. Harmonic analysis is done to know about the origin and cause of the harmonics in the power system. The low order harmonics is monitored because these are very dangerous and cause serious power quality issues. Wavelet networks (WNs) is an effective version of nonlinear signal processing techniques in recent years an adaptive wavelet neural network (AWNN) is the most appropriate for prevailing low-order harmonics estimation. Odd-harmonic components of the voltage/current signal are decomposed into the frequency bands by using the above technique. Instead of one complete cycle data for estimating the harmonics the proposed scheme only requires an only half-cycle data point. The back propagation is used for training of the network parameters which is a easy, fast converging and reliable learning algorithm. The experimental signal which is obtained is examined with the projected method. The output result conforms that AWNN technique is effective in estimating the lower order harmonics, inter-harmonics if they are deviated from the fundamental frequency.

Keywords: harmonics, wavelet, back propagation, neural network.

1. INTRODUCTION

The electric utilities usually deliver sinusoidal voltage with constant magnitude but it is complicated by the harmonic current which is produced by the non-linear loads. Due to that harmonic current the results are distorted voltage and distorted current. Hence the power quality is greatly disturbed. To maintain the power quality the compensation for the harmonic and reactive current is important because of the use of the power electronic devices. When the non linear loads are connected it takes the non linear characteristics, due to that the voltage and the current becomes non sinusoidal. Due to that power quality is disturbed.

If the non linear load is connected it will produce the harmonic current. If the produced harmonic current interact with the system impedance voltage will be distorted. The effects of the harmonics are too dangerous. In the motor it causes increased heating and noise and it will also cause the cogging and crawling of the motor and generator. This effect will be common to the transformer and generator. In case of the power cables it will leads to the stress and the corona. Capacitors may also be affected due to the harmonics which pilots to increased heating and due to that the life of the capacitor gets reduced. In case of the electronic equipment it will alter the zero crossing. Medical instruments are also affected due to the presence of the harmonics [1]-[4].

According to the IEEE standard there are certain limits with which harmonics has to maintained. To maintain that standard we have to control the distortion of the power system current and voltage waveforms and the system should not interfere with any telephone networks. In this paper various algorithms are given which is used to estimate the harmonics accurately.

There are many harmonic estimation methods and to improve their efficiency there are many synchronization methods. There are estimation techniques for both time varying and in-varying signal.

Artificial intelligence is also a technique for harmonic estimation which gives good accuracy. The MLPNN is used to overcome the limitation of the RBFNN [5].

The adaptive wavelet neural network (AWNN) is a robust and simple method to estimate the lower order dominant harmonics. The proposed method has some key features which includes 1) with parameters like input-to-output layer weights, hidden-to-output layer weights, bias, translation, and dilation; 2) wavelets coefficients is used; 3) a heuristic initialization approach [6] is employed which reduces the training time; 4) linear relationship between output and input is mapped directly. Back propagation (BP) algorithm is used for network parameters training which is adaptive in nature. Adaptive in the sense it allows the weight to be adjusted. This method requires only less number of the computations. In this method only lower order harmonics is estimated. From the simulation results we can able to identify that the planned method is precise and efficient in estimating the harmonics.

2. ADAPTIVE WAVELET NEURAL NETWORK

WNN is basically a Feed forward neural network (FFNN). Zhang *et al* found a wavelet neural network (WNN) instead of FFNN. Wavelet neural network mingle the concept of neural network and wavelets together. An AWNN is a multilayer feed-forward network. There are two theories to create the WNN. For estimating lower order dominant harmonics we are using the wavelet network approach [13]-[14]. Some sundry applications of AWNN are wind speed forecasting [12], available transfer capability determination [11], energy price forecasting [7], identification and control of dynamic plants [8] modelling the development of fluid dispensing [9], power

transformer diagnosis [10]. In this paper a heuristic initialization approach is adopted.

2.1 Architecture of the AWNN

AWNN is three layer architecture with multiple layer feed-forward neural network. It is one which has multiple input and multiple output. Input is connected to hidden layer neurons. Hidden layer neuron is also called as wavelons. From the hidden layer it moves towards to the output layer. In this network x = (x1, x2,……,xn) denotes the input of an vector, and W = (f1,f2,……,fm) denotes the weight matrix relations sandwiched between output layer neurons and input layer. V = (v1, v2,……,vm) denotes the weight matrix which is connections between output layer neurons and wavelons. b = (b1, b2,…,bk) is the bias vector [13].

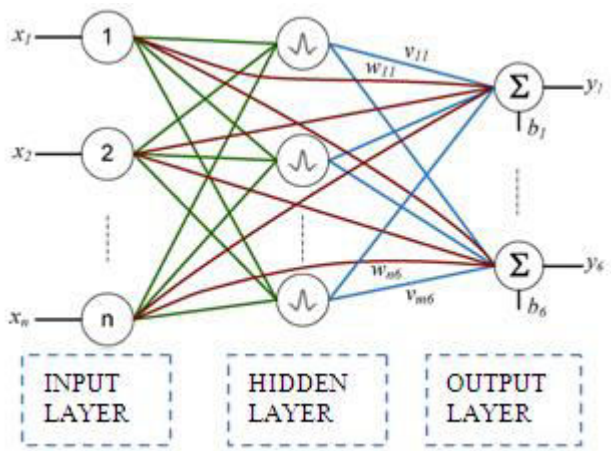


Figure-1. AWNN model.

The mother wavelet is translated and dilated to produce the wavelet family. Morlet, Haar Daubechies and Mexican hat are the mother wavelets [14].

For decomposing multidimensional function, the Mexican hat wavelet function has an numerical equation which can be used to obtain the output. [14]. Mexican hat function is selected here because it is very good in case of the non linear system modelling.

The output for the AWNN architecture can be computed as

$$Y=w.x^n + v^n + b \quad (1)$$

Where $(.)^n$ represents the transpose of the vector/matrix. Parameter learning is an important step in the ANN.

2.2 Parameter learning and network initialization

The adaptive neural network incorporates Parameter learning as one of the essential step. BP algorithm is simple so it is used in this AWNN algorithm. It has ability for fast learning and to update each parameter at the same time. Parameter learning is done to shrink and diminish the error and inaccuracy of the algorithm [13-[14].

$$E=y_e(n)-y(n)$$

Where y_e (n) and the y(n) are the actual and the estimated output of the neural network with respect to the nth input pattern. Mexican hat wavelet utilize, only less number of epochs for training the network. The training time is also comparatively less while comparing with other algorithms.

2.2.1 Network initialization

Initialization of the neural network is the process of choosing the correct initial values. There are many ways to initialize the neural network such as random initialization, cluster technique etc. Cluster technique makes use, of the guess to find the translation process. Heuristic initialization [6] initiates, the parameter of the translation and dilation. Then the weight w between output and input and bias b are set to zero, and wavelon to output v [15] are randomly initialized within constraint. Computation burden and estimation accuracy depends on the selection of the wavelons. If the number of wavelons is decreases, burden in computation is decreased meanwhile the accuracy is increased.

2.3 Problem formulation

The signal output from the simulation may be continuous in time, so it is difficult to analyse harmonics in that signal. So signal is modulated into frequency domain from the time domain. By doing FFT the continuous signal in the time domain is transferred to the function of the different frequency which is suitable for harmonic analysis.

FFT is the unsurpassed method to find the Fourier transform of the data which is in form of discrete values. For that the signal is first sampled. Before sampling a signal anti-aliasing filter is used to prevent aliasing [16].

Sampling is performed by applying a continuous-time signal to an ADC whose output is a serious of digital value. The discrete data point is obtained. The FFT allows computing the Fourier coefficients. NLog2 (N) operations is only required for the FFT to take Fourier of the discrete data. By applying the FFT the signal in the form of the frequency domain is obtained.

The signal in the time domain is represented as

$$x(t)=\sum_{h=H} A_h \sin(2\pi f_h t + \theta_h) \quad (2)$$

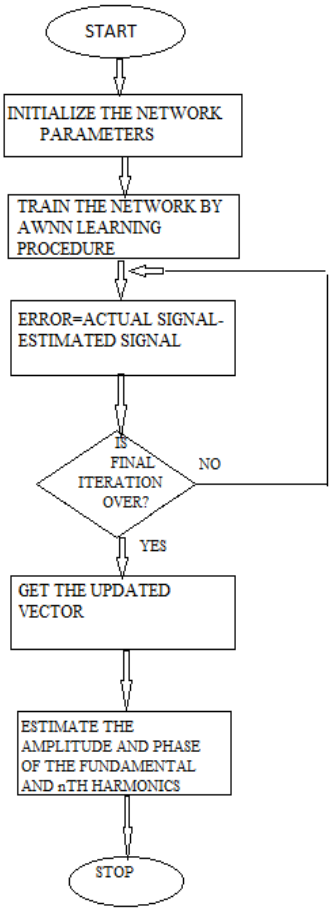
H is the harmonic order in the signal which is distorted [14].

After the sampling of the signals, it becomes

$$x(i)=\sum_{h=H} A_h \sin(2\pi f_h i T_s + \theta_h) \quad (3)$$

where f_h is the frequency of hth component, A_h is the amplitude of hth component and θ_h are the phase angle of the hth component.

The amplitude of the signal can be considered in [17]-[19] as $A_h = F_A(x_i)$.



Flowchart-1. AWNN algorithm to estimate the harmonics

2.4 Algorithm steps

The step for AWNN is formulated below:

a) Input patterns are generated
b) Initialize the network parameters by Heuristic initialization for network training.
c) Set the epochs k=1.
d) Find the Mexican hat wavelet function at the hidden node.
e) Output of AWNN is calculated.
f) Calculate the MEAN SQUARE ERROR (MSE) for the nth pattern.
g) Adjust the weights, dilation and translation.
h) Repeat the procedure until the error becomes small.
i) Now the trained AWNN network is utilised for estimating the harmonic components.

The above steps are followed to implement the AWNN based technique.

The above procedure which is given in the flow chart 1 is done to estimate the harmonics of the signal accurately.

3. EVALUATING THE PERFORMANCE OF AWNN TECHNIQUE

To test the performance of AWNN in the domain of the harmonic estimation, a suitable signal is taken to analyze the AWNN based technique.

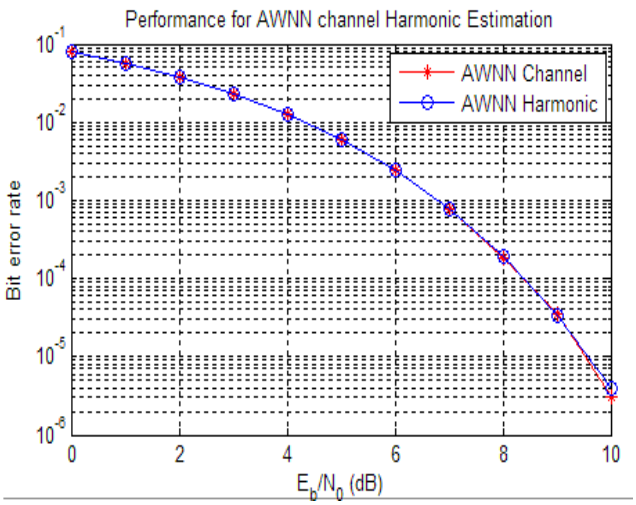


Figure-2. Simulated AWNN channel harmonics estimation.

From the Figure-2, simulated AWNN channel for harmonics estimation is observed. It illustrates that the bit error rate is very much reduced even though the presence of the signal to noise ratio (SNR) is high. From this, it is clearly understood that the AWNN is capable of estimating the harmonics in the presence of the noise and inter-harmonics.

A total root mean square relative error (TRMSRE) for an n input pattern [19] is found by using the

TRMSE=

$$\left(\frac{1}{n.k}\sum_{n=1} n \sum_{k=1} k \left(\frac{yn-y}{yn}\right)^{2}\right) \times 100 \quad (4)$$

3.1 Experimental signal

To test the AWNN technique an signal with noise, distortion, frequency deviation and inter-harmonics is taken which is shown in the Figure-3. The proposed AWNN based technique is implemented on the signal and the algorithm steps is followed.

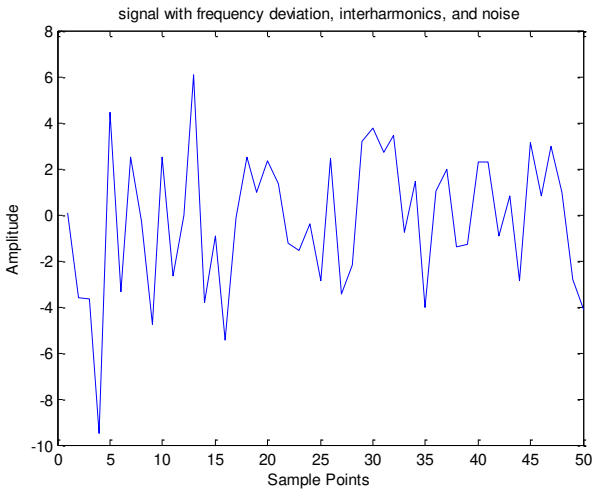


Figure-3. Signal with frequency deviation, inter-harmonics and noise.

From the Figure-4 we can able to observe the Current Spectral Density Waveform, it shows the current signal as the function of the frequency. It clearly shows that it takes only less number of cycle for analysis. It also shows that the TRMSE is reduced in case of the lower order harmonics, but for the other harmonic components error is high.

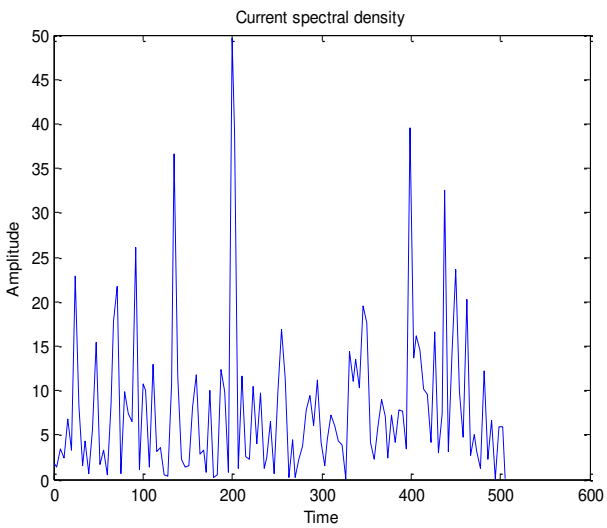


Figure-4. Simulated current spectral density waveform.

Whereas the Figure-5 shows the measured current signal which is tested with the help of the AWNN based technique. In general for the fundamental component AWNN performance is low but generally for fundamental component estimation, the FFT is good.

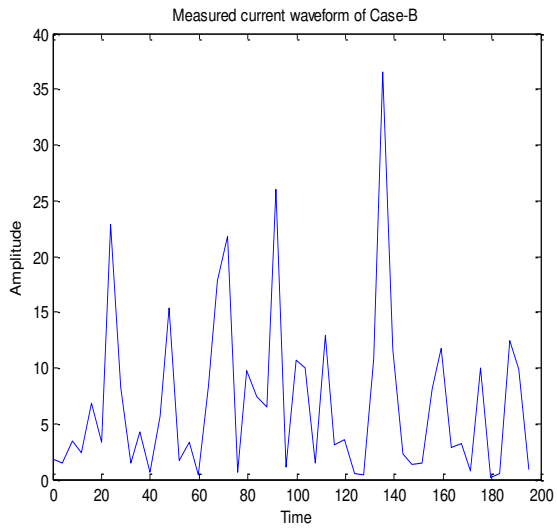


Figure-5. Measured current waveform.

From the above output we can able to know that the output of the AWNN is good in case of the inter-harmonics, harmonics and also during distortion during harmonics.

3.2 Measured PC current signal

Personal computer take the current which is distorted from the supply. In this case a personal computer which is supplied with single phase ac supply at 50 hz is taken. The distorted current taken by the pc is measured which is shown in the Figure-6.

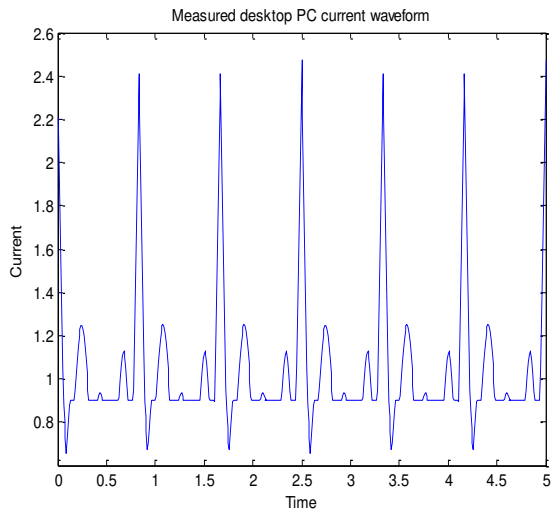


Figure-6. Measured PC current waveform.

Only the lower order dominant harmonics is considered for the anaysis purpose. The harmonic spectrum from the AWNN method is show in the Figure-7. It is clearly understood that the TRMSE error is reduced.

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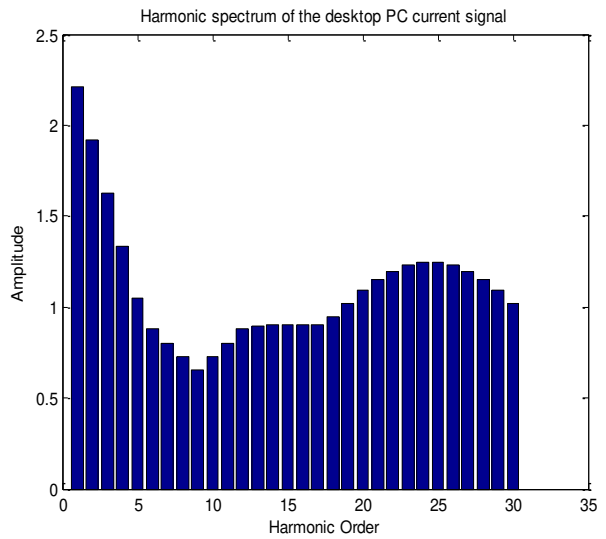

Figure-7. Measured harmonic spectrum from the PC by using the AWNN.

3.3 Single phase fully controlled system

Using SIMULINK an rectifier whose output is DC and AC voltage controller circuit are designed. The voltage signals and current signals of these circuits are used for testing of an the proposed technique. The output waveform that is current and voltage of the single phase ac-dc converter is taken and the proposed AWNN technique is applied. The single phase rectifier is triggered with the different firing angles and the obtained result is analyzed with the proposed AWNN technique [20].

Considering phase angle 30 Degree for single phase fully controlled system, the following waveforms are observed using AWNN algorithm.

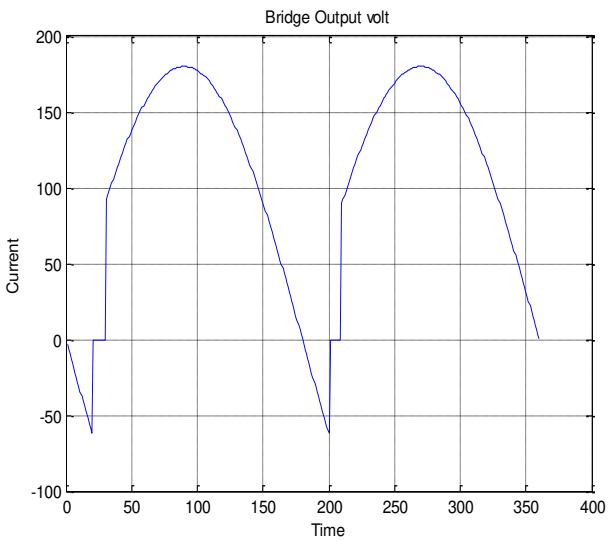

Figure-8. Observed bridge output waveform for 30 degree.

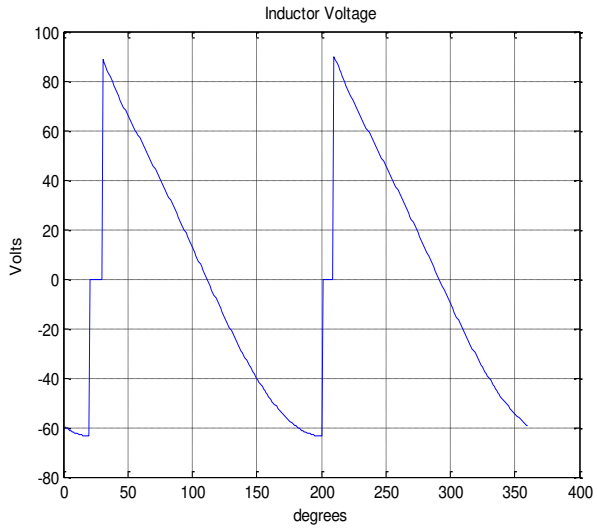

Figure-9. Observed voltage waveform for inductor for 30 degree.

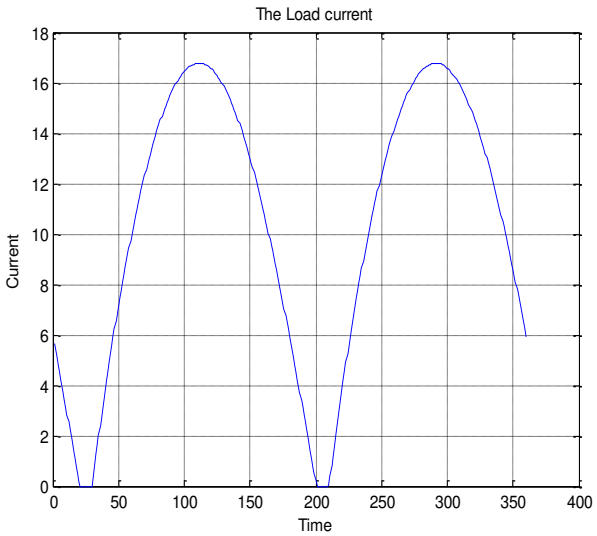

Figure-10. Observed load current waveform for 30 degree

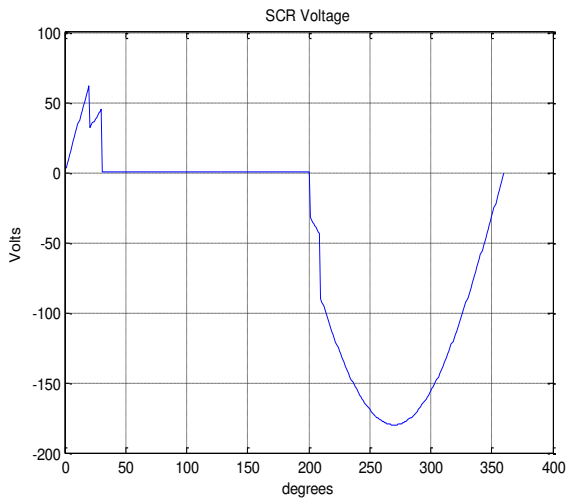

Figure-11. Observed SCR voltage waveform for 30 degree.

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Figure-12 shows the estimated harmonic spectrum which is estimated with the help of the AWNN technique.

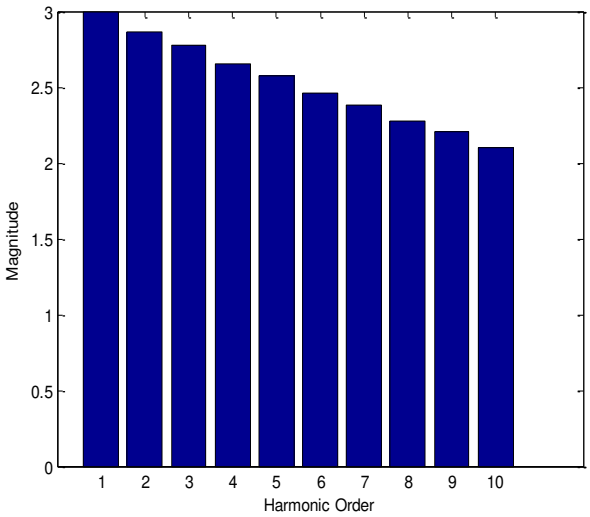

Figure-12. Observed harmonic order for single phase rectifier system for 30 degree.

Considering phase angle 90 degree for single phase fully controlled system, the following waveforms are observed using AWNN algorithm.

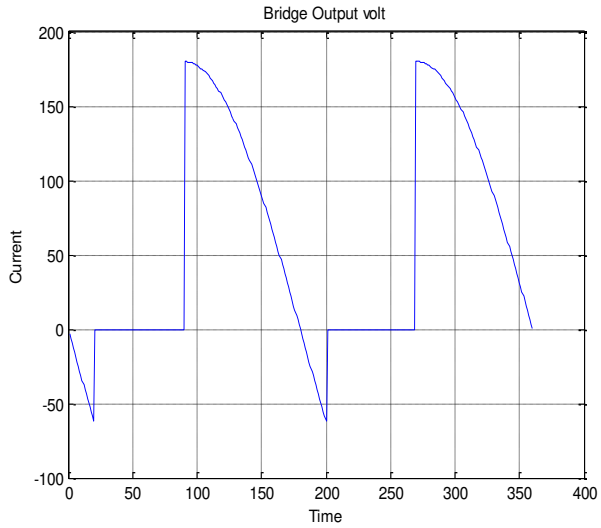

Figure-13. Observed bridge output waveform for 30 degree.

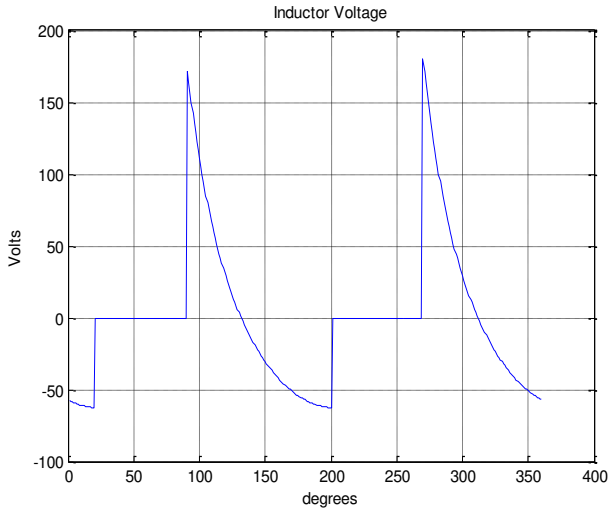

Figure-14. Observed voltage waveform for inductor for 90 degree.

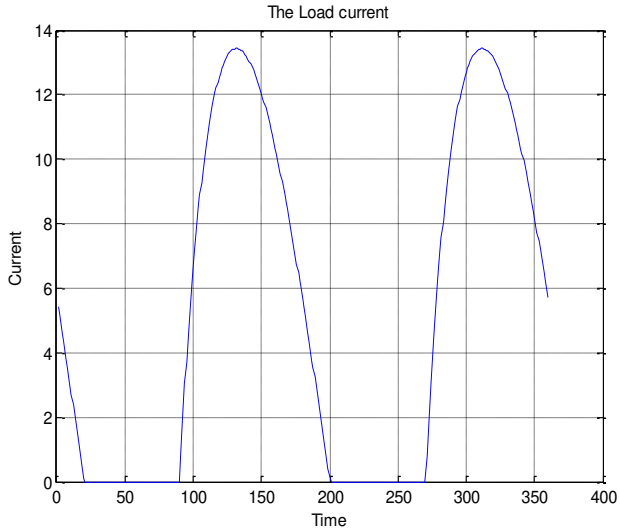

Figure-15. Observed load current waveform for 90 degree.

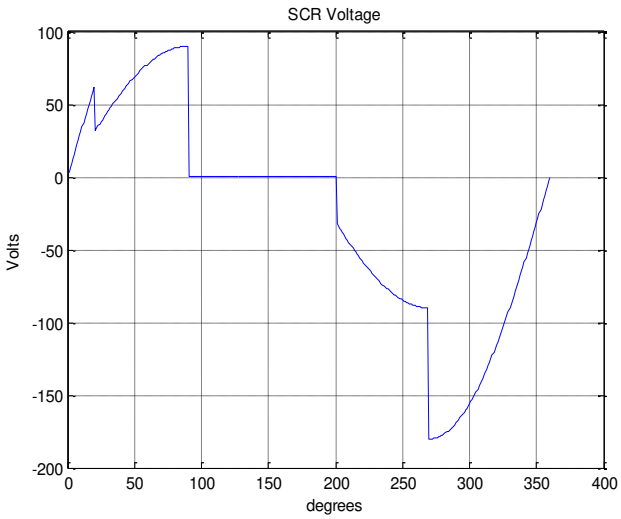

Figure-16. Observed SCR voltage waveform for 90 degree.

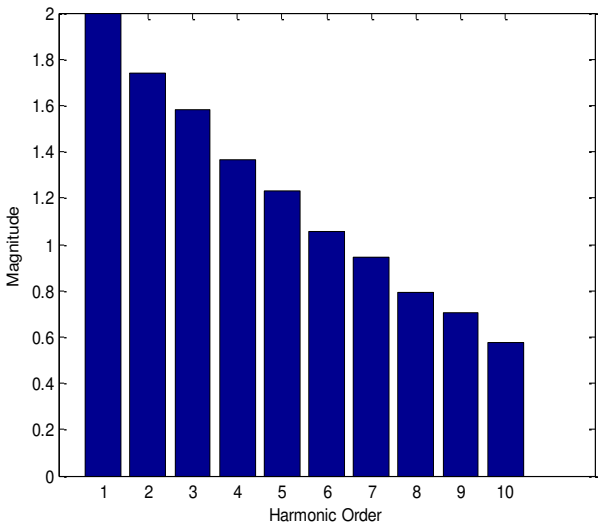

Figure-17. Observed harmonic order for single phase rectifier system for 90 degree.

By triggering the single phase rectifier at an firing angle of 30^0 and 90^0 the bridge output, inductor voltage, load current, SCR Voltage waveforms harmonic order of the spectrum are generated.

For the lower triggering angle of 30^0, the harmonic order is considerably low and vice-versa. For the higher triggering angle of 90^0 the harmonic order is high which is shown in the Figures 12 and 17. Hence the AWNN based technique is accurate even though there is a presence of the inter-harmonics, noise and distortion.

4. CONCLUSIONS

In this paper the muliple layer feed forward neural network based adaptive wavelet neural network (AWNN) is implemented for estimating the harmonics. The proposed scheme is implemented in various signals such as personal computer current signal,measured signal and in the single phase fully controlled bridge rectifier system. The results shows that AWNN is also suitable for the non-linear systems. The result confirm the accuracy of the system even in the presence of the noise,inter-harmonics. AWNN also takes the less cycles of data when compared with other algorithm and technique. In addition to above mentioned advantage the time taken for the computation is low and is suitable for estimating the lower order dominant harmonics in the power system.

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