Estimation of Total Harmonic Distortion in Short Chorded Induction Motors Using Artificial Neural Network

YASAR BIRBIR*, H.SELCUK NOGAY*, VEDAT TOPUZ*
*Marmara University, Technical Education Faculty, Department of Electricity Education
Goztepe, 34722 Istanbul, TURKEY.

Abstract:- In this paper, Artificial Neural Network (ANN) technique has been used for the estimation of voltage THD (Total Harmonic Distortion), current THD and power factor, mainly from input and output measurements of five different chorded induction motors fed from a pulse width modulation inverter voltage supply. A sinusoidal pulse-width modulation (SPWM) inverter feeding five different chorded three-phase induction motors were tested up to first thirty harmonic voltage component at different loads. The results show that the artificial neural network model produces reliable estimates of voltage THD, current THD and power factor.

Keywords :- Artificial Neural Network; Total Harmonic Distortion; Harmonic Estimation, Induction Motors

1 Introduction

ANN models have been applied to a large number of problems because of their non-linear system modeling capability by learning ability using collected data. They offer highly parallel, adaptive models that can be trained by the experience. In fact, ANN models have the universal approximation property that means under mild conditions on the data, they can fit any data set with an arbitrary high precision, provided that there are a sufficient number of parameters in the model. However, when there are too many parameters compared to the number of data available, the over fitting phenomenon appears. The known data used for training are well fitted, but the function has no sense between points used for training [1].

During the last decade ANN models have been applied widely to prediction of the data. Such a prediction study has been completed in this paper, to compare the effectiveness of artificial intelligence approach. A two layer feed forward neural network trained by the back propagation technique employed in the stator voltage THD estimation. Therefore, a sinusoidal pulse-width modulation (SPWM) inverter feeding five different chorded three-phase induction motors were tested up to first thirty harmonic voltage component at different loads and different switching frequencies up to 15Khz. The number of all measurements results obtained from experiments are 663. 10% of this data were used for validation, 10% were used for test and 80% were used for training the neural network . Based on experimental results, the artificial neural network model produces reliable estimates of voltage THD and current THD [2,3].

2 Methodology

2.1 Artificial Neural Network (ANN)

There are multitudes of different types of ANN models. Some of the more popular of them include the multilayer perceptron, which is generally trained with the back propagation algorithm. Back propagation is a training method for multilayer feed forward networks. Such a network including three layers of perceptrons is shown in Figure1 [1].

By the algorithmic approach known as Levenberg-Marquardt backpropagation algorithm, the error is decreased repeatedly. Some ANN models employ supervisory training while others are referred to as none-supervisory or self-organizing training. However, the vast majority of ANN models use supervisory training. The training phase may consume a lot of time. In the supervisory training, the actual output of ANN is compared with the desired output. The training set consists of presenting input and output data to the network. The network adjusts the weighting coefficients, which usually begin with random set, so that the next iteration will produce a closer match between the desired and the actual output. The training method tries to minimize the current errors for all processing elements. This global error reduction is created over time by continuously modifying the weighting coefficients until the ANN reaches the user defined performance level [1, 2].

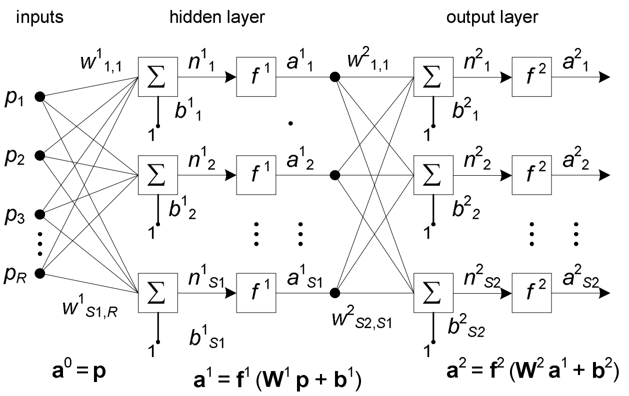

Fig.1 Two-layers feed forward network

This level signifies that the network has achieved the desired statistical accuracy for a given sequence of inputs. When no further training is necessary, the weighting coefficients are frozen for the application. After a supervisory network performs well on the training data, then it is important to see what it can do with data it has not seen before. If a system does not give reasonable outputs for this test set, the training period is not over. Indeed, this testing is critical to insure that the network has not simply memorized a given set of data, but has learned the general patterns involved within an application [1, 2].

2.2 Prediction by ANN Model

In order to use the ANN simulator for any application, first the number of neurons in the layers, type of activation function (purelin, tansig, logsig), the number of patterns, and the training rate must be chosen.

2.3 Designing Process

ANN designing process involves five steps. These are gathering input data, normalizing the data, selecting the ANN architecture, training the network, and validation-testing the network. In the training step, five input variables: rotor speed (n, rpm), current (I_{L1}), force (N), coil pitches angle (k), carrier frequency (Khz) and three output variables: voltage THD, current THD , power factor angle have been used.

2.3.1 Gathering the Input and Output Data

The configuration of the experimental system is shown in Fig. 3. It consists of a three-phase PWM inverter which gives output by comparing the modulating signal with carrier signal technique at variable switching frequencies from one to 15 Khz and supplies 50Hz, 380V (r m s) voltage to a three-phase squirrel cage induction motor under test. A digital power analyzer with 3,2 kHz sampling frequency is used to measure the stator voltage harmonics, stator voltage, stator current and input power to the motor. The operating data of the induction motors are transmitted to the PC through RS-485 for later analysis. Each motor was loaded by an electromagnetic brake which is controlled by the dc voltage applied to the brake provided with two arms, one of which with balances weight for measuring the out put torque of the motor. The brake includes a cooling fan that is supplied by the main voltage. Force applied to the induction motor is measured with a dynamometer which is mounted on the electromagnetic brake's one arm to obtain the applied force. The stator winding of five commercial, 1100W, 36-slots, three-phase, four-pole squirrel cage induction motors were re-wounded with different coil pitches. The coil pitch for each motor was re-wound to pitch 180^0 (Full pitch, 1-10 slots pitch), 160^0 (1-9), 140^0 (1-8) , 120^0 (1-7) and 100^0 (1-6) for M1, M2, M3, M4 and M5 motors, respectively. All the windings were a simple lap configuration. Fig. 2 shows the three-phase double layer windings embedded in slots [4].

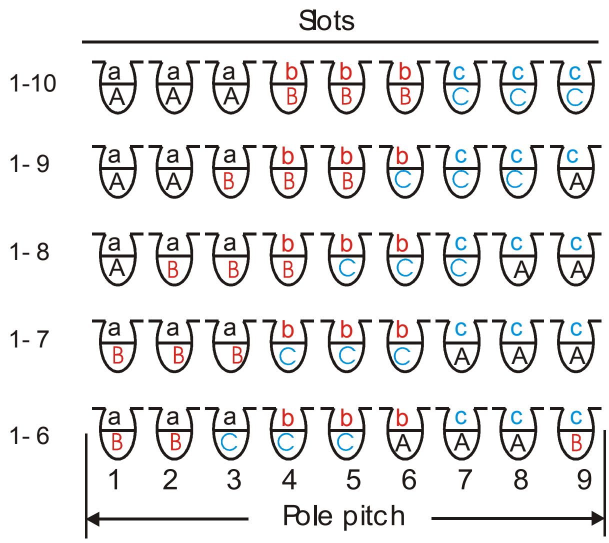

Fig. 2 Three – Phase winding with two layer configuration in the stator slots

The letters (a, b, and c) indicate the conductors corresponding with phases L_1, L_2, L_3 and their vertical position designate conductors in the same slot. The direction of current is indicated by a, A etc. The pole pitch is 9 slots with 3 conductor slots per pole per phase. The slot pitch is 20^0 so for full pitch winding the coil pitch is 180^0 and the coil pitch is reduced by 20^0 each time for other motors resulting in coil pitch of 160^0, 140^0, 120^0 and 100^0 respectively. To measure the winding temperature, K-type thermocouples were attached to the stator winding of all five motors. Motors were loaded with applied torque of from 1 to 9,74 Nm (full load was 8,18 Nm). The power and harmonic analyzer employs the fast Fourier transformation to obtain the harmonic voltage components with PWM supply was used [4].

2.3.2 Normalizing the Data

Normalization of data is a process of scaling the numbers in a data set to improve the accuracy of the subsequent numeric computations and is an important stage for training of the ANN. Normalization also helps in shaping the activation function. For this reason, [+1, -1] normalization function has been used.

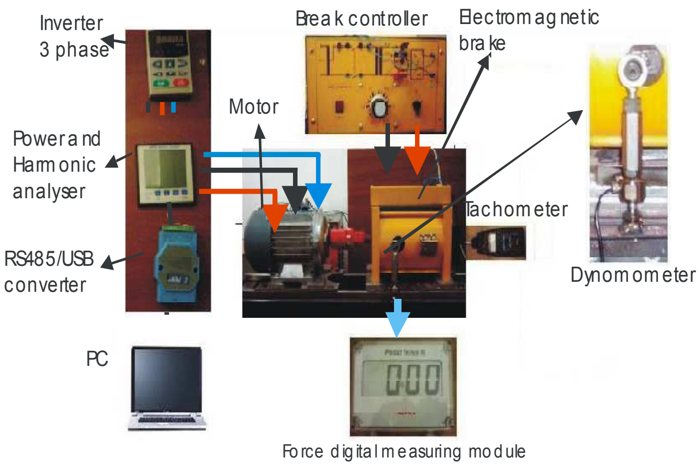

Fig. 3 Experimental setup

2.3.3 Selecting the ANN Architecture

The number of layers and the number of processing elements per layer are important decisions for selecting the ANN architecture. Choosing these parameters to a feed forward back propagation topology is the art of the ANN designer. There is no quantifiable, best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture to their problems. The first rule states that if the complexity in the relationship between the input data and the desired output increases, then the number of the processing elements in the hidden layer should also increase. The second rule says that if the process being modeled is separable into multiple stages, then additional hidden layer(s) may be required. The result of the tests has showed that the optimal number of neurons in the first layer can be chosen as 20 also, the activation function has been chosen as a hyperbolic tangent sigmoid function for all of the layers [2].

2.3.4 Training the Network

ANN simulator has been trained through the 32 epochs. The training process has been stopped when the error has become stable. Variation of the total absolute error through the epochs is shown in Figure 4.

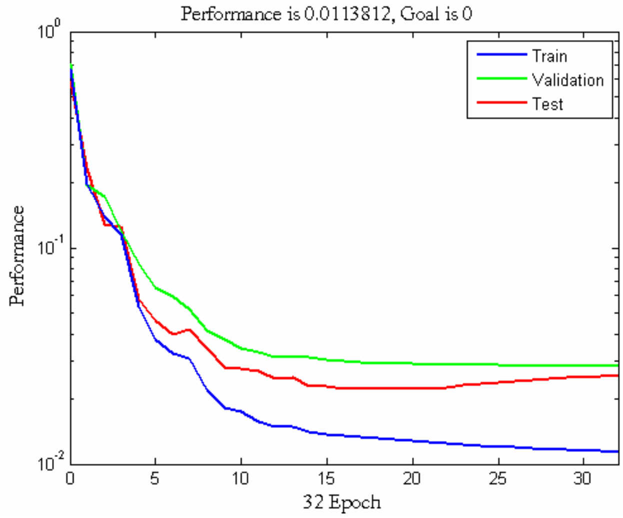

Fig. 4 Variation of the ANN output data together with the target data.

2.3.5 Testing the Network

In the test, an unknown input pattern has been presented to the ANN, and the output has been calculated. Fig. 5 shows an example of obtained from ANN model, together with the target demands. Linear regression between the ANN output and target is performed. After ANN learning and test steps founded regression coefficients (R = 0. 9861 and R = 0. 9874, R = 0.97875) shows that target and ANN output values were very related each other. These regression analyses were shown in figure 6 (a), (b) and (c) respectively for learning step. These coefficient shows that target and ANN output values were very related each other.

3. Conclusion

The results have shown that the prediction error obtained by ANN model is very plausible. So the ANN model produces reliable estimates of voltage THD, current THD and power factor. The results have also pointed out that ANN can implement many other data prediction efforts easily and successfully.

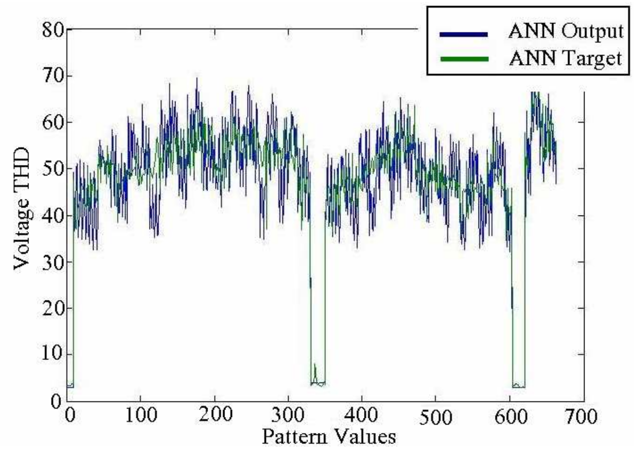

Fig. 5a

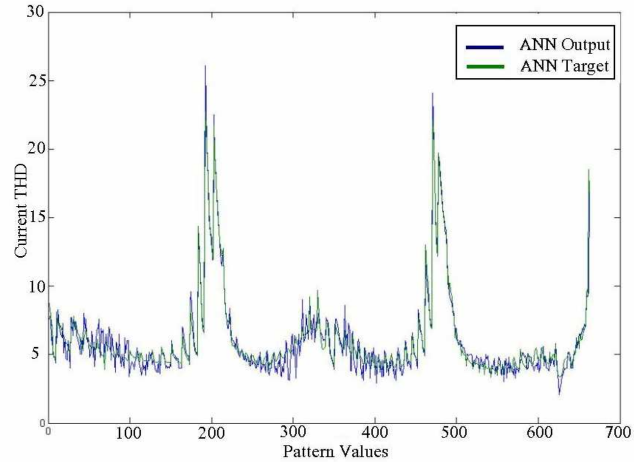

Fig. 5 b

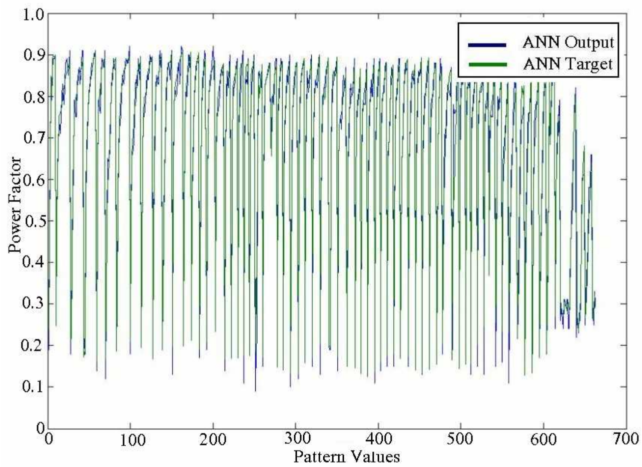

Fig. 5 c

Fig. 5 Variation of the ANN output data together with the target data. a: Voltage THD, b: Current THD, c : Power factor.

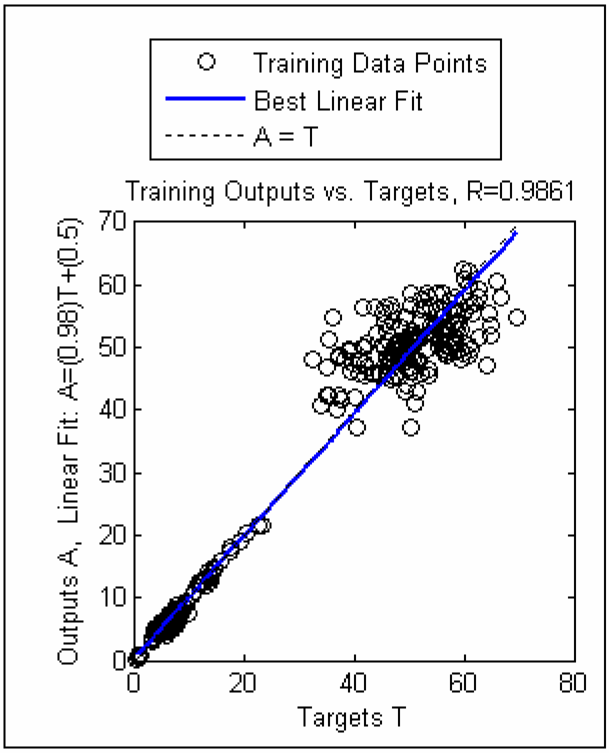

Fig. 6 a

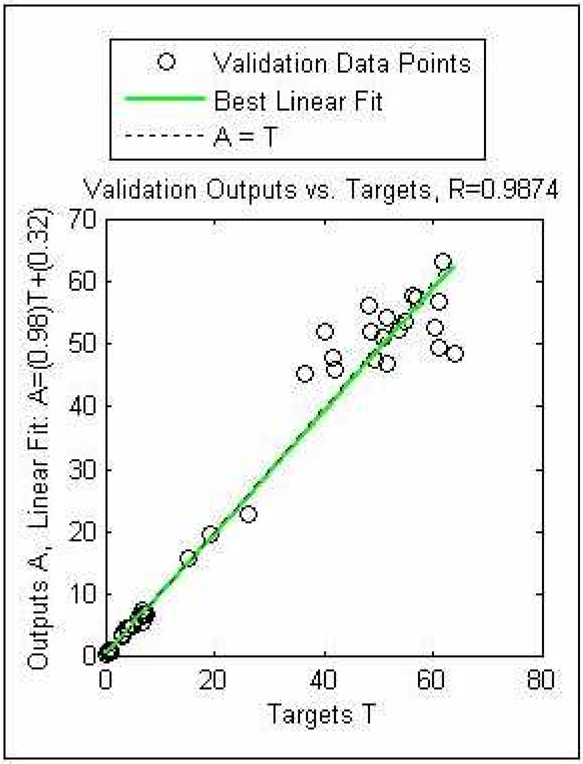

Fig. 6 b

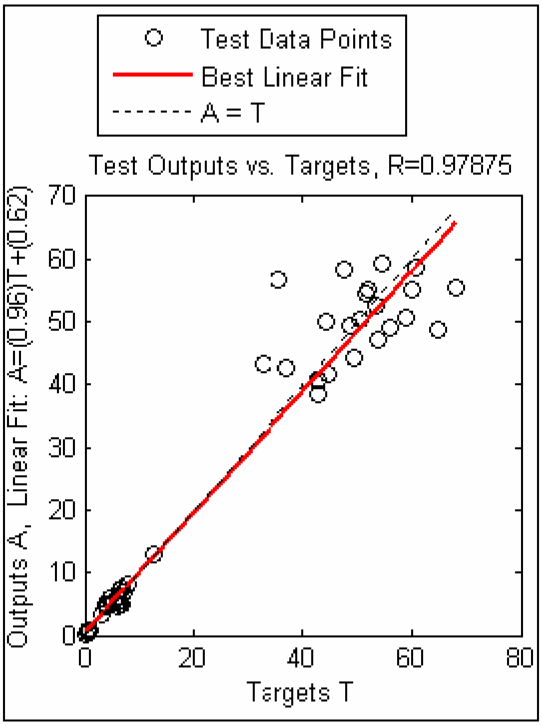

Fig. 6 c

Fig. 6 Linear regression results between the ANN output and target. a: Voltage Regression, b : Current Regression, c: Power Factor Regression

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