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Predicting Load Harmonics in Three Phase Systems Using Neural Networks

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Abstract - This paper proposes a artificial neural network (ANN) based method for the problem of measuring the actual harmonic current injected into a power system network by three phase nonlinear loads without disconnecting any loads from the network. The ANN directly estimates or identifies the nonlinear admittance (or impedance) of the load by using the measured values of voltage and current waveforms. The output of this ANN is a waveform of the current that the load would have injected into the network if the load had been supplied from a sinusoidal voltage source and is therefore a direct measure of load harmonics.

I. INTRODUCTION

The increased use of nonlinear devices in industry has resulted in direct increase of harmonic distortion in the industrial power system in recent years. All loads serviced by the utility are designed to operate at 60 Hz. However nonlinear loads demand nonsinusoidal current and these currents have detrimental effect on the power system. As an example, Fig. 1 shows a typical power distribution network structure.

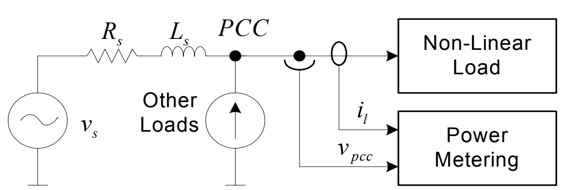

Fig. 1: Simple power system network

When the nonlinear load is supplied from a sinusoidal voltage source, its injected harmonic current i_l is referred to as *contributions from the load,* or load harmonics. Any harmonic currents cause harmonic volt drops in the supply network.

Any other loads, even linear loads, connected to the point of common coupling (PCC), will have harmonic currents injected into them by the distorted PCC voltage. Such currents are referred to as *contributions from the power system*, or supply harmonics. If several loads are connected to a PCC, it is not possible to accurately determine the amount of harmonic current injected by each load, in order to tell which load(s) is injecting the excessively high harmonic currents. Simply measuring the harmonic currents at each individual load is not sufficiently accurate since these harmonic currents may be caused by not only the non-linear load, but also by a nonsinusoidal PCC voltage. This is not a new issue and researchers have proposed various methods like DFT/FFT [1,2], stochastic method [3,4], harmonic impedance measurement [5], and in recent years artificial neural networks (ANN) [6-9] to measure the harmonic content in the load current, or to predict it, but most of them assume a radial feeder supplying a single load through a known feeder impedance, or multiple loads connected to a PCC which has a sinusoidal voltage and with zero impedance in the supply feeder.

This paper proposes a novel method based on Artificial Neural Networks (ANN) to determine the true harmonic current of a nonlinear load in a three phase power system.

II. LOAD MODELING USING NEURAL NETWORKS

Artificial Neural Networks have provided an alternative modeling approach for power system applications. The multi-layer perceptron network (MLPN) is one of the most popular topologies in use today. This network consists of a set of input neurons, output neurons and one or more hidden layers of intermediate neurons. Data flows into the network through the input layer, passes through the hidden layers and finally flows out of the network through the output layer. The network thus has a simple interpretation as a form of input-output model, with network weights as free parameters.

A one-line diagram of a three-phase supply network having a sinusoidal voltage source v_s, network impedance L_s, R_s and several loads (one of which is nonlinear) connected to a PCC is shown in Fig. 2.

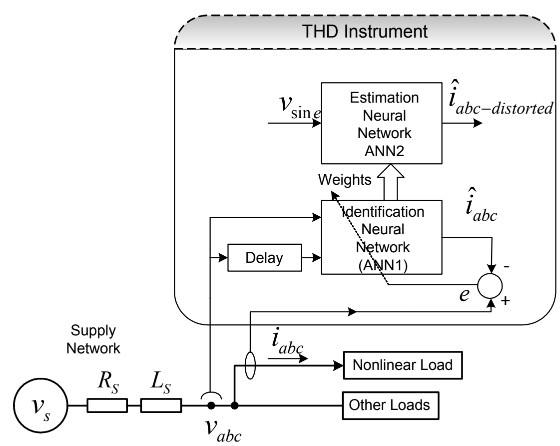

Fig. 2: Simple power system network

The nonlinear load injects distorted line current i_{abc} into the network. The Identification Neural Network (ANN1) is trained to identify the nonlinear characteristics of the load. The Estimation Neural Network (ANN2) predicts the true harmonic current that would be injected by the load into the network, if it were possible to isolate the load and supply it from a pure sinusoidal source. ANN2 is an exact replica of the trained ANN1 structurally. The function of ANN2 can very well be carried out by ANN1; however that would disrupt the continual online training of ANN1 during the brief moments of estimating. The structure of a MLPN is shown in Fig. 3.

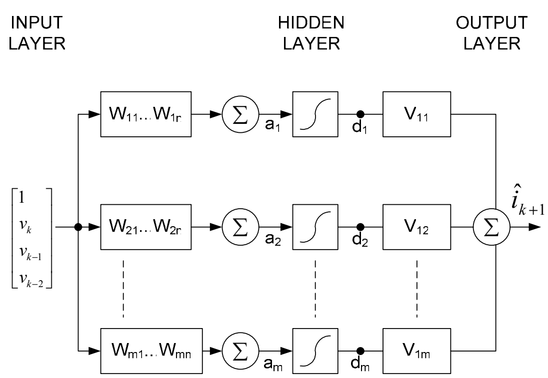

Fig. 3: Structure of a MLPN

The supply configuration at the PCC for a load could be wye connected neural grounded, wye connected neural floating or delta connected. Furthermore, the system could be balanced or unbalanced. The determination of harmonics in a three phase is done on a per phase basis. Hence the inputs to the network are chosen according to the supply configuration.

A. Identification Neural Network (ANN1)

The proposed method measures the instantaneous values of the three voltages v_{abc} (line or phase) at the PCC, as well as the three line currents i_{abc} at the k^{th} moment in time. The neural network is designed to predict one step ahead line current $\hat{i}_{abc}$ as a function of the present and delayed voltage vector values $v_{abc}(k)$, $v_{abc}(k-1)$ and $v_{abc}(k-2)$. When the $k+1^{th}$ moment arrives (at the next sampling instant), the actual instantaneous values of i_{abc} are compared with the previously predicted values of $\hat{i}_{abc}$, and the difference (or error e) is used to train the ANN1 weights. Initially the weights have random values, but after several epochs, the training soon converges and the value of the error e diminishes to an acceptably small value. This process is called identifying the load admittance.

B. Estimation Neural Network (ANN2)

The estimation neural network ANN2 is supplied with a mathematically generated sine wave to estimate its output. The output of ANN2 called $\hat{i}_{abc-distorted}$ therefore represents the current that the nonlinear load would have drawn had it been supplied by a sinusoidal voltage source. Any distortion present in the $\hat{i}_{abc-distorted}$ can now truly be attributed to the nonlinearity of the load admittance.

C. ANN Governing Equations

With reference to Fig. 3, the process of passing the inputs through the neural network structure to its output is known as forward propagation. Every input in the input column vector $\underline{v}$ is fed via the corresponding weight in the input weight matrix W to every node in the hidden layer to determine the activation vector $\underline{a}$. Each of the hidden neuron activations in $\underline{a}$ is then passed through a sigmoid function to determine the hidden-layer decision vector $\underline{d}$.

$$\underline{a} = W\underline{v} \tag{1}$$

$$d_i = \frac{1}{1+e^{(-a_i)}},\; i \in \{1,2,....,m\} \tag{2}$$

where the input column vector $\underline{x} \in R^n$, the hidden layer activation column vector $\underline{a} \in R^m$, the input weight matrix $W \in R^{m\times n}$, n is the number of inputs to the ANN including the bias and m is the number of neurons in the hidden-layer.

The decision vector $\underline{d}$ is then fed to the corresponding weight in the output weight matrix V. The ANN output is computed as;

$$\hat{y} = (V\underline{d})^T \tag{3}$$

For a single output system output weight matrix $V \in R^{1\times m}$ and $\hat{y}$ is a scalar.

The output error is calculated as

$$e = y - \hat{y} \tag{4}$$

The process of passing the output error to the input in order to estimate the individual contribution of each weight in the network to the final output error is known as error back-propagation. The weights are then modified so as to reduce the output error. The change in input weights ΔW and output weights ΔV are calculated as

$$\Delta W(k) = \gamma_m \Delta W(k-1) + \gamma_g \underline{e}_a \underline{x}^T \tag{5}$$

$$\Delta V(k) = \gamma_m \Delta V(k-1) + \gamma_g \underline{e}_y \underline{d}^T \tag{6}$$

where $\gamma_{m,} \gamma_g \in [0,1]$ are the momentum and learning gain constants, e_a is the activation error vector and e_a is the output error vector.

The last step in the training process is the actual updating of the weights:

$$W(k) = W(k-1) + \Delta W(k) \tag{7}$$

$$V(k) = V(k-1) + \Delta V(k) \tag{8}$$

III. Experimental Results

The method of using online trained ANNs to identify the load admittance and utilizing the trained neural network to estimate the harmonic current of nonlinear loads is demonstrated with the help of following circuits. The scheme has to be applied individually to each phase.

A. Variable Speed Drive

The scheme has been applied on a variable speed drive, ABB make ACS 500 (VSD). The clean power source used is a California Instruments 5001 iX harmonic generator which is capable of outputting voltages with programmable distortion levels and zero internal impedance. The experimental setup is shown in Fig. 4.

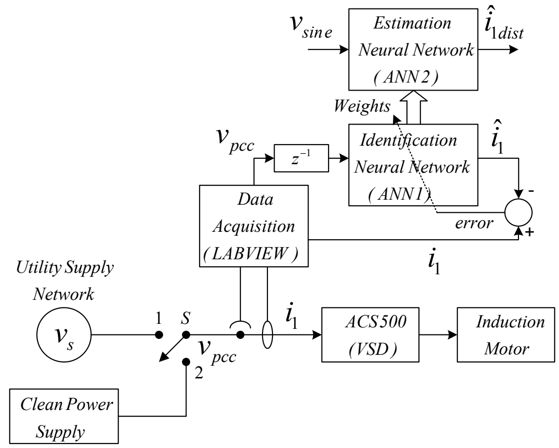

Fig. 4: Experimental Setup for ACS 500 Drive

With switch S in position 1, the VSD is supplied from the utility source. Now with switch S in position 2, the drive is supplied from the clean power source. The measured phase A voltage and current waveforms with switch in position 1 is shown in Fig. 5. Figure 6 shows the measured phase A voltage and current waveforms with switch in position 2. The total harmonic distortion (THD) of the utility voltage is 4.5% and the THD of the CI 5001 iX voltage is 0.2%.

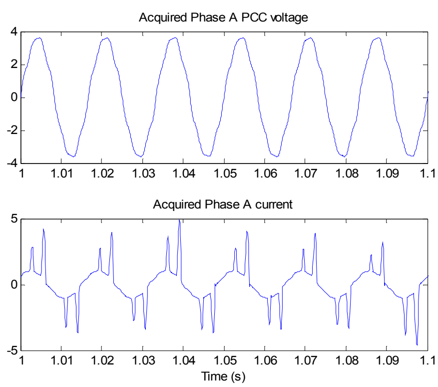

Fig. 5: Measured voltage and current with S in postion 1

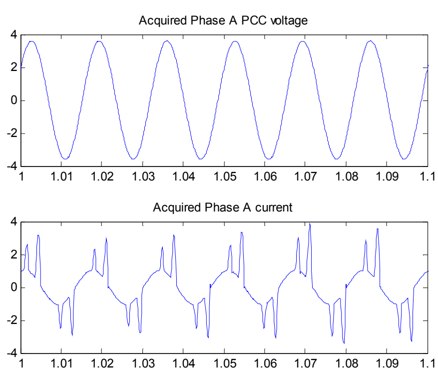

Fig. 6: Measured voltage and current with S in postion 2

The THD of current with S in position 1 is 74.27% and THD of the current with S in position 2 is 67.14%. The FFT spectrums are shown in Fig. 7 and Fig. 8 respectively.

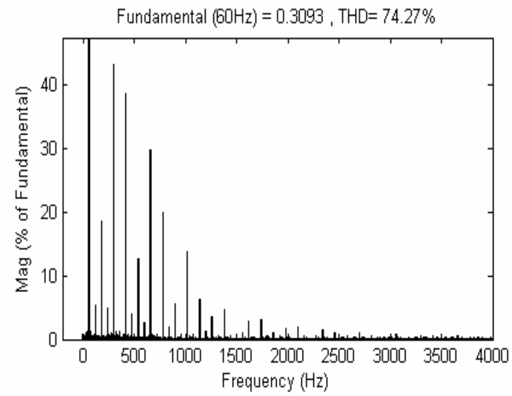

Fig. 7: FFT Spectrum of current with S in postion 1

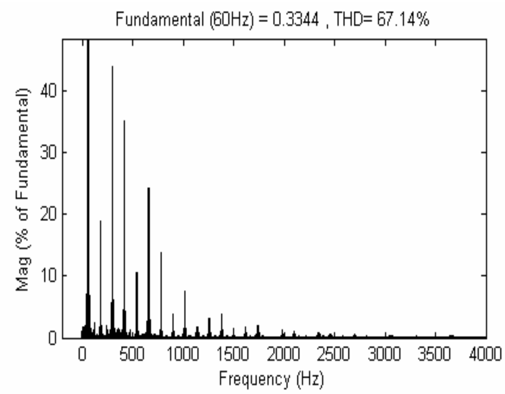

Fig. 8: FFT Spectrum of current with S in postion 2

The data obtained with switch S in position 1 is used to train the neural network ANN1 until the training error converges to near zero, and the output of ANN1 correctly tracks the actual current i_1.

Figure 9 indicates how well the training of ANN1 has converged since its output $\hat{i}_1$ coincides with the actual i_1 waveform.

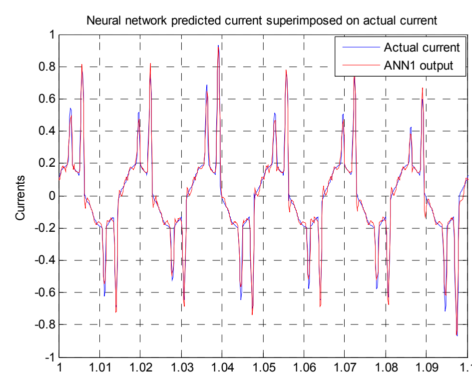

Fig. 9: ANN1 Convergence Result

The convergence of the training can also be verified by looking at the absolute value of the tracking error T_e defined as;

$$T_e = \left|(i_1 - \hat{i}_1)\right| \quad (9)$$

and the Mean Squared Error MSE is defined as

$$MSE = \frac{1}{r}\sum_{1}^{r}\left|(i_1 - \hat{i}_1)\right|^2 \quad (10)$$

where r is the number of epochs. Figure 10 shows the MSE of the ANN1 current tracking.

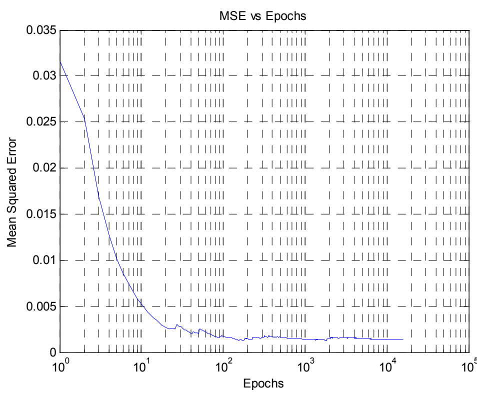

Fig. 10: MSE in Current

The sampling rate for data acquisition is set at 128 samples per cycle. Data acquisition is carried out by National Instruments data acquisition system. The voltage transducers used are LEM LV 25-P and the current transducers used are LEM LAH 25-NP. FFT of the acquired waveforms are computed using the powergui block of SIMULINK.

Once ANN1 has learned the admittance of the phase A of the VSD, the weights of ANN1 are transferred to ANN2. The output of ANN2 is $\hat{i}_{1-dist}$ and is obtained by using a mathematically generated sine wave voltage with zero distortion as its input. Fig. 9 shows what Fig. 5 would have looked like if it were possible to isolate the VSD and supply it from a pure sine wave.

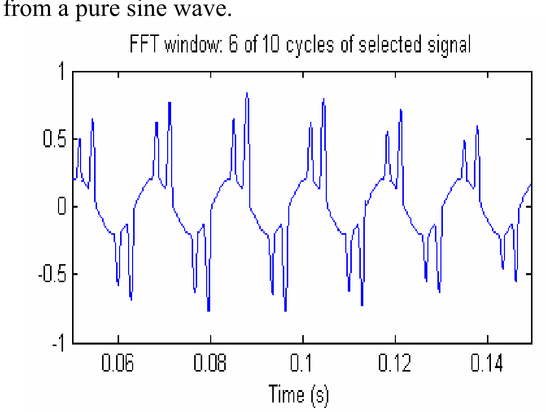

Fig. 11: Output of ANN2

Fig. 12 shows the frequency spectrum of Fig. 11. The true current distortion of $\hat{i}_{1-dist}$ turns out to be **66.69%** (instead of the **74.27%** of Fig. 7). This result agrees well with the measured value of 67.14% of Fig. 8 where the VSD was supplied by a 0.2% distorted voltage.

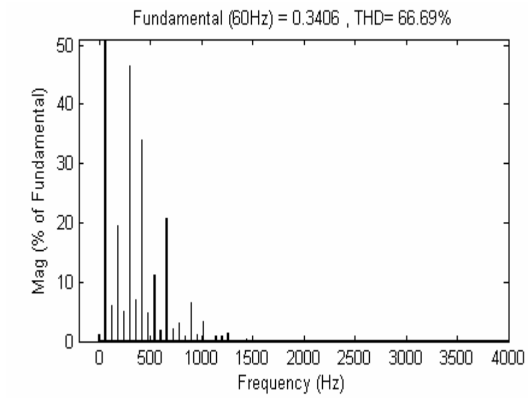

Fig. 12: FFT Spectrum of the ANN2 Output

B. *RXPO Rectifier*

The scheme was also applied to an actual field setup for testing connectors at NEETRAC. The setup shown in Fig. 13 comprises of utility feeding a RXPO series 30 DC rectifier. The rectifier output load varies between 0 and 3000 A DC.

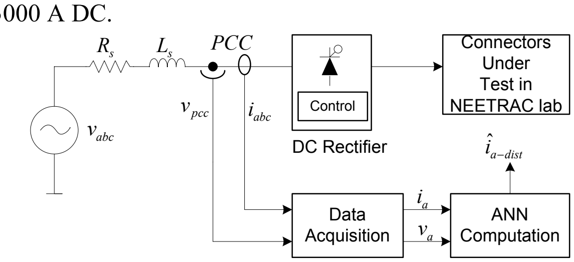

Fig. 13: Experimental Setup for RXPO Series 30 Rectifier

The actual phase A voltage (Line to Neutral) and current THD's are shown in Table 1.

TABLE I
LOAD PROFILE OF RXPO SERIES 30 RECTIFER

DC Load	V_a THD	I_a THD
3000A	3.71%	31.91%
2500A	3.80%	38.54%
2000A	3.39%	46.44%
1500A	2.95%	57.48%
1000A	2.57%	71.36%
500A	1.94%	85.22%

With 2000 A loading, the data acquired is used to train ANN1 until the training error converges to near zero, and the output of ANN1 correctly tracks the current i_a.

Figure 14 indicates how well the training of ANN1 has converged since its output $\hat{i}_a$ coincides with the actual i_a waveform. Figure 15 shows the MSE of ANN1 current tracking.

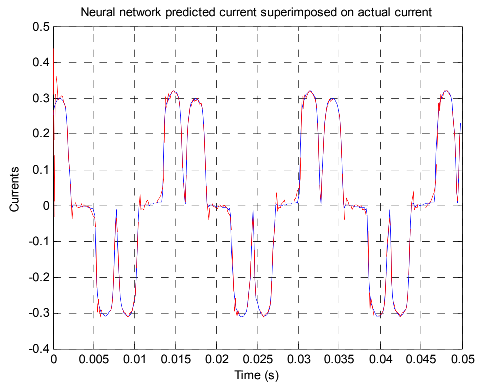

Fig. 14: ANN1 Convergence Result

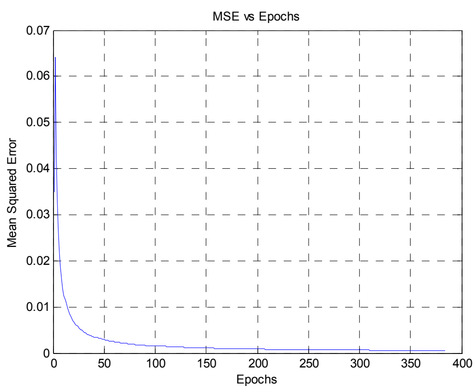

Fig. 15: MSE in Current

The sampling rate for data acquisition is set at 128 samples per cycle. Data acquisition is carried out by Reliable Power Meter software and FFT is computed using the powergui block of SIMULINK.

Once ANN1 has learned the admittance of the DC rectifier circuit, the weights of ANN1 are transferred to ANN2. The output of ANN2 is $\hat{i}_{a-dist}$ and is obtained by using a mathematically generated sine wave voltage with zero distortion as its input. Figure 16 shows what Fig. 14 would have looked like if it were possible to isolate the DC rectifier circuit and supply it from a pure sine wave.

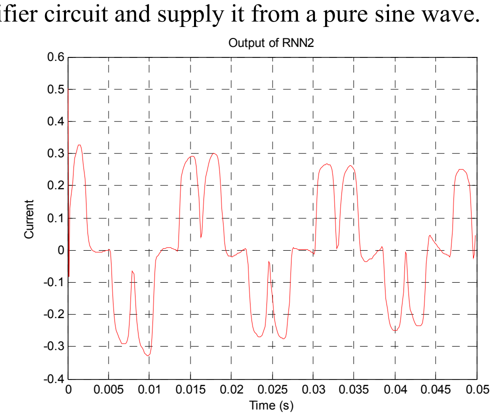

Fig. 16: Output of ANN2

Figure 17 shows the frequency spectrum of Fig. 16. The true current THD of $\hat{i}_{a-dist}$ turns out to be **50.63%** instead of the **46.44%** of Fig. 14.

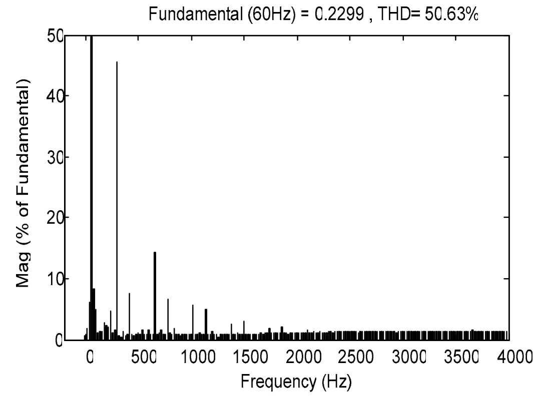

Fig. 17: FFT Spectrum of the ANN2 Output

This result agrees well with fact that current distortion of rectifier loads increase when the applied voltage is a pure sinusoid with low impedance, i.e. stiff power system.

IV. QUANTIFICATION OF RESULTS

The above experiments have shown that there is a difference in the current distortion of a load depending on whether the loads are served by a clean supply or a distorted supply. Any load serviced by a utility is designed and optimized to operate at 60 Hz, however once they are connected to the power system network, they seldom do get a clean 60 Hz supply. For the purpose of quantification of this difference, a new parameter e_m, known as the resultant error in measurement, is introduced and is defined as;

$$e_m = \left(\frac{THD_s - THD_d}{THD_s}\right)\% \qquad (11)$$

where THD_d is i_{THD} from a distorted v_{pcc} ,and THD_s is i_{THD} from a mathematical sine wave.

Table II shows the computed value of e_m for the experiments presented in this paper.

TABLE II
SUMMARY OF RESULTS

Load	THD_d	THD_s	e_m
ACS 500	74.27%	66.69%	-11.37%
RXPO Series 30	46.44%	50.63%	8.28%

e_m can be positive or negative. A positive sign indicates that the current THD of the load is higher when supplied from a clean source. A negative sign indicates that the current THD of the load is lower when supplied from a clean source.

V. NEURAL NETWORK PARAMETERS

The above scheme can also be applied to the two other phases as well for the other loading conditions of the RXPO rectifier. The feasibility of using a single neural network for all the three phases is currently under investigation. Data acquisition is carried out by a National Instruments SCXI system and LABVIEW software. The scheme for data acquisition is shown in Fig. 18 below.

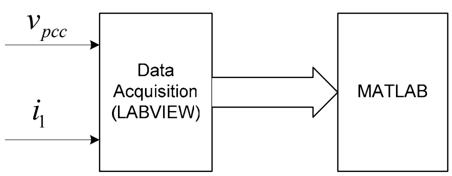

Fig. 18: LABVIEW code for data acquisition

The data is acquired for two seconds (120 cycles), every 30 seconds with a sampling frequency of 8 kHz. The sampling frequency of 8 kHz ensures that harmonics up to 4 kHz can be measured. Harmonics above that frequency range are normally removed by filters.

The code can run as long as the load is running or it can be stopped after a certain time interval. LABVIEW stores data as text files. These text files are then converted to Microsoft excel files and imported to the MATLAB workspace.

The acquired data is used to train the identification neural network. The acquired data contains all the dynamics present in the power system, and hence during training the neural network does not see any particular pattern and is able to incorporate whatever changes that took place in the load current during the measurement time span.

ANN1 starts with random weights and as the acquired data is presented to the neural network, the weights converge towards the desired weights which represent the load admittance. For the experiments presented in this paper, initial convergence requires about five minutes of acquired data.

Once the ANN1 training has converged and the weights transferred to ANN2, four cycles of mathematically generated sine wave are sufficient for the estimation phase of ANN2 to calculate an accurate THD number.

Some of the other experimental details of the neural network implementation are given below:

- Multilayer perceptron neural network with backpropagation training algorithm implemented in MATLAB.
- FFT computation : *powergui* block of SIMULINK
- Number of Neurons in the hidden layer: 20
- Time delayed inputs : 2
- Learning gain: 0.05. Momentum gain not used.
- Sampling frequency for data acquisition: 8 kHz. Power quality instrumentations require approximately 128 samples/cycle.

The accuracy of neural network computations can be further increased by increasing the sampling rate and number of neurons. However that puts additional computational demands on the processor and might make the actual hardware implementation more difficult.

VI. CONCLUSIONS

Standards like IEEE 519 [10-12] provide guidelines for controlling harmonic distortion levels that divide the responsibility between the utility and the customer. The utility has to maintain voltage distortion at the PCC below the specified limits and the customer has to limit the amount of harmonic current injection onto the utility system. However, disputes may arise between utilities and customers regarding who is responsible for the harmonic distortions due to the lack of a reliable single index which can precisely point out the source of the harmonic pollution. The method proposed in this paper aims at solving this problem with the aid of online trained neural networks.

The paper demonstrated the ability of MLPN's to learn the nonlinear characteristics of three phase loads and utilize the trained neural network for estimating the true harmonic distortion caused by that load. This novel method avoids disconnecting any loads from the power system. Experimental results confirm that an error in the measurement is made if the calculation of current THD is done by simply measuring the input current of the nonlinear load.

On a practical system the neural network computations could be carried out on a DSP. A suitable analog to digital interface is required for acquiring the measured values of voltages and currents. Such a system could be installed permanently or be portable from one customer to another in order to simply monitor pollution levels at a particular PCC in the network.

ACKNOWLEDGMENT

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