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Change in Voltage Distortion Predictions at the PCC Due to Changing Nonlinear Load Current Profile Using Plant Startup Data

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Abstract—**Customer loads connected to electricity supply systems may be broadly categorized as either linear or nonlinear. Nonlinear loads inject harmonics in a power distribution network. The interaction of the nonlinear load harmonics with the network impedances creates voltage distortions at the point of common coupling (PCC) which in turn affects other loads connected to the same PCC. When several nonlinear loads are connected to the PCC, it is difficult to predict mathematically how each nonlinear load is affecting the voltage distortion level at the PCC. Typically, customers with nonlinear loads apply harmonic filtering techniques to clean up their current and avoid penalties from the utility. When corrective action is taken by the customer, one important parameter of interest is the change in the voltage distortion level at the PCC due to the corrective action of the customer. This paper proposes a new method based on neural networks to predict the change in the distortion level of the voltage at the PCC if the customer were to draw only fundamental current and filter out its harmonics. The benefit of the proposed method is that it would indicate the impact of the customer's front end filters on the voltage distortion at the PCC without actually having to install the filters. This paper presents the results of the proposed method applied to actual industrial sites.**

Keywords-Harmonic analysis, Neural networks, Power system harmonics, Power quality, Source modeling

I. Introduction

Harmonics are an important *measurable* parameter of power quality. The related economic aspects of harmonics [1] and deregulation [2] have all created a need for extensive monitoring of the power system harmonics. Customers with sensitive equipments use harmonic current monitoring to locate the source of harmonic related problems that might occur. On the other side, utilities try to meet the demands of their customers: they monitor the supply voltage to prove that the quality of the offered power is within the pre-specified standards and to obtain the necessary information for solving problems [3], [4]. The utility also reserves the right to measure the amount of the customer's harmonic current injection at any time. These measurements are usually spot checks to locate harmonic sources. Finally, deregulation creates a challenging and competitive new environment, where power quality is a parameter which needs to be measured and monitored continuously.

Typically in a power distribution system, the interaction of the load current harmonics with the network impedances creates voltage distortions. The voltage at the point of common coupling (PCC) is rarely a pure sinusoid due to many nonlinear loads in the system [5], [6]. When several loads are connected to a PCC, an important parameter of interest would be to be able to predict the change in the voltage distortion level at the PCC, if a particular nonlinear load were to filter out its harmonics. A neural network based tool is designed to predict the change in the distortion level of the voltage at the PCC, if the nonlinear load were to draw only fundamental current and no harmonics [7]. This paper demonstrates the functionality of the proposed method by using the data obtained from a plant startup wherein the load goes from no-load to full-load condition.

II. Prediction of PCC Voltage Distortion

Any nonlinear load distorts the voltage at the PCC which in turn affects other loads connected to the same PCC [8]. When several nonlinear loads are connected to the PCC, it is difficult to predict mathematically how each nonlinear load is affecting the voltage distortion level at the PCC. Typically, customers with nonlinear loads apply harmonic filtering techniques to clean up their current and avoid penalties from the utility. When corrective action is taken by the customer, one important parameter of interest is the change in the voltage distortion level at the PCC due to the corrective action of the customer. A novel method, based on neural networks, is proposed to predict the change in the distortion level of the voltage at the PCC if the customer were to draw only fundamental current and filter out its harmonics. The proposed method is called source modeling since method looks back to the source side from the load side and predicts the voltage distortion change at the PCC. The proposed source modeling method is a dual of the load modeling method presented earlier in this chapter. The source modeling method would indicate what would happen to the THD of v_{pcc} if the load added front end filters to remove it's harmonics.

Georgia Power Company, Atlanta, GA and The National Electric Energy Testing Research and Applications Center, Forest Park, GA.

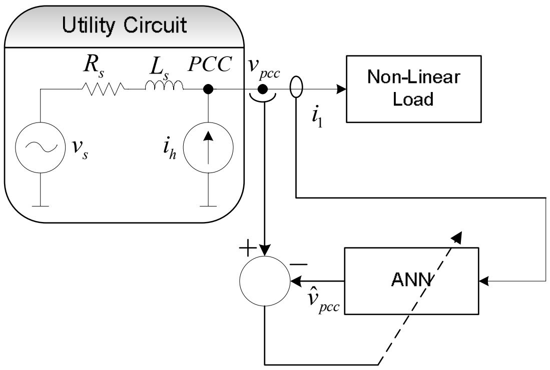

Figure 1. Utility equivalent circuit looking back into the source

As an example, Fig. 1 shows a typical power distribution network consisting of a three-phase supply network having a sinusoidal voltage source v_s , network impedance L_s , R_s , a known nonlinear load and several other loads (which could be linear or nonlinear) represented by i_h . Looking back into the utility side from the nonlinear load, the equivalent circuit now consists of all the other loads (i_h) and the actual source voltage as indicated in Fig. 1.

A. Description of Proposed Method

The schematic proposed for the implementation of source modeling method is shown as a single line diagram in Fig. 2, although it could be used on single as well as three phase systems. The source modeling method is the dual of the earlier proposed load modeling method [9].

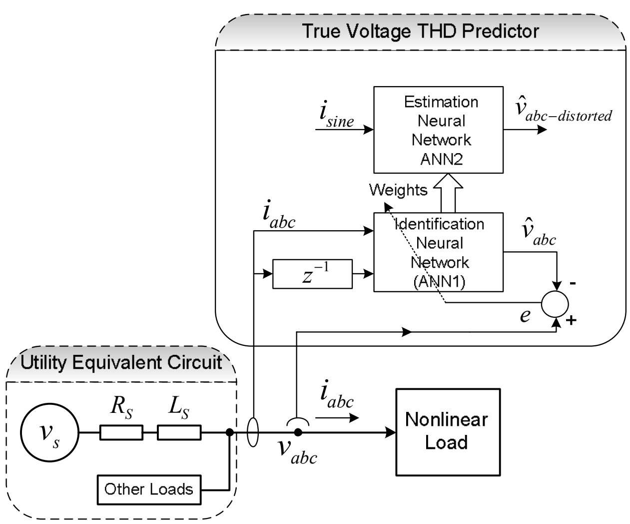

Figure 2. Utility equivalent circuit looking back into the source

The proposed method measures the instantaneous values of the three voltages v_{abc} at the PCC, as well as the three currents i_{abc} at the k^{th} moment in time. These values are fed to identification neural network (ANN1), which uses this to predict the values of v_{abc} at time instant $k+1$, labeled $\hat{v}_{abc}$.

When the $k+1$ moment arrives (at the following sampling instant), and the actual values of v_{abc} are measured, these values are compared with the previously predicted $\hat{v}_{abc}$ values, and the difference (or error e) is used to train ANN1 or adjust its weights. Initially the weights have random values, but after several sampling steps, the training soon converges and the value of e diminishes to an acceptably small value.

If the nonlinear load were to draw a sinusoidal current, then the distortion level of the voltage at the PCC would change due to the absence of harmonic current. At any moment in time after the ANN1 training has converged, its weights are transferred to the estimation neural network (ANN2), and a sine wave current waveform computed in software, is applied to its input instead of the actual measured distorted current of the nonlinear load. The output of ANN2, called $\hat{v}_{abc-lin}$, gives the same information that could have been obtained if in reality the nonlinear load were replace by a similar sized linear load. In other words, $\hat{v}_{abc-lin}$ represents the true voltage distortion at the PCC due to the removal of all harmonic current injection of the nonlinear load in question, except that it is not necessary to actually disconnect the nonlinear load and connect a pure current source to obtain this information. Any change in the voltage distortion levels between v_{abc} and $\hat{v}_{abc-lin}$ can be attributed to the nonlinearity of the load in question.

B. Neural Network Architecture

ANN1 and ANN2 in Fig. 2 are multilayer perceptron neural networks (MLPN) with three layers [10]. Figure 3 shows a detailed structure of ANN1 and the training scheme. Structurally, ANN1 and ANN2 are identical.

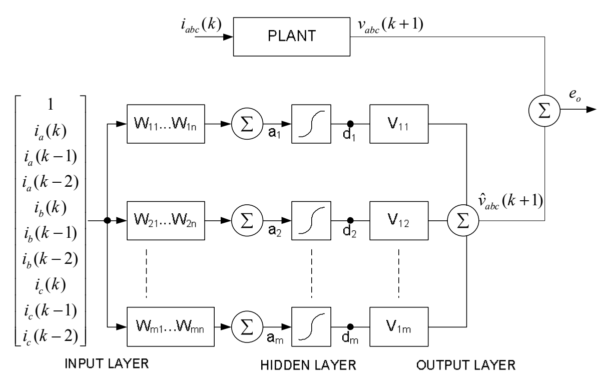

Figure 3. Structure of ANN1 and data flow path

Data flows into the network through the input layer, passes through the hidden layer and finally flows out through the output layer. The network thus has a simple interpretation as a form of input-output model where the weights W and V are updated through training. Essentially, ANN1 has three line currents as inputs and the three phase voltages as outputs. However, each input also requires the present value of the current vector and two time delayed values of the current vector, as well as a bias. So the actual number of inputs to ANN1 is ten. Initially the weights have random values.

C. Implementation of the Proposed Method

The intended application area of the proposed method is utility scale power distribution systems which are three phase systems. The implementation of the source modeling scheme with one identification network and one estimation network for all the three phases is illustrated in Fig. 4. The size of an MLPN is typically defined as ($n \times m \times r$); where n is the number of neurons in the input layer, m is the number of neurons in the hidden layer, and r is the number of neurons in the output layer. For this paper, the size of ANN1 is $10 \times 25 \times 3$. Backpropagation algorithm is used for training ANN1. The error vector e_0 in Fig. 4 is a 3 element column vector and is calculated as;

$$e_0(k+1) = v_{abc}(k+1) - \hat{v}_{abc}(k+1) \quad (1)$$

The error vector e_0 is backpropagated through the network to update the network weights W and V.

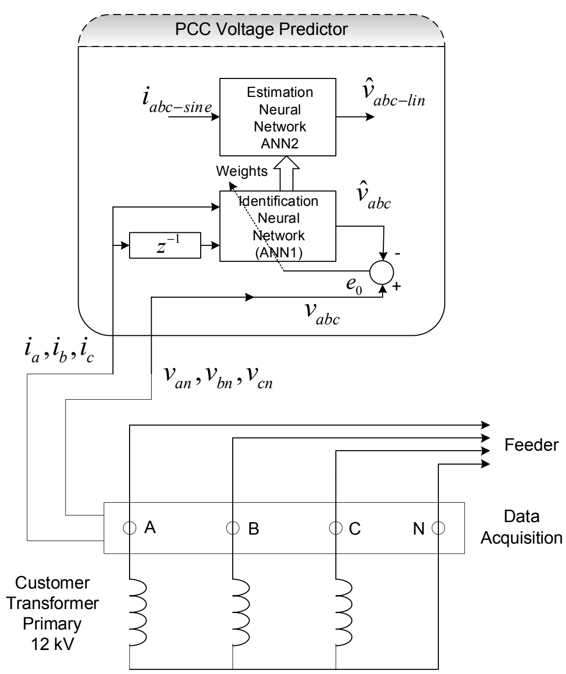

Figure 4. Implementation of source modeling method

III. SIMULATION SETUP FOR SOURCE MODELING

To demonstrate the source modeling method, a simulation circuit with two nonlinear loads connected in parallel to a source through inductance L_s is setup in Simulink. The point of parallel connection is designated as the PCC. The loads are a thyristor controlled converter operated by breaker B1 and a diode bridge rectifier operated by breaker B2 as shown in Fig. 5. The loads are balanced, so currents all three phases are similar. The measurements shown in this section are for the phase A. With breakers B1 and B2 ON, the voltage at the PCC is shown in Fig. 6.The THD of the voltage at the PCC is 7.95%. This exceeds the limit set by IEEE 519 standard [11]. However at this point it cannot be ascertained if this is a violation of the IEEE 519 standard, since the standard states that the voltage distortion should be less than 5% if the load current distortion is within the prescribed limits. With both the breakers on, it is not possible to say, which of the two loads is affecting the voltage more severely.

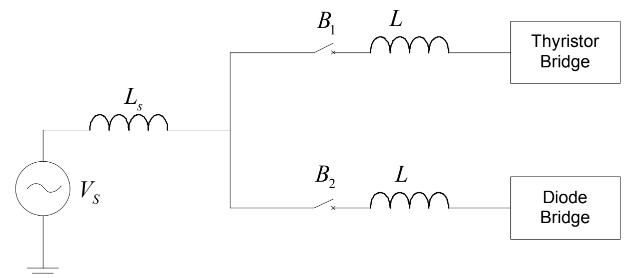

Figure 5. Simulation circuit block diagram for validation of source modeling

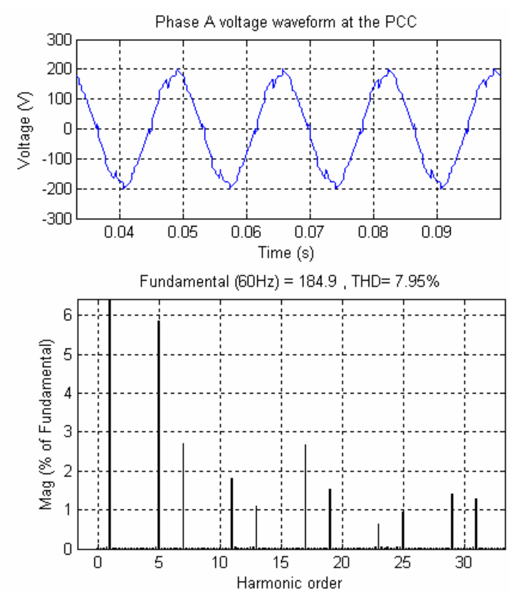

Figure 6. Voltage at the PCC with both breakers B1 and B2 ON

As a next step, the total current distortion at the PCC is measured. The current has a THD of 10.08% and the harmonics in this current includes the contributions from both the loads. The individual current distortion of the thyristor bridge is 30.29 % and the diode bridge is 7.61 %. Even though the current THD of the thyristor converter is 30.29%, the THD of the net current at the PCC is only 10.08%. This indicates the possibility that some amount of harmonic cancellation may have taken place, which results in a current with lower distortion at the PCC.

This is the primary reason why utilities do not see a high distortion in the total current at the PCC, while individual loads connected to the PCC have high current distortions. Hence it is extremely important to be able to predict the actual amount of voltage distortion caused by the harmonics of a particular nonlinear load. With breaker B1 open, the thyristor converter is isolated from the network. The voltage and current distortion at the PCC are 4.81 % and 7.85 % (impact of the diode bridge).

The voltage THD at the PCC is now 4.81% which is within the limits of IEEE 519. Hence in this case, the thyristor load is distorting the voltage at the PCC. When the thyristor load is replaced by a similar sized current source with only fundamental current and no harmonics, the voltage THD at the PCC changed to 4.87%, which is still within the IEEE 519 limits.

A. Neural Network Training and Prediction

In a real-life situation, loads with only fundamental current and no harmonics are impractical and probably do not exist. For determining the impact of a specific load on the voltage distortion, the only means the utility has is to disconnect the load and measure the voltage THD at the PCC. This is not a desirable action. This is where the merit of the proposed source modeling lies in that the effect of the nonlinear load harmonics can be evaluated on the voltage distortion without interrupting the load.

To validate the source modeling method, the thyristor converter from the test circuit described in Fig. 5 is treated as the nonlinear load of interest. The phase A input current i_a of the thyristor converter is used to train the neural network ANN1 until the output of ANN1 correctly tracks the voltage at the PCC v_a. The voltage waveform predicted by ANN1 ($\hat{v}_a$) is plotted along with the actual voltage at the PCC v_a. Figure 7 indicates how well the training of ANN1 has converged since its output coincides with the actual voltage waveform at the PCC.

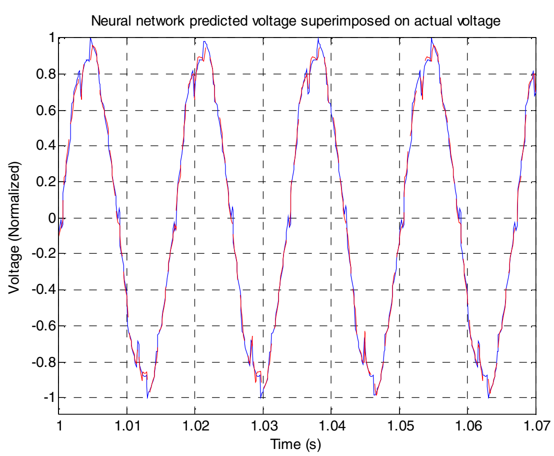

Figure 7. ANN1 training convergence

The weights of ANN1 are now transferred to ANN2. The output of ANN2 ($\hat{v}_{a-lin}$) is obtained by using a mathematically generated sine wave current with zero distortion. The output of ANN2 thus predicts the voltage at the PCC if it were possible to disconnect the nonlinear load and replace it by a similar sized linear load which also has front end filters so that its current is purely sinusoidal. Any change in the THD of voltage at the PCC can now be attributed to the thyristor converter.

Figure 8 show the output of ANN2 and the frequency spectrum. The voltage THD at the PCC turns out to be **5.41%** instead of the **7.95%** as measured in Fig. 6. A comparison of the individual harmonics between the actual measured current (normalized) and the output of ANN2 is shown in Table I.

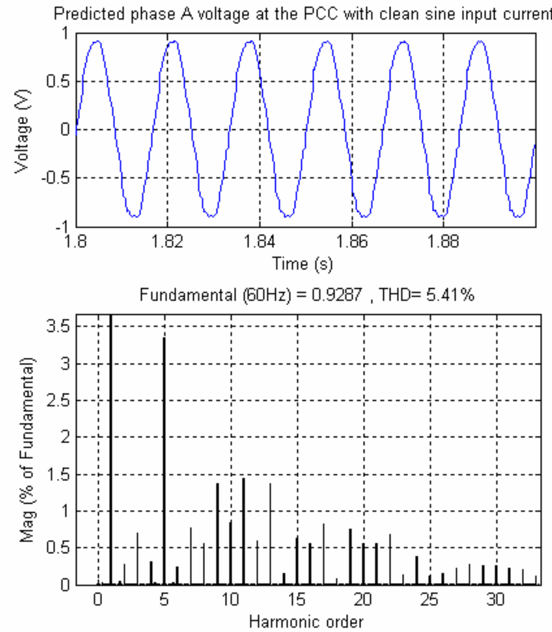

Figure 8. True phase A voltage waveform ($\hat{v}_{a-lin}$) as predicted by ANN2

TABLE I. COMPARISON OF MEASURED AND PREDICTED VOLTAGE HARMONICS AT THE PCC

Harmonic	Simulation Current	ANN2 Predicted Current	Error
DC	6.33E-04	5.25E-04	-1.08E-04
1	0.9253	0.9284	3.10E-03
5	0.0312	0.0211	-1.01E-02
7	0.0142	0.0162	2.00E-03
11	0.0128	0.0108	-2.00E-03
13	0.0076	0.0064	-1.20E-03
THD	4.87%	5.41%	

This result agrees well, though not entirely accurate, with the measured value of 4.87% which was obtained from simulation by replacing the nonlinear load with a similar sized current source.

IV. SITE MEASUREMENTS

This section demonstrates the functionality of the proposed source modeling method by using the data obtained from a plant startup wherein the load goes from no-load to full-load condition. This condition normally happens during a planned shutdown of plant. During restart, as the loads start coming on, there are sudden surges in the harmonics and then as all the other loads are operational, harmonic interactions between the different loads either result in an increase or decrease in the overall current harmonics. The power system configuration at the measurement site is a 3 phase 4 wire wye connection. Waveforms of the three phase voltages (line-neutral) and the line currents were acquired as 6 cycle snapshots, every 1 minute, for a period of 7 hours. Each 6 cycle snapshot measurement is designated as an event. Hence there are 416 events recorded. Data was acquired at the rate of 256 samples per cycle. Figure 9 shows the total harmonic distortion (THD) of the phase A voltage and current over the entire measurement period. Figure 10 shows the RMS values of the phase A voltage and current. Phases B and C exhibited similar characteristics.

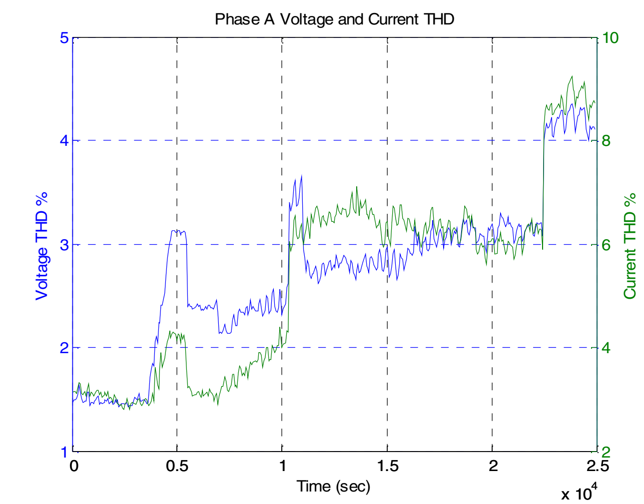

Figure 9. Phase A voltage and current THD

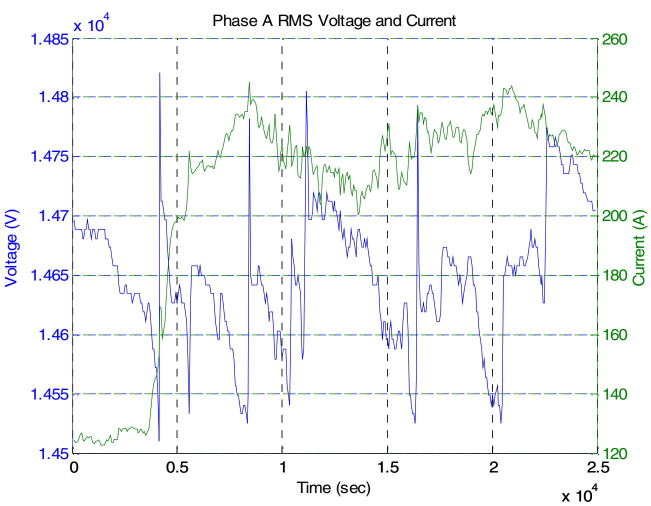

Figure 10. Phase A voltage and current RMS values

The system is balanced and voltage level is 14.4 kV. The voltage THD for all the three phases varied from 1.5% to about 4.2% over the entire measurement period. The potential transducer (PT) output is a 120 V measurement of a 25 kV line-line service. Hence a PT ratio of 14400/120 is applied. Initially the current is about 120 A. After event 60, the current starts to increase and after event 110, it reaches a value of about 220A. For the remaining duration of measurement, the current remains at that level. The THD in current varied between 3% and 9% over the entire measurement period.

V. FIELD EXPERIMENTAL RESULTS

The meter used for data acquisition is a Metrosonics PA 9 plus. The data is downloaded from the meter to a PC running the neural network software. The implementation of the proposed method requires one identification neural network and one estimation neural network for all three phases. The neural network structure now has three phase voltages as inputs and three currents as outputs. However, each input also requires the present value of the current vector and two time delayed values of the current vector, as well as a bias. So the actual number of inputs to the neural network is ten.

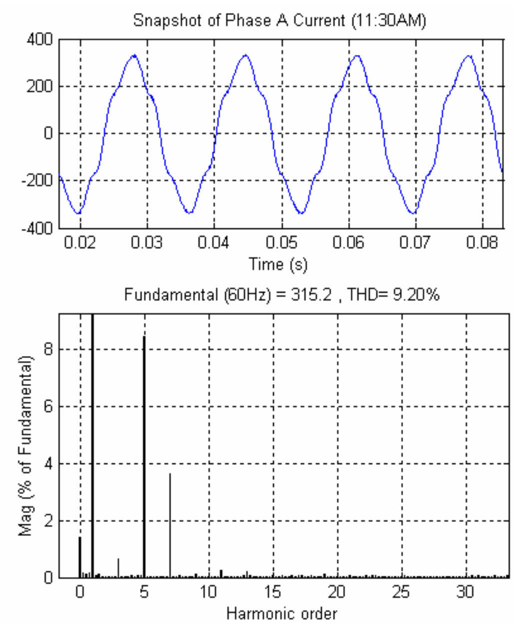

Figure 11. Phase A current snapshot of event 397

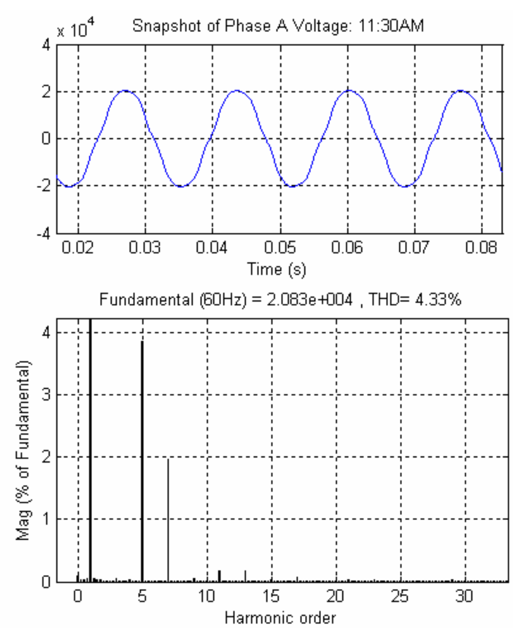

Figure 12. Phase A voltage snapshot of event 397

The training process begins with ANN1 predicting the phase voltages v_{abc} as a function of present and delayed current vector values. Initial weights of ANN1 are set to random values between ± 1. Both ANN1 and ANN2 are multilayer perceptron neural networks and have 25 neurons in the hidden layer. ANN1 is trained with snapshots of data acquired at different times once the plant current has ramped up to its rated value, i.e., with randomly picked data from events 100 to 416. The snapshot data of the phase A current and voltage for event 397 is shown in Figs. 11 and 12.

Convergence in ANN1 training with data from event 397 is demonstrated by the fact that the neural network predicted voltage waveforms coincide with the actual voltage; they practically lie on top of each other as shown in Fig. 13. The value of the Mean Squared Error (MSE) shown in Fig. 14 for each phase is sufficiently low to indicate that the neural network is trained.

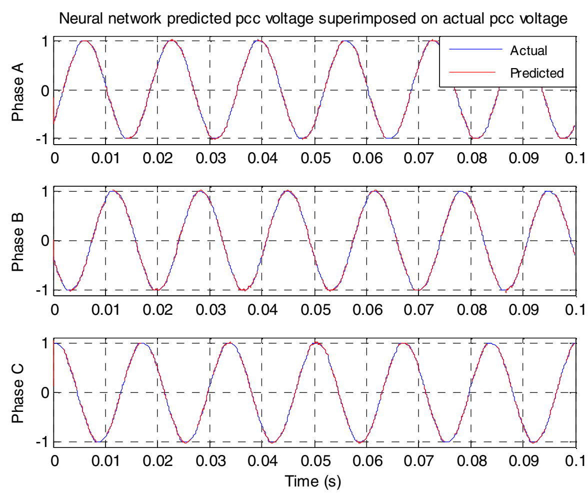

Figure 13. Training result for ANN1

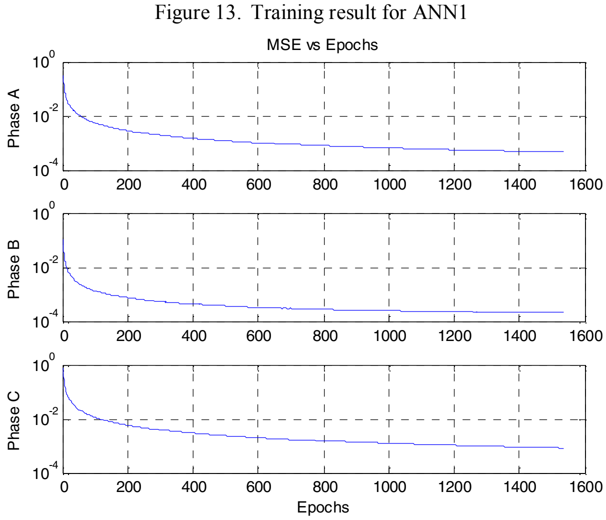

Figure 14. Mean Squared Error voltage training

The trained neural network is now supplied with the current waveform of event 28, and the predicted value of the voltages is compared with the actual voltages of event 28. Event 28 is chosen since at that instant the plant is in idling mode and the current harmonics are low, and hence impact of the harmonic volt drops on the PCC voltage is considerably reduced. Table II shows the comparison of the measured voltage THD at the PCC and the ANN2 predicted voltage at the PCC. Figure 15 shows the ANN2 predicted phase A voltage waveform at the PCC for event 28.

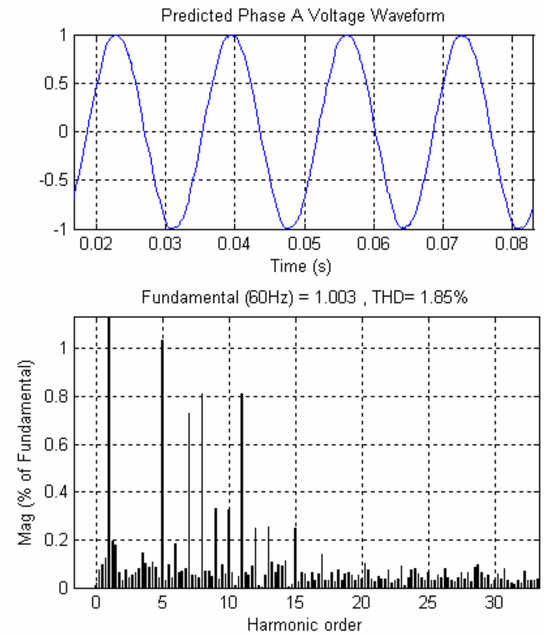

Figure 15. Predicted phase A pcc voltage for event 28

ANN2 is further supplied with a balanced 3 phase mathematically generated sine wave representing the load current with no harmonics. The ANN2 predicted result is shown in Fig. 16.

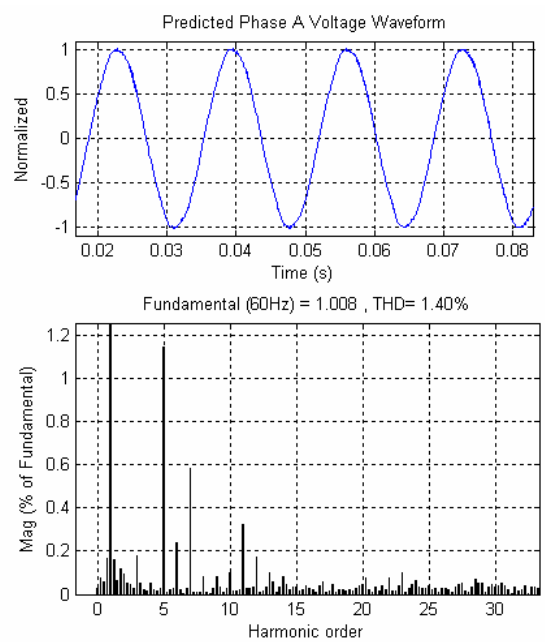

Figure 16. Predicted phase A pcc voltage with clean sinusoidal input current

The outputs of ANN2 are the predicted voltage waveforms that would be expected at the PCC if the customer were to apply filtering techniques to clean up the harmonic currents which it was injecting into the network. The predicted voltage waveforms are then compared with the actual measured voltages of event 28 to determine the difference that the load's filtering action will have on the voltage distortion at the PCC. Figure 16 shows the ANN2 predicted phase A voltage waveform at the PCC with a clean sinusoidal input current.

TABLE II. COMPARISON OF VOLTAGE DISTORTIONS

	Measured PCC Voltage THD (Event 28)	**ANN2 Predicted PCC Voltage THD (Event 28)**	**ANN2 Predicted PCC Voltage THD with clean current**
Phase A	1.49 %	1.85 %	1.40 %
Phase B	1.41 %	1.74 %	1.35 %
Phase C	1.52 %	1.75 %	1.35 %

The above results give us an indication of the impact of the harmonic filtering action by a load on the voltage THD at the PCC without actually having to install the harmonic filter [12], [13]. To give a quantitative meaning to the THD values predicted by ANN2, a percentage change is computed as;

$$\frac{(Measured\,Voltage\,THD - Predicted\,Voltage\,THD)}{Measured\,Voltage\,THD} \times 100\% \qquad (2)$$

For this particular site, the phase A voltage THD reduced by 6 %, phase B voltage THD reduced by 4.2 % and phase C voltage THD reduced by 11 %.

The data acquisition process is illustrated in Fig. 17. Data preprocessing involves manipulating the data into a suitable form which can be processed further by the neural network. Due to the nature of the activation function, the inputs are limited to values between ± 1 .

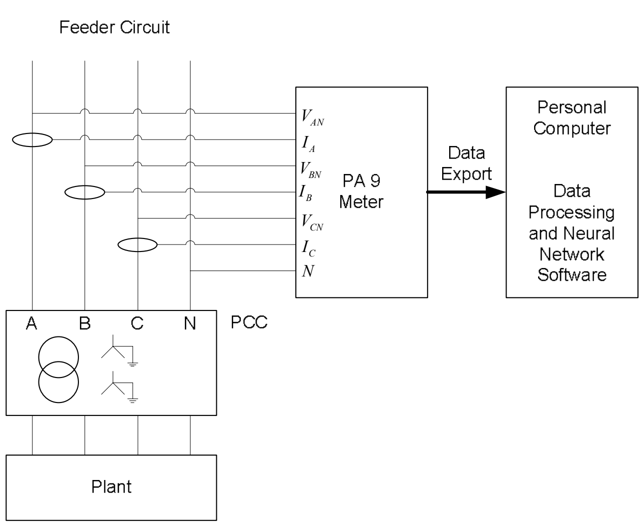

Figure 17. Data acquisition and export to a computer

For carrying out the neural network computations, the data is downloaded from the PA 9 plus meter to the PC and preprocessed to fall within the limits of ± 1 . The scaling is done in software. The data is now suitable for training the neural network.

VI. CONCLUSIONS

The results from Table II show that the neural network predicted voltage THD's values are close to the actual voltage THD values obtained from the field measurement. The neural network has not seen the values of event 28 during training; however it is able to approximate the actual voltage waveform. Furthermore, when the neural network is supplied with a clean sinusoidal current, the predicted voltage THD's are even lower than that of event 28. Over the entire measurement period, it was observed that as the current THD decreased, the voltage THD also decreased.

In general, this paper demonstrated the ability of the source modeling scheme to predict the change in the voltage distortion at the PCC due to the implementation of corrective filtering actions by a customer. The paper also shows the feasibility of applying the proposed scheme to actual field data and the possibility of training the neural network with snapshot data.

The largest benefit of the source modeling scheme is that it is possible to obtain results and draw conclusions regarding the impact of a customer's harmonic current injection without the need for the customer to actually take the corrective actions. Due to the phenomenon of harmonic cancellations, it is also possible that corrective actions by a customer may actually deteriorate the voltage distortion levels at the PCC. The source modeling scheme is designed in software and hence can be integrated into any commercially available power quality diagnostic instrument.

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