Application of Artificial Neural Network for Harmonic Estimation in Different Produced Induction Motors

H. Selcuk Nogay, Yasar Birbir

***Abstract*—** Artificial Neural Network (ANN) technique has been used for the prediction of voltage THD (Total Harmonic Distortion), mainly from input and output measurements of three phases, squirrel cage induction motors fed from a pulse width modulation inverter voltage supply. The induction motors have different construction, different power and produced by different firm. A sinusoidal pulse-width modulation (SPWM) inverter feeding three-phase induction motors were tested up to first thirty harmonic voltage components at different loads. The results show that the artificial neural network model trained with experimental data sets, produces reliable estimates of voltage THD for squirrel cage three phase induction motors that produced different firm.

***Keywords*—** Artificial Neural Network, Total Harmonic Distortion, Harmonic Estimation, Induction Motors

I. Introduction

DUE to the increasing requirement of precise control and equipment performance of a modern facility, the appearance of voltage harmonics in the power system has drawn great attention recently. In a power system, induction motors constitute the largest component of the load and are widely used in industrial, commercial and residential applications. Once the power system gets polluted harmonics, the operation characteristics of induction motors will be affected first. Therefore, studying the impacts of induction motors under harmonic voltages has drawn the attention of many researchers. Variable speed drives employing sinusoidal pulse-width modulation (SPWM) inverter fed induction motors are now widespread throughout industry. Unfortunately, losses in an inverter fed machine are always greater than those for the same machine operating on a sinusoidal supply and in some cases this requires derating of the motor. Rotating machines are considered a source of harmonics because the windings are embedded in slots which can never be exactly sinusoidal distributed so that the mmf is distorted.

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It is a well known fact that when a neural network is trained in order to minimize the mean square error or the cross entropy between the target and the network outputs, it provides after learning, estimates of the 'a posteriori' probabilities of the classes. The resulting algorithm establishes some bridge between parametric and non-parametric techniques of a posteriori probability estimation. Applications such as harmonic estimation, financial data analysis and communications can exploit this property.

In this paper, a prediction study has been completed 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 produced 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 196. 19 number of this data were used for validation, 19 number of this data were used for test and 156 numbers of data were used for training the neural network. Based on experimental results, the artificial neural network model produces reliable estimates of voltage THD [2], [3].

II. Related Definitions and Classifications of Harmonics

It is well-known that voltage and current harmonics in the power system can come from a number of sources in the network. Theoretically, any non-sinusoidal periodical waveform can be transformed into a different order harmonic waveform through Fourier analysis. Therefore, the non-sinusoidal voltage and current waveform can be expressed as:

$$v(t) = \sqrt{2}\left[V_1 \sin \omega_o t + \sum_{k=2}^{\infty} V_k \sin\left(k\omega_o t + \phi_k\right)\right] \quad (1)$$

$$i(t) = \sqrt{2}\left[I_1 \sin \omega_o t + \sum_{k=2}^{\infty} I_k \sin\left(k\omega_o t + \theta_k\right)\right] \quad (2)$$

where
V_1, I_1 are the fundamental voltage and current,
V_k, I_k are the k^{th} order harmonic voltage and current,
ϕ_k, θ_k are the phase angles of the k^{th} order harmonic voltage and current, and
ω_0, is the radian frequency of the fundamental wave.

When a non-sinusoidal voltage source is supplied to a three-phase induction motor, the corresponding slip S_k to the various harmonics can be expressed as:

$$S_k = \frac{kN_s + (1-s)N_s}{kN_s} = \frac{k + (1-s)}{k} \quad (3)$$

According to the rotational direction of magneto-motive force (MMF), the $(3n + l)^{th}$ order harmonics (positive sequence harmonics) contribute MMF and torque in the positive (forward) direction; the $(3n+2)^{th}$ order harmonics (negative sequence harmonics) provide counter MMF and torque; and the $(3n)^{th}$ order harmonics (zero sequence harmonics) do not contribute any rotating MMF or torque. Although the positive sequence harmonics would add a boost to the positive sequence (forward) torque and thus be beneficial, the heating effects of the harmonics offset the benefit of the positive sequence torque [1,17].

According to the definition of IEEE-519 [2], the total voltage harmonics distortion factor (THD_v) is defined as:

$$THD_v(\%) = \sqrt{\frac{\sum_{k=2}^{\infty} V_k^2}{V_1^2}} \times 100\% \quad (4)$$

and the amount of voltage distortion due to the kth order harmonic is measured by the voltage distortion factor (VDF) as: [17]

$$VDF(\%) = \frac{V_k}{V_1} \times 100\% \quad (5)$$

III. Methodology

A. 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 back propagation 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].

(8) 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], [17].

B. 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.

C. Designing Process

(9) 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, twenty one (21) input variables: pole numbers, phase currents and voltages, phase powers, production number, carrier frequency (kHz) and output variable: voltage THD has been used.

D. Gathering the Input and Output Data

The configuration of the experimental system is shown in Fig. 2. 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

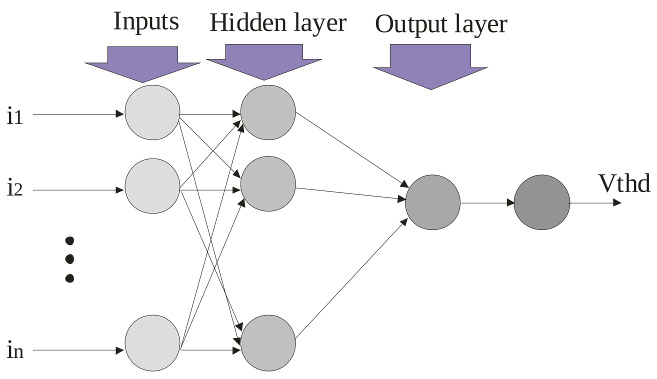


Fig.1 Two-layers feed forward network

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, different power, different pole, three-phase, squirrel cage induction motors were loaded with applied torque of from 1 to 9,74 Nm for 1.1 kW and 7.8 Nm for 0.75 kW (full load was 8,18 Nm for 1.1 kW and 6.2 Nm for 0.75 kW). The power and harmonic analyzer employs the fast Fourier transformation to obtain the harmonic voltage components with PWM supply was used [17]-[20].

E. 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.

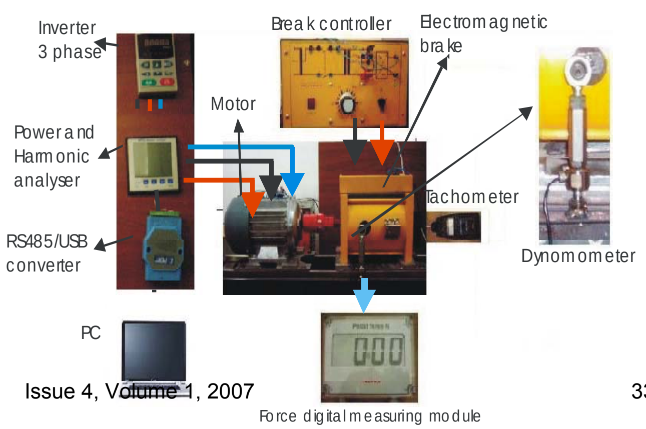


Fig.2 Experimental setup

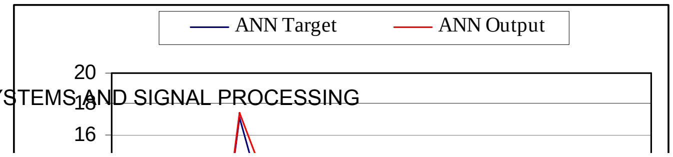
F. Selecting the ANN architecture

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].

G. Training the Network

ANN simulator has been trained through the 100 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 3.

H. Testing the Network



In the test, an unknown input pattern has been presented to the ANN, and the output has been calculated. Fig. 4 and Fig 5 show variation of the ANN output, together with the target data for testing and validation the ANN. In Fig.6 variation of the all ANN output data together with the all target data is shown (Including test, validation and training process). Linear regression between the ANN output and target is performed [17], [19].

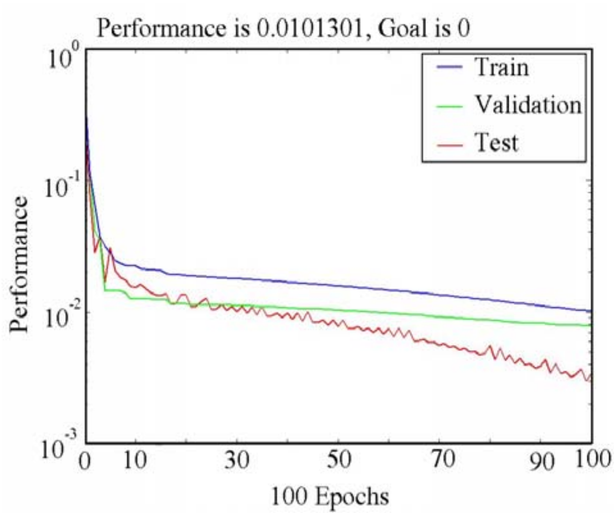


Fig.3 Variation of the ANN output data together with the target data.

After ANN learning and test steps founded regression coefficients shows that target and ANN output values were very related each other. These regression analyses were shown in figure 7 (a), (b) and (c) for learning step [4]-[6], [36].

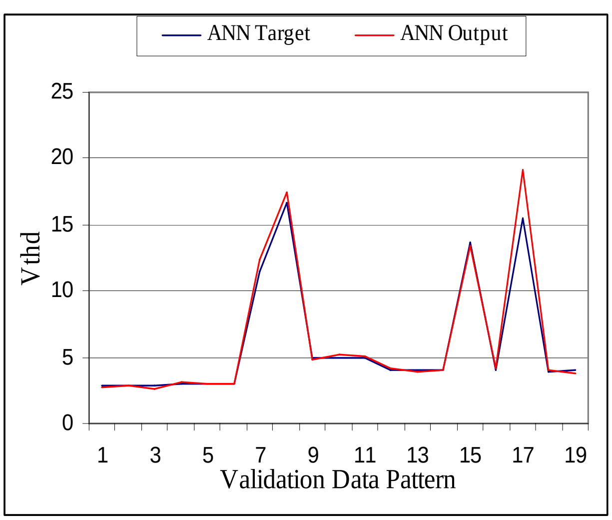


Fig.5 Variation of the ANN output data together with the target data for validation.

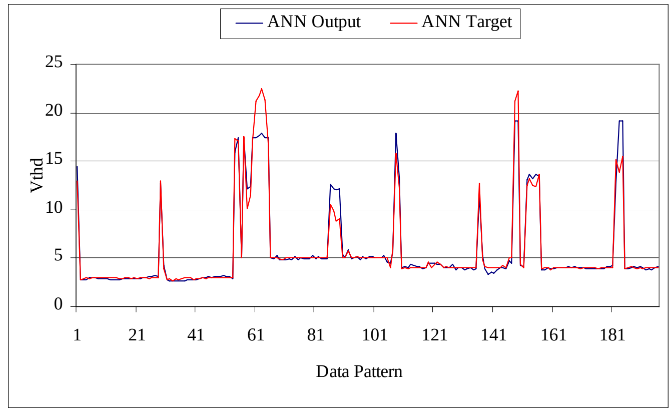


Fig. 6 Variation of the ANN output data together with the target data

157	3.9	3.7304
161	4	3.9231
164	4	4.0408
170	3.9	4.067
172	4	3.9225
175	4	3.8745
187	4.1	4.0506

TABLE 3
VALIDATION RESULTS OF ANN MODEL

Place	ANN Target	ANN Output
3	2.9	2.7522
19	2.9	2.8451
32	2.9	2.632
45	3	3.1007
46	3	3.0041
52	3	3.0465
59	11.5	12.377
65	16.7	17.4572
75	5	4.7963
99	5	5.1468
103	5	5.0477
116	4	4.1187
125	4.1	3.9681
129	4	4.0447
156	13.7	13.4615
181	4	4.2196
184	15.5	19.1197
191	3.9	3.9771
194	4	3.83

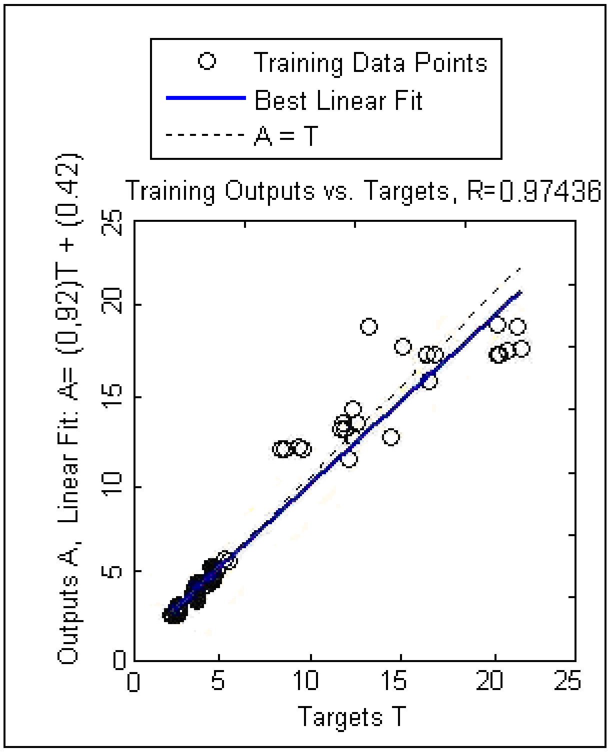
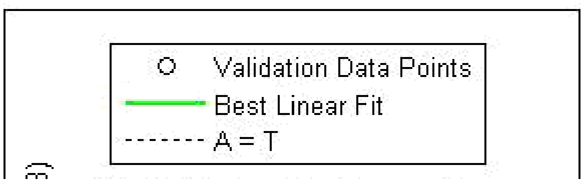


Fig. 7 a



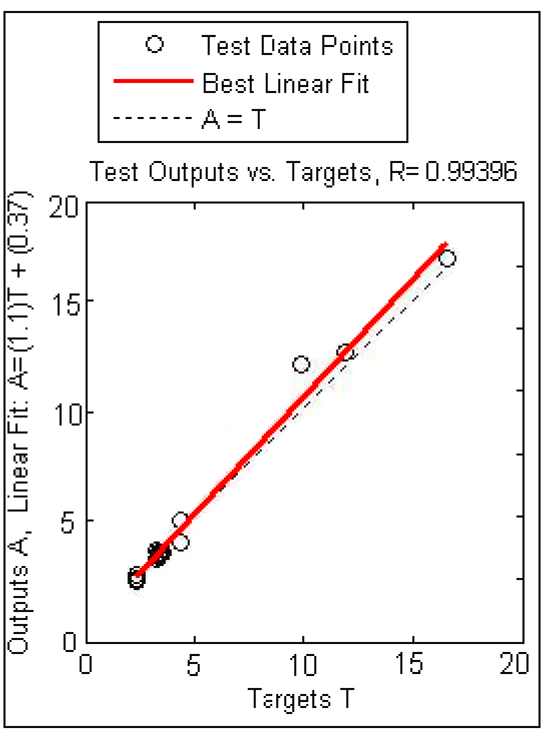


Fig. 7 c

Fig. 7 Linear regression results between the ANN output and target. a: Training Regression, b : Validation Regression, c: Test Regression

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