Simulation Model of Direct Torque Control for Induction Motor Based on Artificial Neural Networks

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Abstract

Direct torque control became the most popular technique for induction motor control through the last two decades, because of its simple structure, accurate and fast torque response, but it has some drawbacks such as torque and stator flux ripples. Therefore, an accurate and fast estimation of stator flux and torque values is required. In this paper a proposed model for two Multi-layer Feed-Forward Neural Network (MFFNN) to simulate and train the direct torque control data of three phase induction motor for estimation of electromagnetic torque, stator flux, and flux angle at two different sampling frequencies. The feed-forward neural networks proposed consist of three layers. The input layer consists of four neurons (stator voltages and currents) and the output layer consists of three neurons (electromagnetic torque, stator flux and flux angle). Quick back-propagation algorithm is used to train the proposed networks. Simulation model is performed using MATLAB. The results have been compared according to computation time and accuracy.

Key words: Direct Torque Control, Artificial Neural Networks, and Induction Motor.

الخلاصة

أصبحت سيطرة العزم المباشر من المسيطرات الشائعة الاستخدام للسيطرة على المحركات الحثية في العقدين الأخيرين، وذلك بسبب بساطة تركيبها ودقة المنظومات التي تعمل من خلالها وسرعة الاستجابة للعزم المطلوب، مقارنة مع المسيطرات الأخرى. إلا أنه في نفس الوقت توجد بعض المشاكل، خصوصا في حالات بدء التشغيل والانتقال من حالة تشغيل إلى أخرى، مما يؤدي إلى حصول تموجات في فيض الساكن والعزم الناتج، لذا فهي تحتاج إلى دقة في معرفة وتخمين قيمة الفيض ومن ثم تحديد العزم المطلوب.

تم في هذا البحث تصميم ومحاكاة شبكات عصبية اصطناعية متعددة الطبقات بعدد اثنين، لتنفيذ مسيطر العزم المباشر لمحرك حثي ثلاثي الطور لغرض التخمين والسيطرة على قيم العزم الكهرومغناطيسي وفيض الساكن وزاوية الفيض وعند ترددي تقطيع مختلفين، حيث تتكون كل شبكة عصبية من ثلاث طبقات، تتكون الطبقة الأولى من أربع خلايا عصبية تمثل الإدخال (فولتيات وتيار الساكن) في حين تتكون الطبقة الثالثة من ثلاث خلايا عصبية تمثل الإخراج (العزم الكهرومغناطيسي وفيض الساكن، وزاوية الفيض). تم استخدام الخوارزمية ذات الانتشار العكسي المطورة في تدريب الشبكات العصبية المقترحة، وتم تدريبها واختبارها بعد ان تم نمذجة المعادلات والعلاقات الرياضية الخاصة بهذا النوع من المسيطرات لغرض الحصول على معلومات الإدخال والإخراج. تمت النمذجة والمحاكاة باستخدام المختبر الرياضي MATLAB ، وقورنت النتائج المتحصلة من حيث سرعة التنفيذ والدقة.

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1. Introduction

Since the first developments of the Direct Torque Control (DTC) concept which is proposed in 1986 [1, 2]. DTC became most popular controller for controlling induction motor and it has been used in many ac drive applications including paper machines, traction, and mill drives [1].

This popularity comes from its simple structure, fast torque response, robustness against machine parameters variations, and absence of co-ordinate transforms. The simple structure is due to using hysteresis comparators for both torque and flux, and its fast response is due to using switching table. However, a direct torque controlled motor has some drawbacks, such as torque and flux ripple (especially in a low speed ranges). This is because the fast response and the small back emf of the motor, and the switching frequency used varies according to the desired motor speed, and another disadvantage of DTC lies in the requirements of torque and flux estimation [2, 3].

In this paper, the use of neural network with direct torque control of induction motor has been investigated. In the next section, a brief introduction about DTC of induction motor has been presented.

Neutral network based multi-layer feed-forward has explained in section 3. The simulation model and results is presented in section 4.

2. Direct Torque control

Direct Torque Control (DTC) Technique aims at controlling the flux directly rather than controlling the current as it's done in vector control technique [2]. Therefore, the basic idea of the DTC concept, whose block diagram is shown in Figure 1, is to choose the best vector voltage, which makes the flux rotates and produces the desired torque [1, 4].

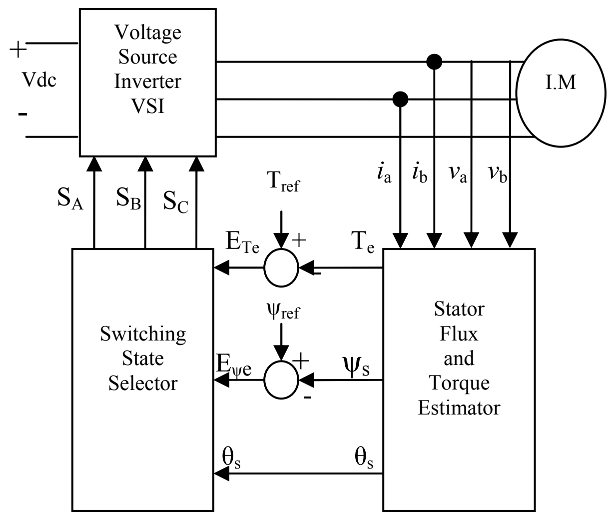

Fig. 1. Basic DTC block diagram.

During this rotation, the amplitude of the flux rests in a predefined band. With a three phase voltage source inverter, there are six non zero voltage vectors and two zero vectors as shown in Figure 2, which can be applied to the machine terminals. The developed electromagnetic torque in induction motors is the product of the magnitude of stator and rotor flux linkages and the angle between them [1].

DTC controls the electromagnetic torque and flux directly and independtly. This enables the machine to achieve an excellent dynamic. Performance as the rotor time constant is much larger in a large cage induction machine, the rotor flux linkage can be assumed to be invariant in magnitude as well as in position, if it is observed for a small time interval. The magnitude of the stator flux linkage can be changed, or it can be rotated in forward or backward direction, by applying appropriate voltage to the stator winding, so that the angle between the stator and rotor flux linkages can be increased or decreased, this modifies the electromagnetic torque and hence can be adjusted to meet the load requirements [1, 4, 5, 6].

The circular trajectory of the stator flux is divided into six symmetrical sectors referred to inverter voltage vectors. For each sector or section, a proper vector set is proposed. The certain vectors are applied to motor so that amplitude of the flux and torque remain constant.

The three switches used in the inverter generate $2^3=8$ possible switching states. Therefore, there are eight voltage vectors (Six none zero vectors in the 360^0 space, and two zero vectors) which can be applied to the machine terminals as shown in Figure 2 (the zero vectors are not shown) [1, 4, 5, 6].

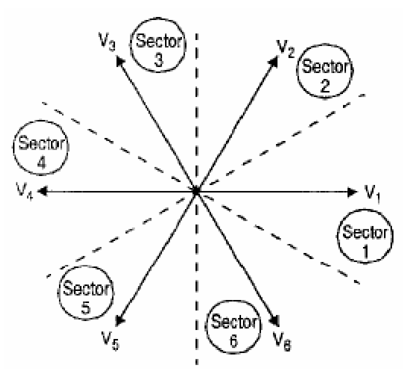

Fig. 2. Voltage source inverter vector.

In the DTC drive system the feedback signals can be calculated by using the following equations [6, 7].

The d-q components of stator voltage can be calculated as:

$$v_{ds} = \frac{Vdc}{3}\left(S_A - \frac{S_B + S_C}{2}\right) \tag{1}$$

$$v_{qs} = \frac{Vdc}{\sqrt{3}}(S_B - S_C) \tag{2}$$

Where Vdc is D.C link voltage of voltage source inverter, and S_A, S_B, and S_C are the states of switching.

The d-q components of stator currents can be calculated as:

$$i_{ds} = is_a \tag{3}$$

$$i_{qs} = \frac{1}{\sqrt{3}}(is_a + 2 * is_b) \tag{4}$$

Where is_a and is_b are stator current values of any two lines of the three power lines to which the motor is linked.

Therefore, the d-q of stator flux can be calculated as:

$$\Psi_{ds} = \int (v_{ds} - R_s * i_{ds})dt \tag{5}$$

$$\Psi_{qs} = \int (v_{qs} - R_s * i_{qs})dt \tag{6}$$

Where R_s is the stator resistance.

The flux linkage phase angle is given by:

$$\theta_s = tan^{-1}\left(\frac{\psi_{qs}}{\psi_{ds}}\right) \tag{7}$$

and the developed electromagnetic torque is given by:

$$T_e = \frac{3}{2} * P * (i_{qs} * \psi_{ds} - i_{ds} * \psi_{qs}) \tag{8}$$

Where P is the number of poles of the motor.

3. Neural Networks Algorithm

Artificial Neural Networks (ANN's) have been studied for many years desiring to reach human like performance [8, 9].

In the case of artificial net, the neuron is a node or processing element, which processes weighted inputs and produces outputs which might be used as inputs to other nodes. These ANN models are classified based on the network, the activation function applied and the method for training [9-11].

Artificial neural networks can be described as a universal approximation. They approximate complicated functions using several layers of neurons, structured in a similar way to the human brain. ANN’s posses the properties of learning capability and generalization. The learning capability makes ANN’s very powerful in control applications. In order to deal with the highly non-linear behavior of induction motor, neural networks have been developed [8, 10, 11].

Back-propagation training algorithm is the trainable layered neural networks employing the input data. In the case of layered network training, the error can be propagated into hidden layers so that the output error information passes backward. Themechanism of the backward error transmission is used to modify the synaptic weights of internal and input layers. It was designed to minimize the Mean Square Error (MSE) between the actual output of a multi-layer FFNN and the desired output [9, 13].

An approximation and modification of Newton's method for updating the weight of networks is called Quick or Marquardt-Levenberg back-propagation algorithm. This method is adopted for input/output data training in this paper [13, 14].

4. Description of Simulation Model and Results

Simulation model of Direct Torque Control (DTC) of induction motor is developed. The model based on the equations of DTC mentioned in the section 2 from (1) to (8), to generate the required data for input/output for training process in the proposed design of neural networks. The stator flux is estimated using Forward Euler Method corresponding to equations (5) and (6). The input data of the model represent the stator voltage and current transformations (v_{ds}, v_{qs}, i_{ds}, i_{qs}), while the output data represent electromagnetic torque (T_e), stator flux (ψ_s) and flux angle (Θ_s). The model was used to generate data over the possible operating zones of the motor. The simulation model is performed at two different sampling frequencies of 1 kHz, and 10 kHz respectively, with wide range of operating points of the motor to show the effect of sampling frequency on electromagnetic torque, stator flux and flux angle values. Therefore, two neural networks must be designed in this paper for both cases. Figures 3, 4, and 5 show the electromagnetic torque, stator flux, and flux angle responses respectively at sampling frequency of 1 kHz.

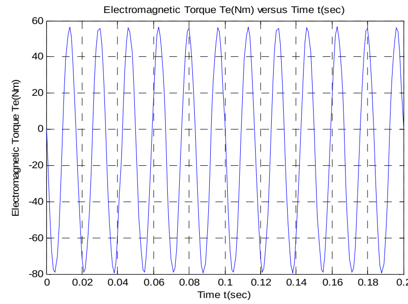

Fig. 3. Electromagnetic torque response at 1 kHz.

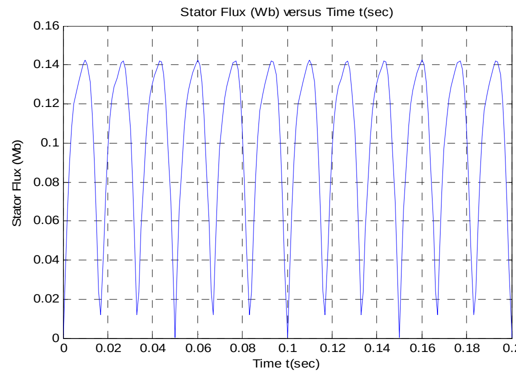

Fig. 4. Stator flux response at 1 kHz.

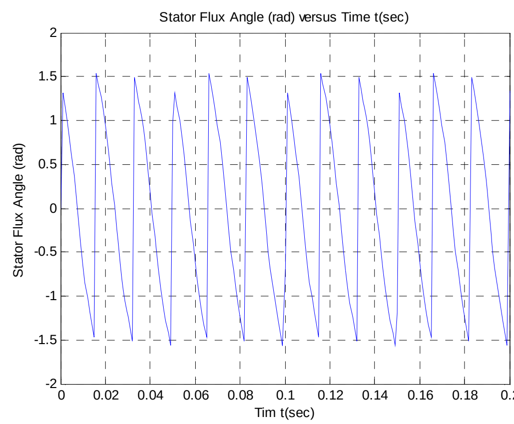

Fig. 5. Stator flux angle response at 1 kHz.

The first proposed feed-forward neural network consists of three layers. The first layer has four tansig input neurons (stator voltages and currents), the third layer has three purline neurons as output (electromagnetic torque, stator flux, and stator flux angle). The number of neurons of hidden layer was chosen randomly starting from the criterion of (2N+1) where N is the number of inputs of neuron. Therefore, by trail and error procedure, the number of hidden layer neurons that meets the training goal reaches to twelve neurons. The generated data of input/output signals are normalized and converted in per unit form and then feed to the neural network, this process done to avoid the local minima phenomenon. Figure 6 shows the first proposed design of multi-layer feed-forward neural network.

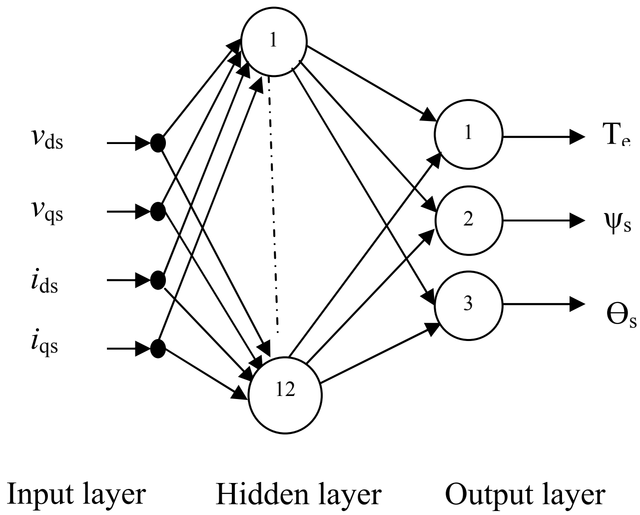

Fig. 6. First FFNN of data training for DTC.

Figure 7 shows the MSE as a function of number of epochs.

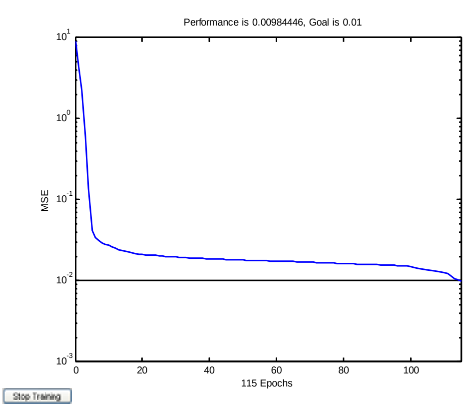

Fig. 7. MSE as a function of number of epochs.

Figure 8 shows the training performance between the actual and estimated output.

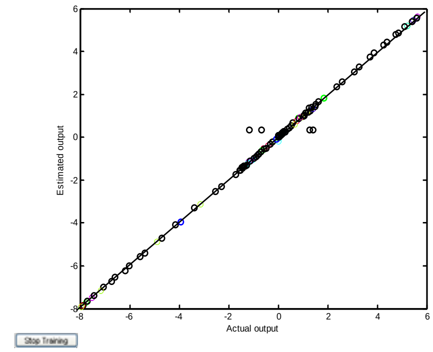

Fig. 8. Training performance between the actual and estimated output.

The main parameters of the trained artificial neural network proposed in Figure 6 are shown in Table I.

Table I
Parameters of the Trained Artificial Neural Network.

Input	v_{ds}, v_{qs}, i_{ds}, i_{qs} (normalized), (p.u)
Output	T_e, ψ_s, θ_s (normalized), (p.u)
Maximum input value	$v_{ds\,(max.)}$=3.80 (p.u), $v_{qs\,(max.)}$=5.38(p.u) $i_{ds\,(max.)}$=1.56(p.u), $i_{qs\,(max.)}$=2.22(p.u)
Minimum input value	$v_{ds(min.)}$=-3.80(p.u), $v_{qs(min.)}$=-5.38(p.u) $i_{ds(min.)}$=-1.56(p.u), $i_{qs(min.)}$=-2.22(p.u)
Maximum output value	$T_{e\,(max.)}$=5.64 (p.u), $\psi_{s\,(max.)}$=0.15(p.u) $\theta_{s\,(max.)}$=1.55(p.u)
Minimum output value	$T_{e(min.)}$=-7.9(p.u), $\psi_{s(min.)}$=0(p.u) $\theta_{s(min.)}$=-0.155(p.u)
Functions	Tansigmiodal
Hidden nodes	12
Number of epochs	115
Learning rate (η)	0.1
Momentum coefficient(α)	0.3
Mean squared error	$1*10^{-2}$

The simulation model is performed at sampling frequency of 10 kHz and the responses of electromagnetic torque, stator flux, and stator flux angle is obtained, and input/output data are collected for the second neural network training.
Figures (9), (10), and (11) show the electromagnetic torque, stator flux, and flux angle

responses respectively at sampling frequency of 10 kHz.

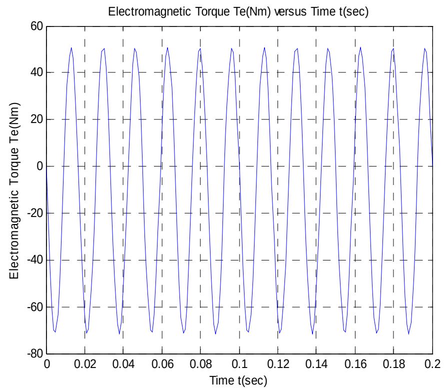

Fig. 9. Electromagnetic torque response at 10 kHz.

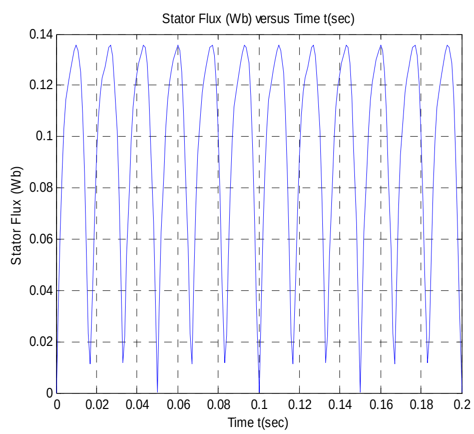

Fig.10. Stator flux response at 10 kHz.

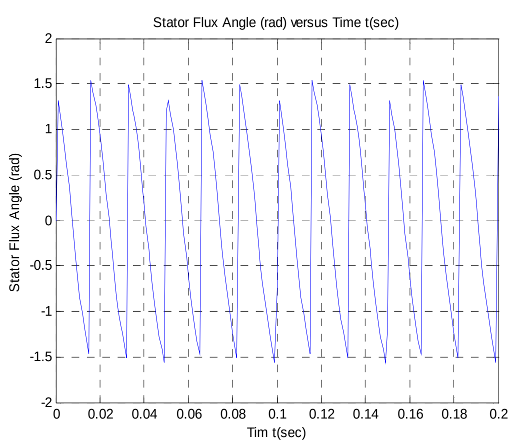

Fig.11. Stator flux angle response at 10 kHz.

The second proposed feed-forward neural network consists of three layers. The first layer has four tansig input neurons (stator voltages and currents). The third layer has three purline neurons as output (electromagnetic torque, stator flux, and stator flux angle). The number of neurons of hidden layer was chosen with the same procedure of the first network Therefore, the number of hidden layer neurons that meets the training goal reaches to ten neurons. Also the generated data of input/output signals are normalized and converted in per unit form and then feed to the neural network. Figure 12 shows the second proposed design of multilayer feed- forward neural network.

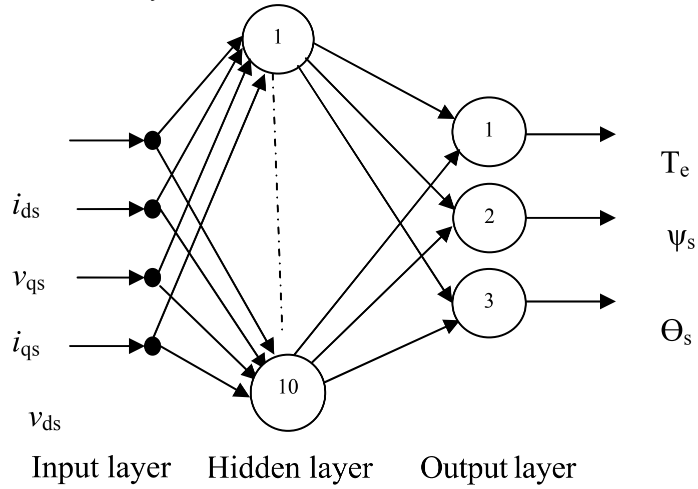

Fig. 12. Second FFNN of data training for DTC.

Figure 13 shows the MSE as a function of number of epochs.

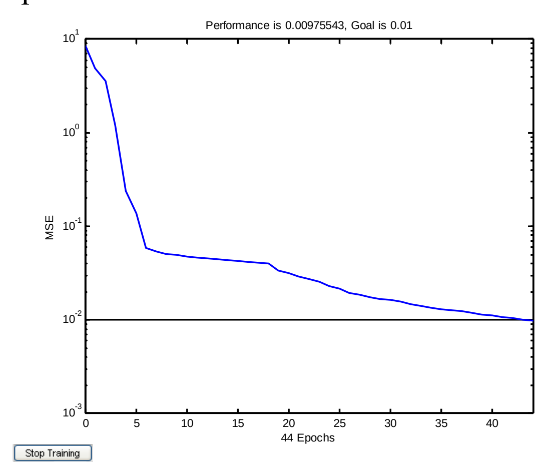

Fig. 13. MSE as a function of number of epochs.

Figure 14 shows the training performance between the actual and estimated output.

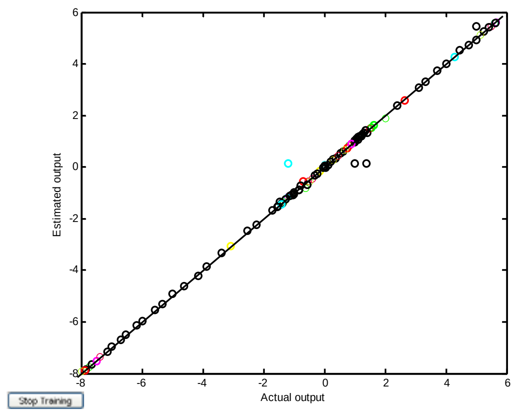

Fig. 14. Training performance between the actual and estimated output.

The main parameters of the trained artificial neural network proposed in Figure 12 are shown in Table II.

Table II
Parameters of the Trained Artificial Neural Network.

Input	v_{ds}, v_{qs}, i_{ds}, i_{qs} (normalized), (p.u)
Output	T_e, ψ_s, θ_s (normalized), (p.u)
Maximum input value	$v_{ds\,(max.)}$=3.80 (p.u), $v_{qs(max.)}$=5.38(p.u) $i_{ds\,(max.)}$=1.56(p.u), $i_{qs\,(max.)}$=2.22(p.u)
Minimum input value	$v_{ds(min.)}$=-3.80(p.u), $v_{qs(min.)}$=-5.38(p.u) $i_{ds(min.)}$=-1.56(p.u), $i_{qs(min.)}$=-2.22(p.u)
Maximum output value	$T_{e\,(max.)}$=5.08(p.u), $\psi_{s\,(max.)}$=0.135(p.u) $\theta_{s\,(max.)}$=1.5 (p.u)
Minimum output value	$T_{e(min.)}$=-7.15(p.u), $\psi_{s(min.)}$=0(p.u) $\theta_{s(min.)}$=-1.55 (p.u)
Functions	Tansigmiodal
Hidden nodes	10
Number of epochs	44
Learning rate (η)	0.1
Momentum coefficient(α)	0.4
Mean squared error	$1*10^{-2}$

After data training is completed, test program is performed for both networks in order to test the training success. It can be noticed that the sampling frequency effects the instantaneous values of electromagnetic torque, stator flux, and stator flux angle, while if the sampling frequency is increased the error values are likely to be reduced which means the torque and flux ripples decrease. Moreover the error between the actual and estimated trained values will be very small.

5. Conclusion

Simulation model of Direct Torque Control (DTC) for induction motor has been investigated. The model is used to generate input/output data for two neural networks training based on the use of Multi-layer Feed-Forward Neural Network (MFFNN) with PC/ MATLAB at two different sampling frequencies. The use of neural networks with DTC show fast response for producing the estimated output signals of electromagnetic torque, stator flux, and flux angle with fast and high response. The estimated results are near to the actual values according to the value of mean square error based on the use of quick back-propagation training algorithm. This simplifies the development with better performance and fast computations of such adjustable speed control drive when applying neural network in such highly non linear motor control applications.

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Parameter	Value
Power	3(hp)
Voltage	220(V)
Frequency(Hz)	60(Hz)
Number of poles	4
Rated current(I_s)	9.1 (A)
Sartor resistance(R_s)	0.435(Ohm)
Rotor resistance(R_r)	0.816(Ohm)
Stator leakage inductance(L_{ls})	2(mH)
Rotor leakage inductance(L_{lr})	2(mH)
Magnetizing inductance(L_m)	69.31(mH)

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Appendix (A)

Induction Motor Parameters.