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Neural Network Solution to Low Order Odd Current Harmonics in Short Chorded Induction Motors

Y.Birbir, H.S. Nogay, and Y. Ozel

Abstract— In this paper, Artificial Neural Network (ANN) technique has been used for the estimation of low order odd current harmonics mainly from input and output measurements of five different chorded induction motors. A sinusoidal pulse-width modulation (SPWM) inverter feeding five different chorded three-phase induction motors were tested for low-order odd harmonic current component from half load to overload. The results show that the artificial neural network model produces reliable estimates of low order odd current harmonics.

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

I. Introduction

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. Multilayer feed forward neural network trained by the back propagation technique employed in the stator low order odd current harmonic estimation. Therefore, a sinusoidal pulse-width modulation (SPWM) inverter feeding five different chorded three-phase induction motors were tested from low load to over load. The motors were tested at different switching frequencies up to 15Khz. The number of all measurements results obtained from experiments is 220. 166 of this data were used for training, 54 were used for testing the neural network. Based on experimental results, the artificial neural network model produces reliable estimates of low order odd current harmonics [2],[3].

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II. The Experimental Investigation of the Harmonic Variations

A. Configuration of the Experimental System

Flow chart of the experimental system is shown in Fig. 1. 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.

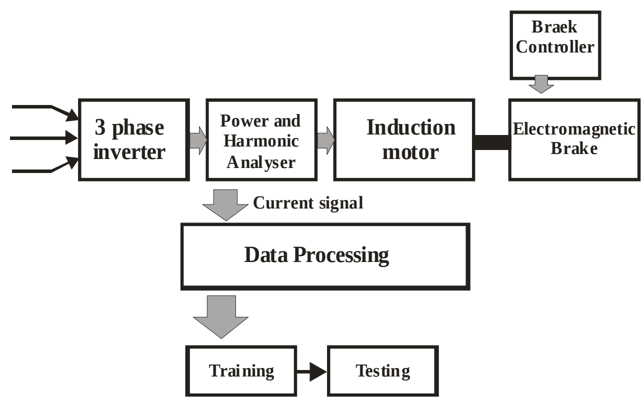

Fig. 1 Flow chart of experimental system

B. Harmonic Variations

Figs. 2–4 are the stator low-order current harmonics for the different motors with (1-10), (1-9), (1-8), (1-7) and (1-6) coil pitch at half load, full load and overload, respectively. If the coil pitch is shortened by 1/n of the pole pitch then the nth harmonic will be suppressed or the harmonics near to n will be with low voltage, because of the harmonic cancellation at that coil pitch[3], [19].

As the motor full pole pitch is (1-10) and for M5 (1-6) motor the coil pitch is reduced by 44,44 % of the full pole pitch, the 5th harmonics voltage is reduced dramatically compared to other motor with a different coil pitch. The same effect occurs at all loads as seen from Figs. 2–4. If we consider motor M4 (1-7), the coil pitch is reduced by 33.33%

of pole pitch, so the 3rd, harmonics voltage is reduced at half load and at full load. Also the 7th, 9th and 11th order harmonics voltages are reduced as seen in Figs. 2–4 [19].

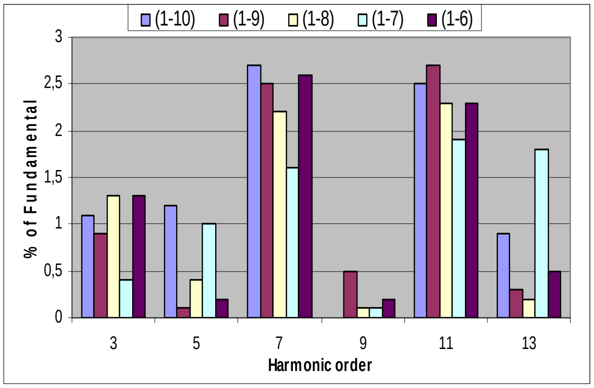

Fig. 2 Low – order current harmonics at half load

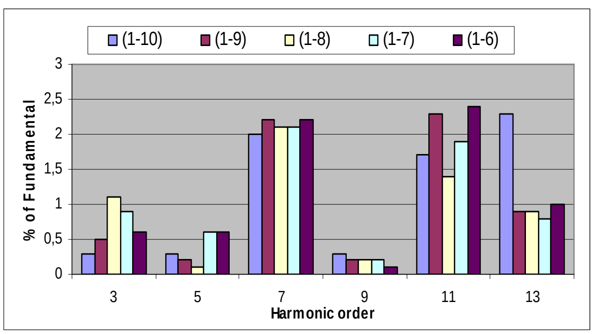

Fig. 3 Low – order current harmonics at full load

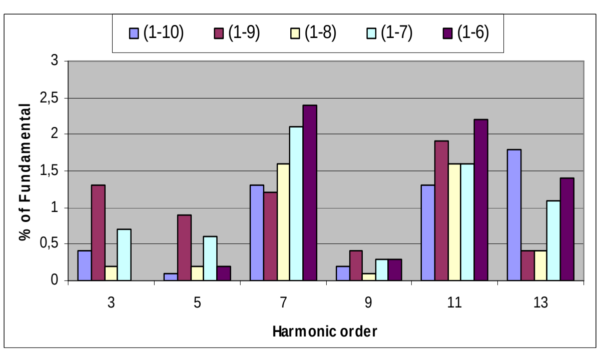

Fig. 4 Low – order current harmonics at over load

In motor M3 (1-8) the coil pitch is reduced by 22.22%, the 5th harmonics is suppressed at all load in fig. 2-4. The 7th harmonics is less than in the (1-9) and (1-10) motors (Fig. 6). If we consider motor M2 (1-9) the coil pitch is reduced by 11, 11%, the 13th harmonics voltage and current are reduced compared almost all motors with different coil pitch. So there are more possibilities of harmonics cancellation in motor M5. The effect of chording can be seen in THD in current due to 3rd, 5th, 9th, 11th and 13th harmonics (Table 1).

Low-order harmonics in stator voltage of three phase induction motor fed by PWM voltage could be reduced by chording the stator winding. This suppresses particular harmonic components with different type of coil pitch but also aids the other low order harmonics.

TABLE 1. % VALUE OF THD AT ALL LOADS

	Half load	Full load	Over load
Coil Pitch	THD I	THD I	THD I
180	8,4	6.9	5.1
160	7	6.3	6.1
140	6.5	5.8	4.1
120	6.8	6.5	6.4
100	7.1	6.9	6.5

III. NEURAL NETWORKS

A. *Artificial Neural Network (ANN)*

The neural networks are very efficient to solve many sorts of problems, because does not require previous knowledge on the system to be predicted, has a large tolerance to noise and is very robust.

An artificial neural network is an information-processing system inspired on some characteristics of the biological neural networks. It consists on a large number of simple processing elements called neurons, units, cells or nodes. Each neuron is connected to other neurons by means of direct communication links, each with an associated weight. The weights represent information being used by the net to solve a problem. Neural nets can be applied to a wide variety of problems such as storing and recalling data of patterns, classifying patterns, performing general mappings from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems.

Each neuron as an internal state called its activation or activity level, which is a function of the inputs it as received. Typically, a neuron sends is activation as a signal to several other neurons. It is important to note that a neuron can send only one signal at a time, although that signal is broadcast to several other neurons [6].

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. Such a network including three layers of perceptrons is shown in Figure 5 [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].

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].

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.

B. 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, twenty input variables: Phase voltages and currents (V_{L1}), (I_{L1}), coil pitches angle (k), carrier frequency (kHz) and output variable: Low order odd current harmonics , (3rd, 5th and 7t h harmonics)

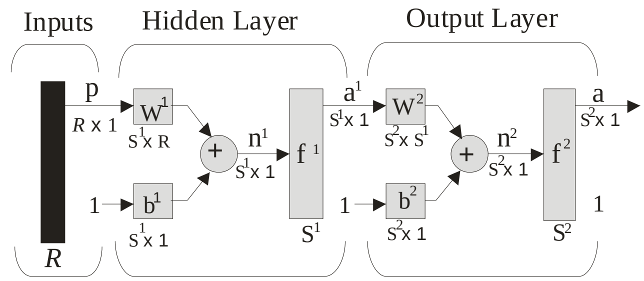

Fig.5 Two-layers feed forward network

C. Data Pre-Processing

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. 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. 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). To measure the winding temperature, K-type thermocouples were attached to the stator winding of all five motors. The power and harmonic analyzer employs the fast Fourier transformation to obtain the harmonic voltage components with PWM supply was used [5]-[9].

D. 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.

E. 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 16 also, the activation function has been chosen as a hyperbolic tangent sigmoid function for all of the layers [2].

F. Training the Network

ANN simulator has been trained through the 20 epochs. The training process has been stopped when the system has been stable.

G. Testing the Network

In the test, an unknown input pattern has been presented to the ANN, and the output has been calculated. Fig. 4 shows an example of obtained from ANN model, together with the target demands. Linear regression between the ANN output and target is performed.

Test results of ANN model for 3^{TH} ,5^{TH} and 7^{TH} harmonic of current from first training epoch until 20^{th} training epoch was shown in Tables 1, 2 and 3 respectively [5]-[8], [37],[38].

TABLE 1
TEST RESULTS OF ANN MODEL FOR 3^{TH} HARMONIC OF CURRENT

Epochs No	MSE Values
1	0.109546/1e-007
2	0.055821/1e-007
3	0.03695/1e-007
4	0.0233878/1e-007
5	0.0212403/1e-007
6	0.0207093/1e-007
7	0.0204133/1e-007
8	0.0201212/1e-007
9	0.020044/1e-007
10	0.0180244/1e-007
11	0.0165099/1e-007
12	0.0152717/1e-007
13	0.0136373/1e-007
14	0.0100856/1e-007
15	0.0091511/1e-007
16	0.0080818/1e-007
17	0.00743411/1e-007
18	0.00663942/1e-007
19	0.00628233/1e-007
20	0.00597929/1e-007

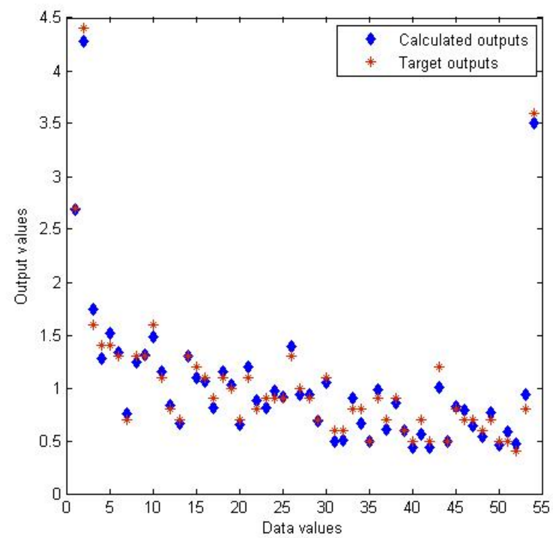

Fig. 6 The ANN output of system data together with the target data for 3^{TH} HARMONIC of current

TABLE 2
TEST RESULTS OF ANN MODEL FOR 5TH HARMONIC OF CURRENT

Epochs No	MSE Values
1	0.342368/1e-007
2	0.187303/1e-007
3	0.110984/1e-007
4	0.0826951/1e-007
5	0.0771614/1e-007
6	0.0738092/1e-007
7	0.0674827/1e-007
8	0.0637188/1e-007
9	0.0601145/1e-007
10	0.0572291/1e-007
11	0.0547439/1e-007
12	0.0527739/1e-007
13	0.051013/1e-007
14	0.0495189/1e-007
15	0.0482354/1e-007
16	0.0470753/1e-007
17	0.0459903/1e-007
18	0.0449562/1e-007
19	0.0439059/1e-007
20	0.0427786/1e-007

TABLE 3
TEST RESULTS OF ANN MODEL FOR 7TH HARMONIC OF CURRENT

Epochs No	MSE Values
1	0.411193/1e-007
2	0.282313/1e-007
3	0.113071/1e-007
4	0.105021/1e-007
5	0.0972137/1e-007
6	0.0950704/1e-007
7	0.0935306/1e-007
8	0.0923088/1e-007
9	0.0912871/1e-007
10	0.0903939/1e-007
11	0.0895827/1e-007
12	0.0888289/1e-007
13	0.0881257/1e-007
14	0.0874738/1e-007
15	0.0868715/1e-007
16	0.0863142/1e-007
17	0.0857958/1e-007
18	0.0853105/1e-007
19	0.0846256/1e-007
20	0.079333/1e-007

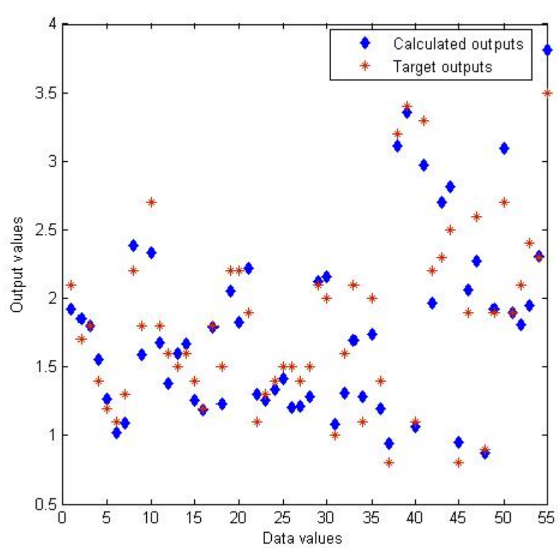

Fig. 7 The ANN output of system data together with the target data for 5TH HARMONIC of current

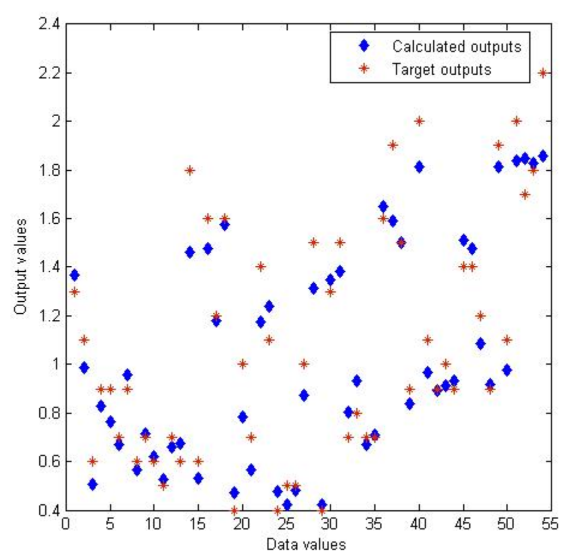

Fig. 8 The ANN output of system data together with the target data for 7TH HARMONIC of current

IV. CONCLUSION

After ANN learning and test steps founded regression coefficients (R = 0. 9688) shows that target and ANN output values were very related each other. The regression analysis was shown for learning step in figure 9, figure 10 and 11 for

3^{TH} harmonic of current, 5^{TH} harmonic of current and 7^{TH} harmonic of current respectively. The regression analysis shows that target and ANN output values were very related each other. The ANN output of system data together with the target data for 3^{TH}, 5^{TH} and 7^{TH} harmonic of current was shown in figure 6, 7 and 8 respectively. So the ANN model produces reliable estimates of low order odd current harmonics. The results have also pointed out that ANN can implement many other data prediction efforts easily and successfully [37]-[38].

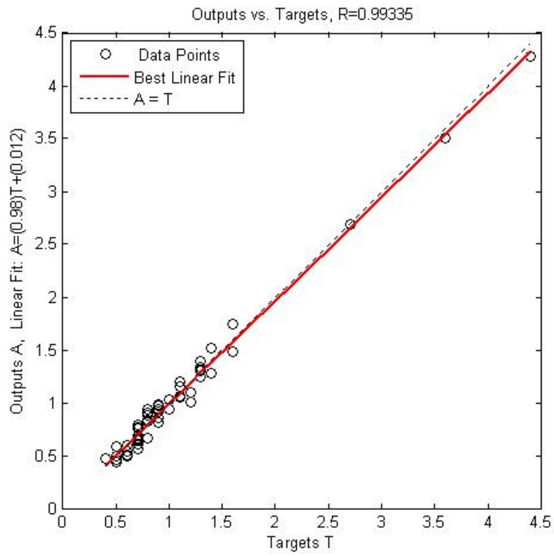

Fig. 9 The ANN output of system data together with the target data for 3^{TH} HARMONIC of current

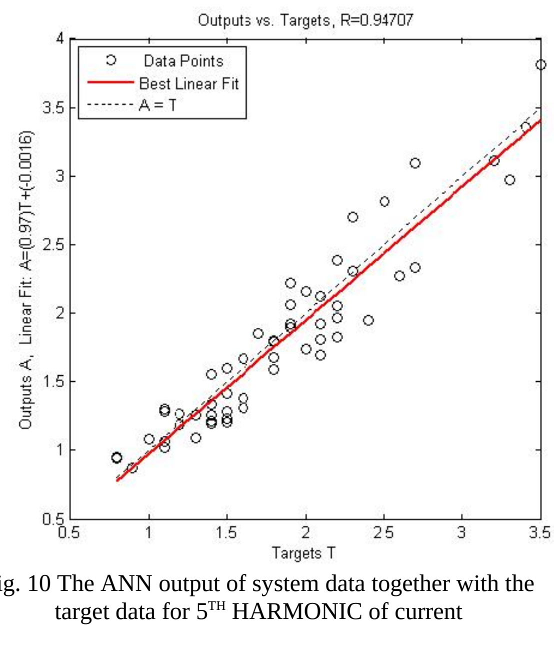

Fig. 10 The ANN output of system data together with the target data for 5^{TH} HARMONIC of current

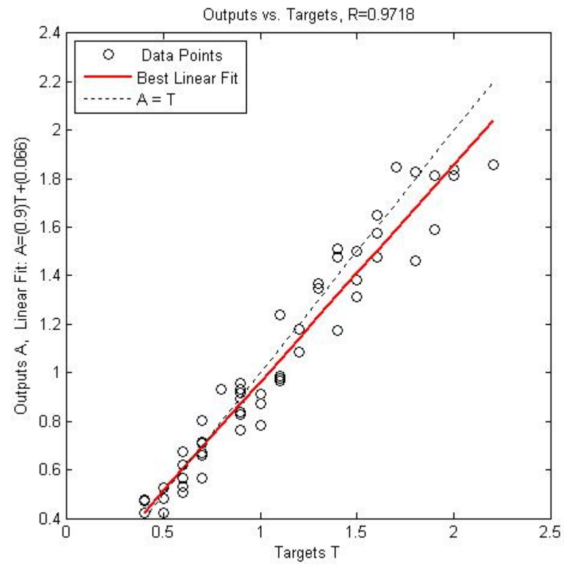

Fig. 11 The ANN output of system data together with the target data for 7^{TH} HARMONIC of current

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