ADAPTIVE MODEL FOR THREE-PHASE INDUCTION MOTOR USING NEURAL NETWORKS

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ABSTRACT

This paper proposes a method for the modeling of induction motor using neural networks. The use of artificial neural networks (ANN) in this paper is due to their benefits such as fast computation, ability of implementation, and easy interpolation. The neural network is trained by an experimental data over a wide range of voltages, frequencies and load torques. At each value of frequency and applied voltage the motor is loaded from no-load to full load. Therefore, the training data cover all the possible operating range of the motor under different frequencies and voltages. The advantages of the proposed model using ANN, is that the knowledge of the electrical parameters of the motor is not necessary, and the change in these parameters with operating conditions doesn't effect on performance of motor model. The inputs of the ANN motor model are voltage, frequency and current and the model gives the motor speed, torque and efficiency as the outputs. By these three values another motor performance characteristics can be calculated. The proposed model with (ANN) can be used in speed and torque sensorless estimation depending on the motor inputs, which will give an efficient and better performance for an induction motor.

يقدم هذا البحث نموذجا للمحرك الحثى ثلاثى الأوجه باستخدام الشبكات العصبية، وذلك لما تمتاز به الشبكات العصبية من سرعة الحساب وسهولة التنفيذ والقدرة الفائقة على الحساب الدقيق لخواص المحرك عند ظروف تشغيل بين القيم التى تم تدريب الشبكة العصبية بها. ويتغلب هذا النموذج على مشكلة تغير ثوابت الدائرة المكافئة للمحرك الحثى أثناء ظروف التشغيل والتحميل المختلفة وذلك من خلال تدريب نموذج الشبكات العصبية المقترح باستخدام قيم معملية. وتمثل قيم الجهد والتردد والتيار دخل للشبكة العصبية وقيم السرعة والعزم والكفاءة خرج الشبكة. ومن خلال هذه القيم يمكن استنتاج خواص الأداء الأخرى للمحرك. وتم بناء نموذج معملى يتيح إمكانية تحميل المحرك الحثى بأحمال مختلفة عند قيم متعددة للجهد والتردد. وخلص البحث إلى أن النموذج المقترح يقدم تمثيلا دقيقا للمحرك الحثى ويمكن استخدامه فى كثير من التطبيقات باستخدام مغيرات السرعة الحديثة.

Keywords: Induction motors, induction motor modeling, induction motor control, induction motor variable speed and artificial neural networks.

1. INTRODUCTION

Induction motors have undergone rapid development in their usage for all industry categories. Induction motors represent over eighty percent of all electric motors used in domestic, commercial and industrial applications. The use of ANN in electrical machine field is not strange, samples about the researchers efforts in this field are introduced below. The neural network is used to have an adaptive speed control for induction motor drives with two–degree of freedom controller and its parameters adaptively tuned by neural network [1-2]. The ANN technique is also used in fault detection in induction motors and power transformers as shown in [3-4]. The neuro-fuzzy technique is used in efficiency optimization and direct torque control of induction motors [5-6]. There are many applications to use ANN in synchronous

machines [7-9]. In this paper, feed – forward network and backpropagation training algorithm is used to have an adaptive model of three-phase induction motor. The neural network is trained using an experimental data over a wide range of voltages, frequencies and load torques. The inputs of ANN motor model are stator voltage, stator current and stator frequency while the outputs of the model are motor speed, torque and efficiency. Other performance characteristics of the motor can be deduced from model inputs and outputs.

2. EXPERIMENTAL MODEL

The description of experimental model is shown in Fig. (1). It consists of a squirrel cage induction motor of 2-hp, 4-pole and 380/660 V, frequency converter and an autotransformer. An eddy current brake is

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used to load the motor by different values of load torques.The stator of the motor is supplied by an autotransformer to control the magnitude of the stator voltage. The auto-transformer is supplied by the frequency converter to change the stator frequency.
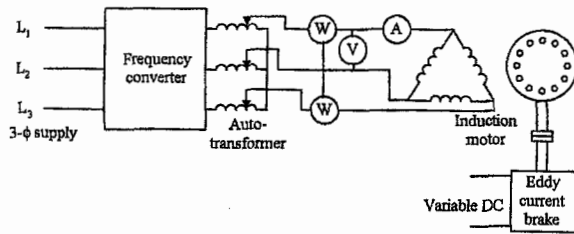

Fig. 1 Schematic diagram for the experimental model

The frequency of the frequency converter is varied to cover the range from 10 Hz to 100 Hz with a step of 10 Hz. The eddy current brake is used to load the motor with different values of torques from no-load to full load. The autotransformer is used to vary the motor voltage at all frequencies. Table (1) shows the range of training data which are taken in the laboratory and at each frequency and voltage the motor is loaded from no load to full load.

Table 1 Range of experimental training data

Frequency (Hz)	10	20	30	40	50, 60, 70, 80, 90, 100
Voltage (V)	70	75, 150	110, 220	75, 150, 300	180, 220, 260,340 ,380

3. ANN MODEL

The ANN model is built up using the feed forward network and back-propagation training algorithm. Back-propagation technique is used in this research due to its ability to deduce relations between input and output. Properly trained back-propagation networks tend to give reasonable outputs when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output. This generalization property makes it possible to train a network on a representative set of input and target pairs. There are generally four steps in the training process:

1. Sample the training data
2. Create the network object
3. Train the network
4. Simulate the network response to new inputs

The ANN network here consists of three layers two of them are hidden layers (one of them taking the input), and the third layer is the output one. According to the back-propagation technique the first and second layers consist of a number of neurons, each of them contains Tan–Sigmoid (tansig) transfer function. This is due to the ability of Tan–Sigmoid function to approximate the function between any training data, but in limited range. The last layer contains neurons of pure-line (purelin) transfer function, because if linear output neurons are used the network outputs can take any value.

The ANN model has three inputs (motor voltage, frequency and current) and three outputs (motor speed, torque and efficiency) as shown in Fig. (2).
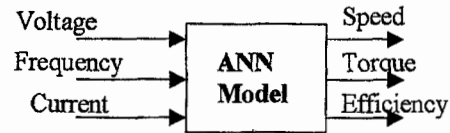

Fig. 2 Block diagram of motor model

The ANN model is trained by real values of input and target pairs coming from laboratory tests, which are described in previous section. The training data enter the network as arrays.

Inputs are written as:

$$P = [V; f ; I]$$

$$P = \begin{bmatrix} V_1 \ldots\ldots\ldots V_n \\ f_1 \ldots\ldots\ldots f_n \\ I_1 \ldots\ldots\ldots I_n \end{bmatrix}$$

The targets are written as:

$$T = [n; T_d; \; eff \;]$$

$$T = \begin{bmatrix} n_1 \ldots\ldots\ldots\ldots n_n \\ T_{d1} \ldots\ldots\ldots\ldots T_{dn} \\ eff_1 \ldots\ldots\ldots eff_n \end{bmatrix}$$

The network is trained to obtain the nearest output to the target. During training the weights (the input weights and layer weights) and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed-forward networks is the mean square error (mse), which is the average squared error between the network outputs and the target outputs. The net is properly learning with the aid of the training data (Input/Target) pairs. The training process is done with a certain number of iterations (epochs), which should be specified in the net algorithm, with a certain performance goal. Finally, the network can deduce any output with certain inputs for all the ranges in the training data.

4. RESULTS

The results of this research are introduced in the form of comparisons among experimental, theoretical and ANN models. Figure (3) shows the variation of mean square error with numbers of epochs. Figures (4-21)

show samples of results of varying speed, load torque and efficiency with input current at (10Hz, 70V), (30Hz, 110V, 220V), (50Hz, 180V, 380V), (60Hz, 300V, 380V), (80Hz, 300V, 380V) and (100Hz, 300V, 220V), respectively. These curves are samples of experimental data. The agreement between experimental and ANN curves show the great benefit of ANN model to give motor characteristics at any operating point. The errors between theoretical and experimental curves show the disadvantages of conventional equivalent circuit of induction motor due to the variation of motor parameters with different loading conditions and these parameters must be modified at different loading conditions. The motor parameters, which are obtained from DC, no-load and blocked rotor tests, are shown in Appendix 1. It is noticed from all the curves that, the ANN model is so efficient for all cases and operating conditions.
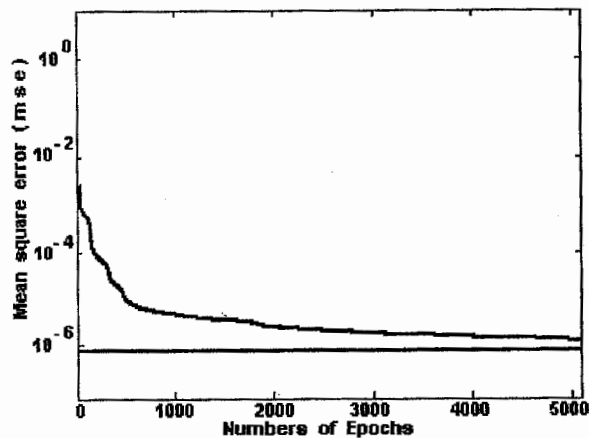
Fig. 3 Variation of mean square error with numbers of epochs
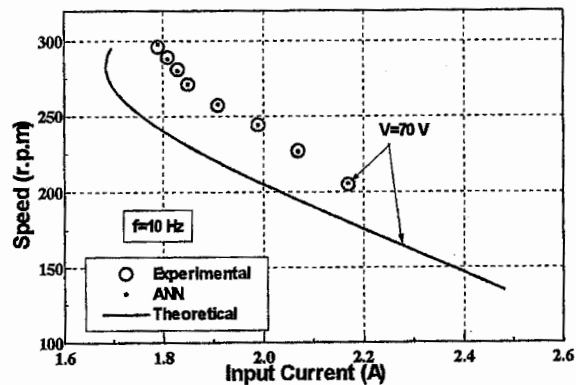
Fig. 4 Variation of speed with input current at 10 Hz and 70 V
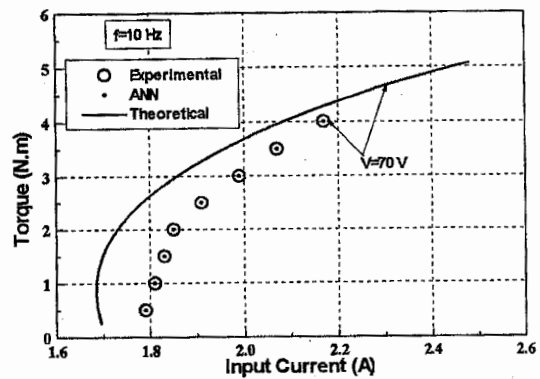
Fig. 5 Variation of toque with input current at 10 Hz and 70 V
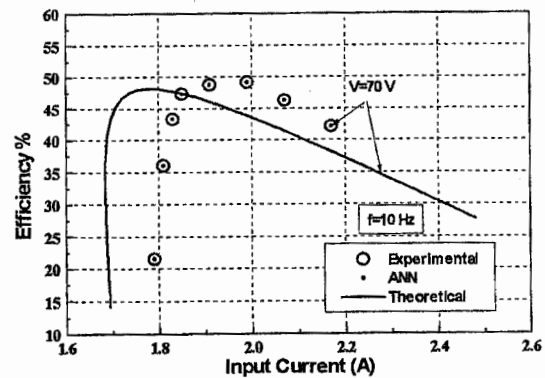
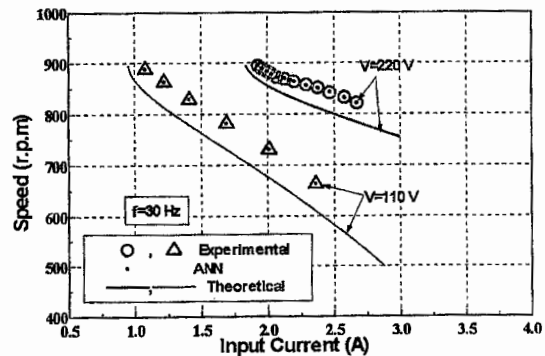**Fig. 6** Variation of efficiency with input current at 10 Hz and 70 V

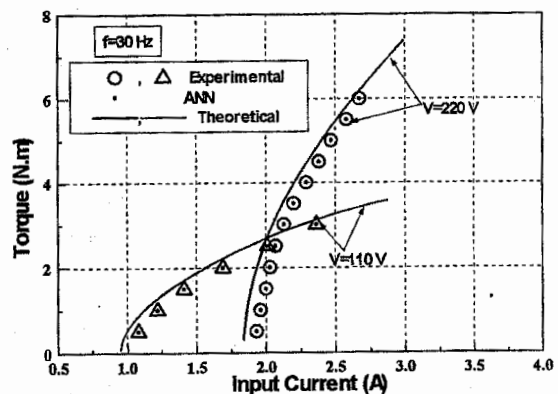**Fig. 7** Variation of speed with input current at 30 Hz and different voltages

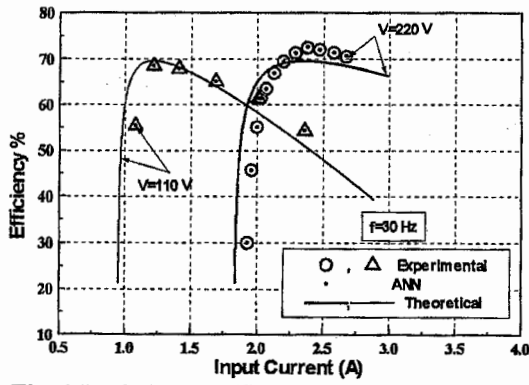**Fig. 8** Variation of torque with input current at 30 Hz and different voltages

Fig. 9 Variation of efficiency with input current at 30 Hz and different voltages
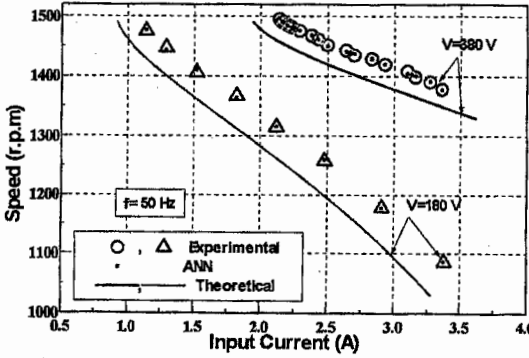

Fig. 10 Variation of speed with input current at 50 Hz and different voltages
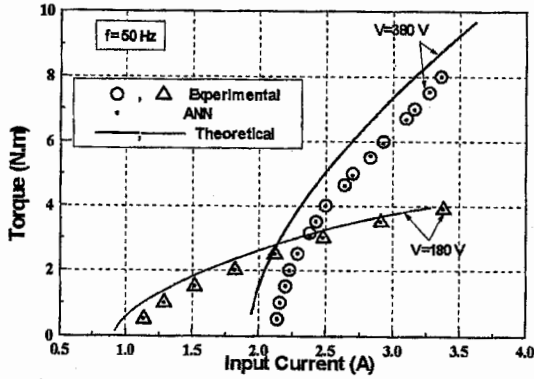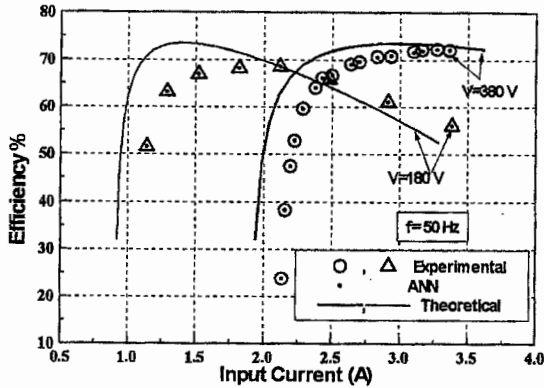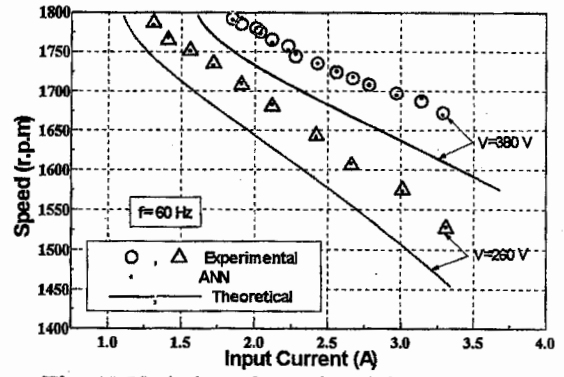

Fig. 11 Variation of torque with input current at 50 Hz and different voltages

Fig. 12 Variation of efficiency with input current at 50 Hz and different voltages

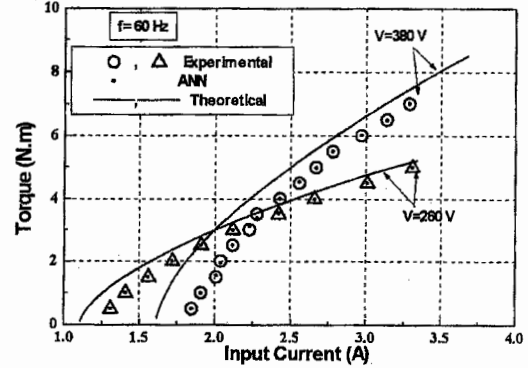**Fig. 13** Variation of speed with input current at 60 Hz and different voltages

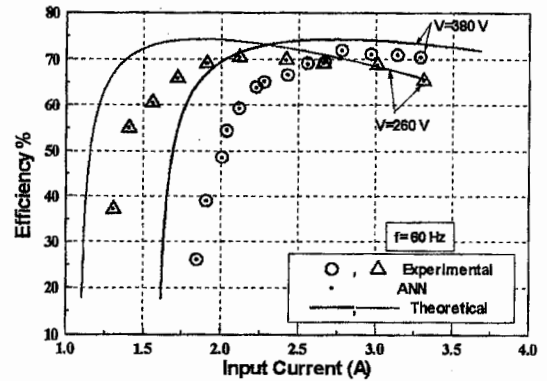**Fig. 14** Variation of torque with input current at 60 Hz and different voltages

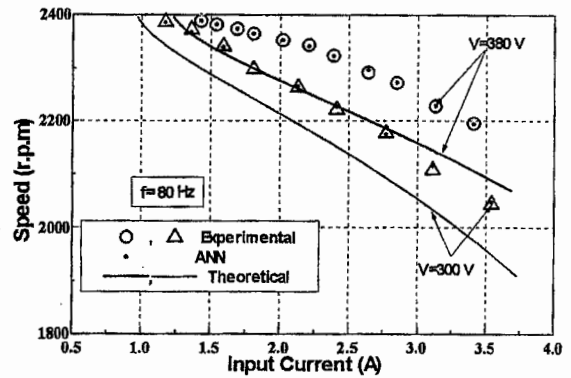**Fig. 15** Variation of efficiency with input current at 60 Hz and different voltages

Fig. 16 Variation of speed with input current at 80 Hz and different voltages
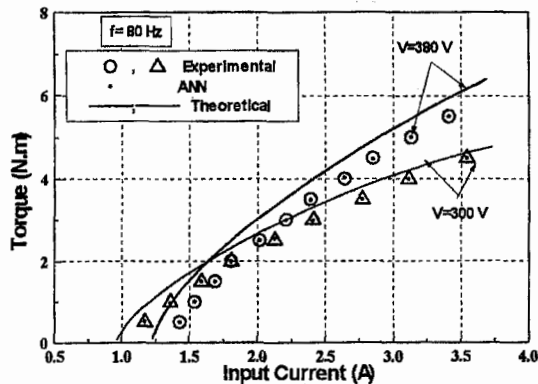
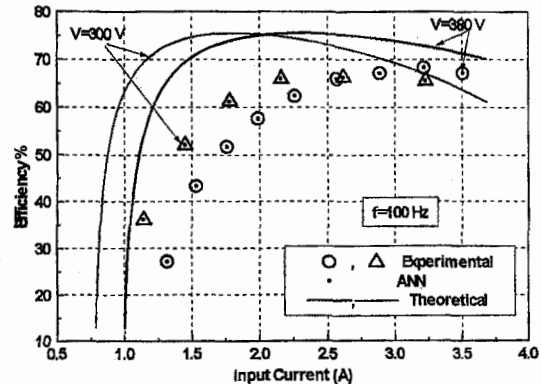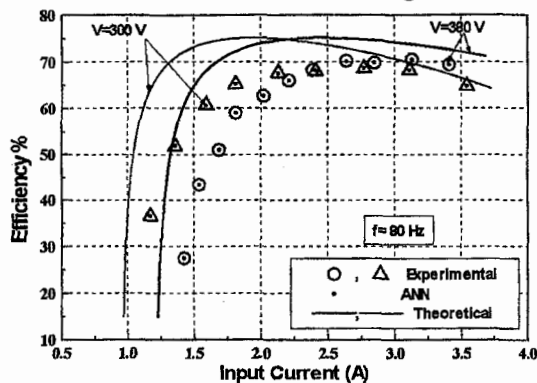**Fig. 17** Variation of torque with input current at 80 Hz and different voltages

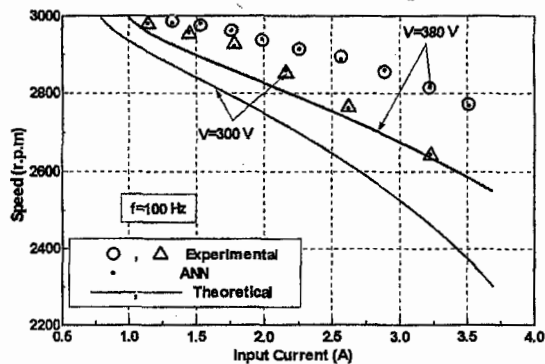**Fig. 18** Variation of efficiency with input current at 80 Hz and different voltages

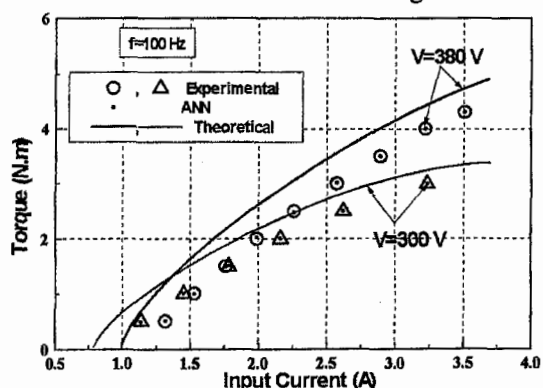**Fig. 19** Variation of speed with input current at 100 Hz and different voltages

Fig. 20 Variation of torque with input current at 100 Hz and different voltages

Fig. 21 Variation of efficiency with input current at 100 Hz and different voltages

5. CONCLUSIONS

The ANN model is an accurate model for an induction motor as shown from the agreement between the experimental and ANN results. It can be deduced or verified from this paper that, there is no more need for the equations of induction motor equivalent circuit because they can be replaced by this simple adaptive model of induction motor using the ANN. This model depends on real values coming from experimental laboratory tests, which introduce the inputs and targets of this model and cover all possible operating cases. This model can be used in sensorless speed estimation depending on the motor input variables with the ability of ANN for better computation, easy implementation, and efficient interpolation. This method gives all motor performance characteristics by measuring the input current, voltage and motor frequency without any need of a tachometer to measure speed or a torque transducer to measure motor torque and this increases the motor reliability.

6. REFERENCES

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Appendix

The nameplate data and parameters of experimental motor are: 2hp, 4-pole, 380 / 660 V and 3.5 / 2 A

Stator resistance	= 15.655 Ω
Stator leakage inductance	= 0.0768 H
Magnetizing inductance	= 1.02011H
Referred rotor resistance	= 2.30917 Ω
Referred rotor leakage inductance	= 0.0768 H
Core loss resistance	= 2250 Ω