Improvement Of Direct Torque Control Of Induction Motor Drives Using Neuro-Fuzzy Controller

Eng. Ahmed Hassan Adel, Dr. Salama Abo-Zaid, Dr. Amr Refky
Dept. of Electrical Engineering
Al-Azhar University
Cairo, Egypt
ahmedhassanadel@yahoo.com

***Abstract*— Direct torque control (DTC) is an advanced and simple control method for induction motor drive has many advantages over other variable frequency control methods, but it has a common disadvantage of high torque ripple. This paper introduces design and analysis for DTC of induction motor drives using the switching table, hysteresis controllers and flux and torque estimator. This paper also proposes improvement of the conventional DTC using the improvement of the switching table and the application of the artificial intelligent techniques to minimize the torque, flux and current ripples and to get better performance of the motor. At the end of this paper there is a comparison between the conventional DTC and the proposed one.**

Keywords*— Induction Motor Drive; Direct Torque Control (DTC); switching table; flux and torque estimator; artificial neural networks (ANN) ; Fuzzy logic control (FLC).

I. INTRODUCTION

In many variable speed drive applications(e.g. traction drives for electric vehicles), torque control is required or desired, but precise, closed-loop control of speed is not necessary. Torque control provides greatly improved transient response, avoidance of nuisance over-current trips, and elimination of load dependent controller parameters[1]. DTC was introduced by Takahashi (1984) in Japan and then in Germany by Depenbrock (1985)[2].

DTC method is characterised by its simple implementation and a fast dynamic response. Furthermore, the inverter is directly controlled by the algorithm, i.e. a modulation technique for the inverter is not needed. The main advantages of DTC are absence of coordinate transformation and current regulator, absence of separate voltage modulation block[3].

Common disadvantages of conventional DTC are high torque ripple, It also needs flux and torque estimators and therefore, accurate machine parameters are required. For that reason the application of artificial neural network and fuzzy logic control attracts the attention of many scientists from all over the world. The reason for this trend is the many advantages which the architectures of ANN have over traditional algorithmic methods [3],[4].

II. STRATEGY OF DIRECT TORQUE CONTROL

DTC technique can be easily implemented using two hysteresis controllers (one for flux and the other for torque), torque and flux estimators and a switching table to select the proper voltage vector[5]. The basic functional blocks used to implement the DTC scheme are represented in Fig.1.

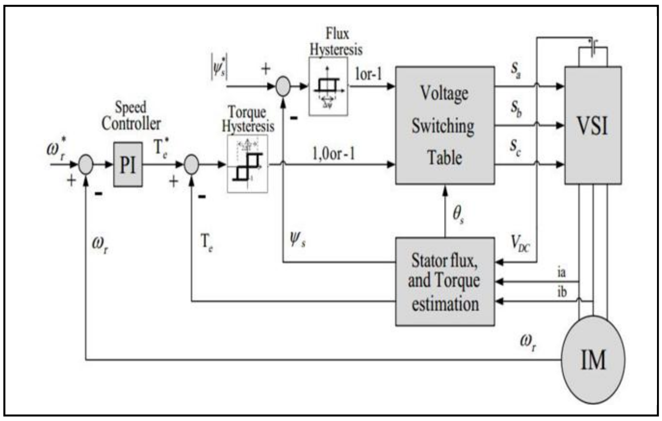

Fig. 1. *Block diagram of DTC of I.M drives*

The torque control of the inverter fed machine is carried out by hysteresis control of magnitude of stator flux and torque that selects one of the six active and two zero inverter voltage vector $V_s(i)$[6]. The use of a switching table for voltage vector selection provides fast torque response, low inverter switching frequency and low harmonic losses without the complex field orientation by restricting the flux and torque errors within respective flux and torque hysteresis bands with the optimum selection being made[5].

In a voltage fed three phases, the switching commands of each inverter leg are complementary So for each leg a logic state C_i (i=a,b,c) can be defined ; C_i is 1 if the upper switch is commanded to be closed and 0 if the lower one in commanded to be close (first)[7]. The following equation give the voltage vectors:

$$V_s = \sqrt{\frac{2}{3}} U_0 \left[C_1 + C_2 e^{\frac{j2\pi}{3}} + C_3 e^{\frac{j4\pi}{3}} \right] \qquad (1)$$

Eight switching states can be taken according to equation (1): two zero voltage vectors and six non-zero voltage vectors show by Fig. 2[7].

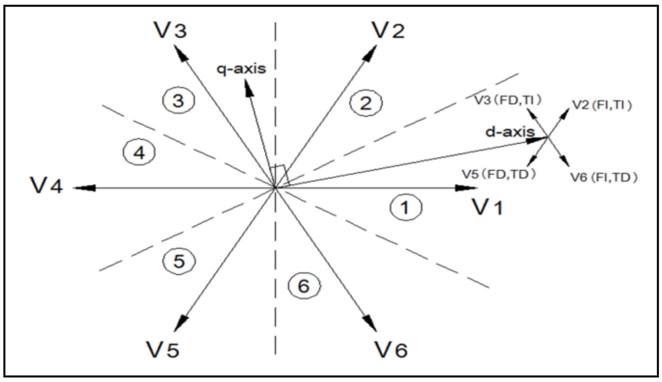

Fig. 2. *Partition of the dq plane into 6 angular sectors*

In Fig. 2 the stator flux is represented by the direct axis and the torque is represented by the quadrature axis ,It can be seen that selecting the proper voltage vector results in maintaining the torque and stator flux within the limits . The switching table proposed by Takahashi is given by Table1:

TABLE I. SWITCHING TABLE FOR CLASSICAL DTC

Sector		1	2	3	4	5	6
H_ψ	H_{Te}						
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_6	V_1	V_2	V_3	V_4	V_5
-1	1	V_3	V_4	V_5	V_6	V_1	V_2
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_5	V_6	V_1	V_2	V_3	V_4

The voltage vector table receives the flux level H_ψ , the torque level H_{Te} and the sector number and generates appropriate control for the inverter from a look-up table as in Table 1[6].

Table 1 can be simply modified by applying zero voltage vectors (V_0 , V_7) for the torque decrease states (-1) ,and this modification will result in decreasing the torque ripple largely , a considerable reason for this decrease is that applying the zero voltage vectors result in reducing the inertia of the motor at this instant and this result in reducing the torque with a percent which is more suitable than the percent given by applying the vectors in table 1 for the torque decrease states[8]. Table 2 illustrates this modification.

TABLE II. SWITCHING TABLE FOR MODIFIED CLASSICAL DTC

Sector		1	2	3	4	5	6
Hψ	*HTe*						
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_0	V_7	V_0	V_7	V_0	V_7
-1	1	V_3	V_4	V_5	V_6	V_1	V_2
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_0	V_7	V_0	V_7	V_0	V_7

III. DIRECT TORQUE CONTROL USING FUZZY LOGIC

Fuzzy logic controller can be used to replace the switching table of the conventional DTC, and this result in improving the performance of the motor and reducing the torque ripple. Fig. 3 shows block diagram for DTC of I.M using fuzzy logic controller.

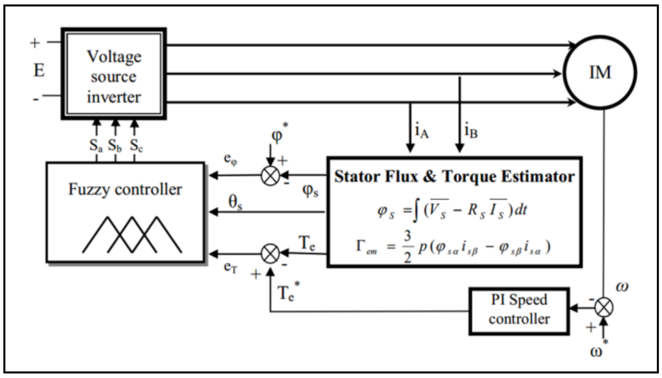

Fig. 3. *Block diagram of DTC using fuzzy logic controller*

A. Design of DTC using fuzzy logic

A designer of Fuzzy logic controller must choose memberships for input and output variables and put the rules for the control process. Figure 4 shows functional block diagram for fuzzy logic controller; in this diagram the decision making is made according to fuzzified inputs and rule base which the designer put according to data base, then the output is deffuzified.

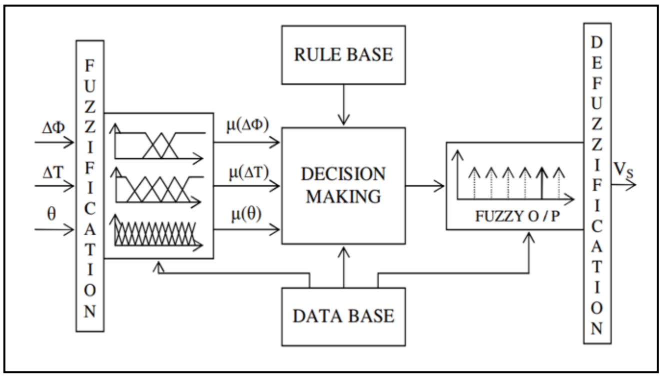

Fig. 4. *Functional block diagram for the fuzzy logic controller*

B. *Input and Output variables*

Flux error, torque error and flux position are the input variables of fuzzy logic controller and the stator voltage vector (V_0 - V_7) is the output variable. Figures 5-8 show memberships for the inputs and output variables.

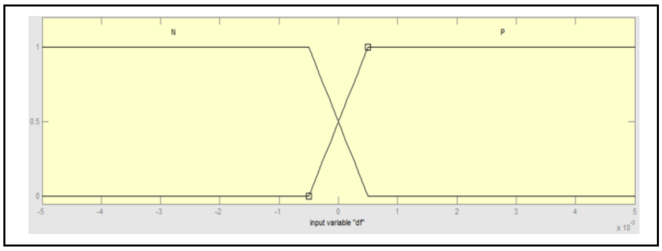

Fig. 5. *Membership for the flux error*

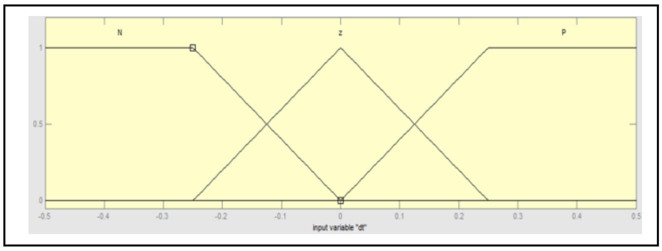

Fig. 6. *Membership for the torque error*

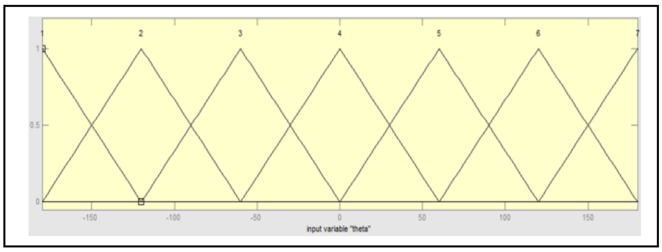

Fig. 7. *Membership for the flux position*

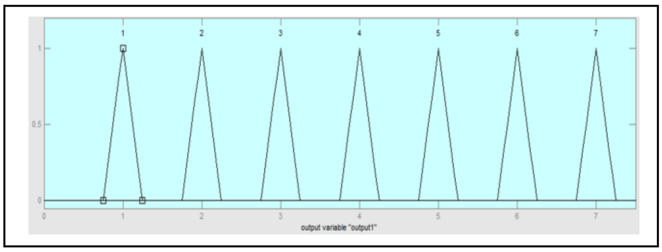

Fig. 8. *Membership for the stator voltage vector*

C. *Rule base*

As shown in figure 4 decision making is made according to the inputs and the rule base. A designer of FLC puts the rules according to data base for the control method used for the system to be controlled. The rules of DTC using fuzzy logic is put according to figure 2 and table 2 mentioned above.

IV. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) are, as their name indicates, computational networks which attempt to simulate, in a gross manner, the networks of nerve cell (neurons) of the biological (human or animal) central nervous system[9]. Neural networks are composed of simple elements called neurons operating in parallel. As in nature, the connections between elements largely determine the network function[10].

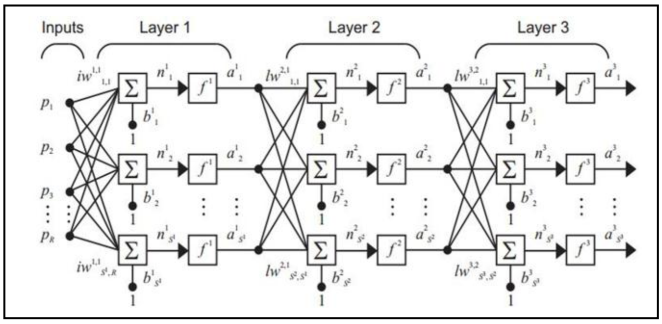

Fig. 9. *Multiple Layer Neural Network*

$$a_i = f\left(\sum_{j=1}^{R} w_{ij} p_j + b_i \right) \qquad (2)$$

where;

R : number of elements in input vector.
S : number of neurons.

A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output[10]. Neural networks have self-adapting compatibilities which makes them well suited to handle non-linarites, uncertainness and parameter variations. Neural networks are capable of generalization in regions of the input space, where little or no training data are available[11].

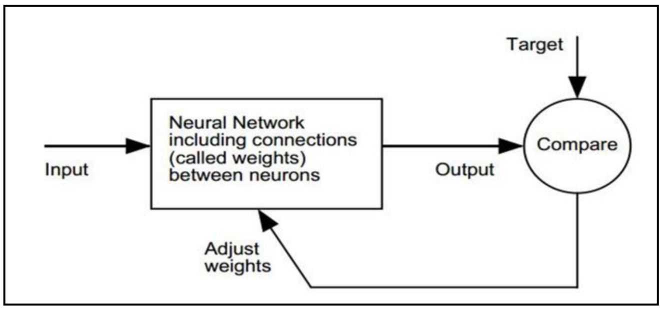

Fig. 10. *Basic principle of operation for the ANN*

A neural network is designed and trained so that it can replace the conventional PI speed controller to get the desired response. Network given is feed forward with one input, three hidden and one output layer. The hidden layers has 'log-sigmoid', 'tan-sigmoid' and 'pure line' as transfer functions. The training is done using Levenberg–Marquardt Back-propagation Algorithm with 20 neurons in each hidden layer using Matlab simulink.

V. SIMULATION OF DIRECT TORQUE CONTROL

A. *Model and Parameters*

Figure 11 shows simulink model of DTC for induction motor drive, while Tables III. ,IV. and V. show the parameters of the induction motor, DTC and speed controller respectively.

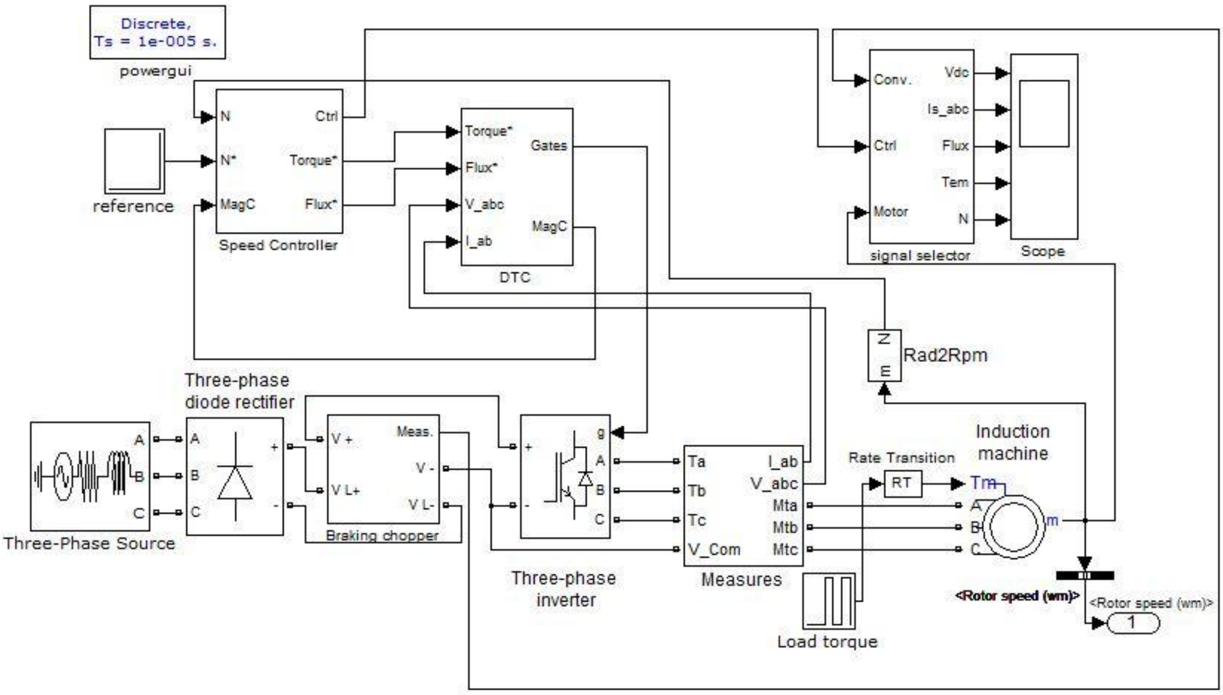

Fig. 11. *Simulink model of DTC*

TABLE III. PARAMETERS FOR INDUCTION MOTOR

Rated voltage	Rated power	Rated frequency	Pole pairs	Stator resistance	Stator inductance	Rotor resistance	Rotor inductance	Mutual inductance
220	2238	60	2	0.435	2	0.816	2	69.3
V	VA	Hz	—	Ω	mH	Ω	mH	mH

TABLE IV. PARAMETERS FOR DIRECT TORQUE CONTROL

Sampling time	Hysteresis torque band width	Hysteresis flux band width	Max. switching frequency	Initial flux
20	0.5	0.01	20	0.3
μs	N.m	wb	KHz	wb

TABLE V. PARAMETERS FOR SPEED CONTROLLER

Upper limit torque	Lower limit torque	Sampling time	Cut off frequency	Ki	Kp	Ramp 2 speed	Ramp 1 speed
17.8	-17.8	7*20	100	10	5	1800	-1800
N.m	N.m	μs	Hz	–	–	r.p.m	r.p.m

The following simulation results is drawn in per unit values for a base values of 12.5 N.m for the torque , 1705 r.p.m for the speed ,0.3 wb for flux and 25A for the stator current.

B. Results

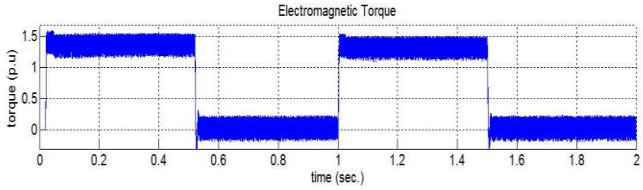

Fig. 12. *Electromagnetic torque for classical DTC*

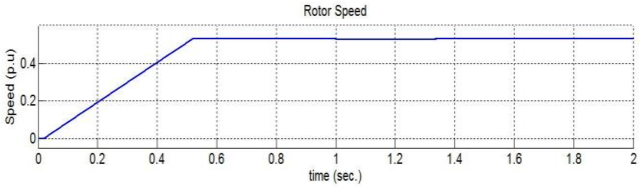

Fig. 13. *Rotor speed for classical DTC*

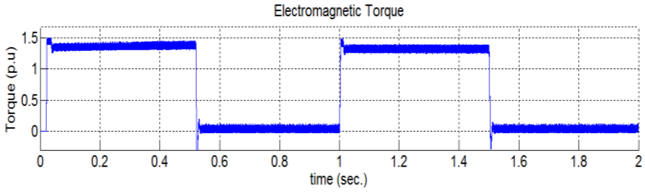

Fig. 14. *Torque for modified classical Fuzzy DTC*

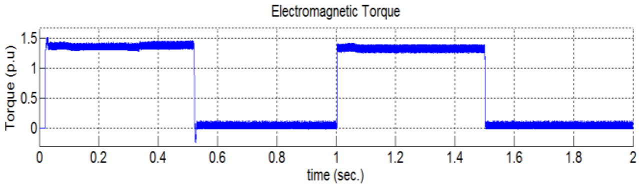

Fig. 15. *Torque in (p.u) for Neuro-Fuzzy DTC*

Fig. 12 shows electromagnetic torque in per unit for the classical DTC which has unaccepted ripple value of torque (0.38 p.u.). Fig. 14 shows electromagnetic Torque in (p.u) for modified classical Fuzzy DTC the ripple value of torque is reduced and became 0.175 p.u. which is an accepted. Also, it is clear the fast dynamic response of the torque and the under and over shoots presented in the torque results . Fig. 15 shows electromagnetic torque in (p.u) for Neuro-Fuzzy DTC, here the under and over shoots are reduced.

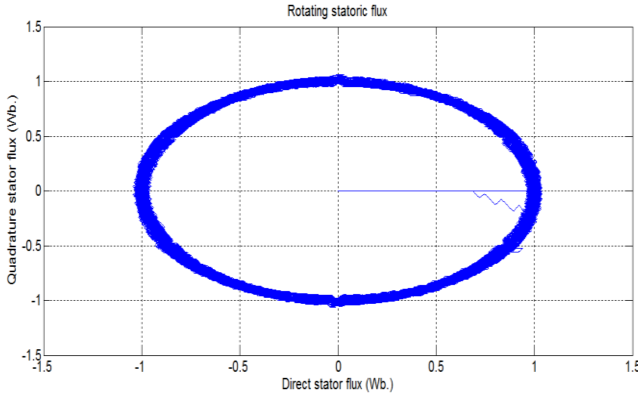

Fig. 16. *Stator flux circle for classical DTC*

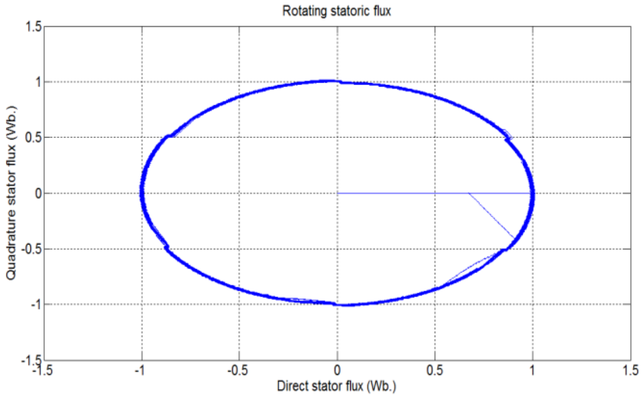

Fig. 17. *Stator flux circle for modified fuzzy DTC*

Fig. 16 shows Stator flux circle for classical DTC which has a large value of ripple, while Fig. 17 shows Stator flux circle for modified fuzzy DTC which has a minimum value of ripple.

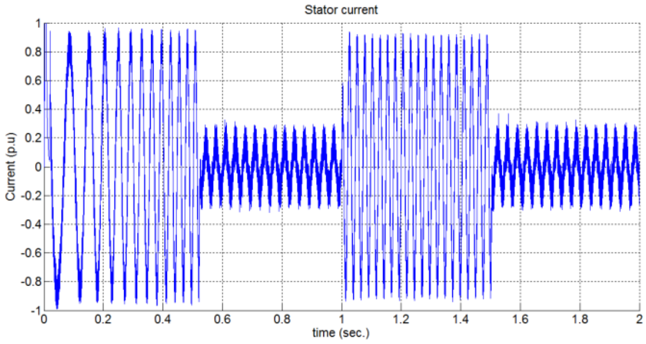

Fig. 18. *stator current in per unit for classical DTC*

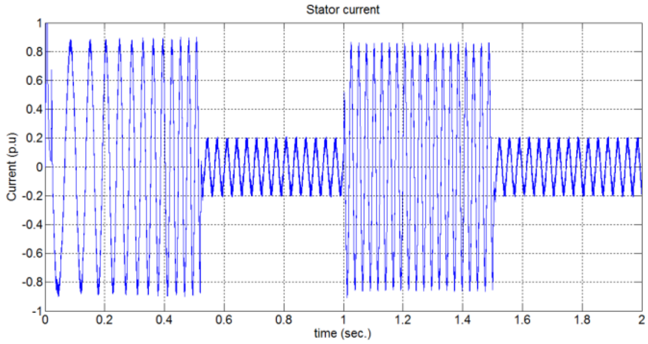

Fig. 19. *stator current for the modified fuzzy DTC*

Fig. 18 shows Stator current for classical DTC which has a large value of ripple, while Fig. 19 shows Stator current for modified fuzzy DTC which has a minimum value of ripple. Figures 20-23 shows a comparison between the conventional and proposed methods of DTC. Swift speed response for the proposed method is obvious.

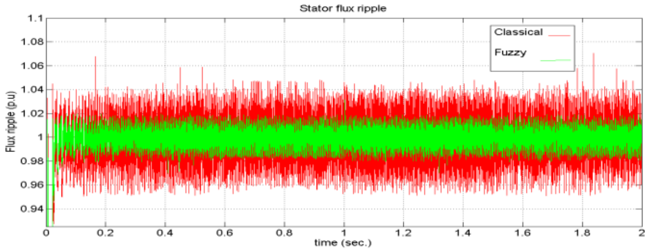

Fig. 20. *stator flux ripple in per unit for classical and fuzzy DTC*

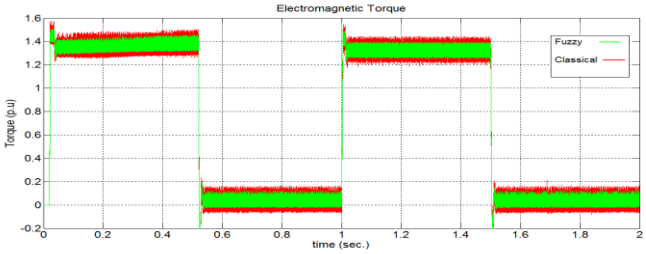

Fig. 21. *Electromagnetic torque in per unit for classical and fuzzy DTC*

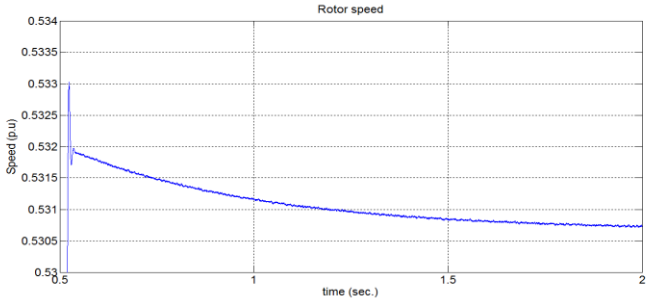

Fig. 22. *Speed response for Classical DTC*

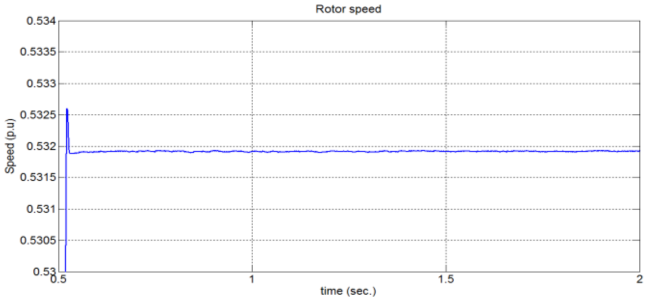

Fig. 23. *Speed response for Neuro-Fuzzy DTC*

VI. CONCLUSION

This paper proposes improvement of DTC using FLC as switching state selector based on modified classical DTC and neural speed controller. It can seen from the simulation results above for the simulation model given and the parameters mentioned above that flux, torque and current ripples is reduced remarkably for the proposed method. The simulation results show that the torque has very good dynamic response for the mentioned DTC methods. Applying ANN to replace conventional PI speed controller result in reducing the over and under shoots and lead to swift speed response as shown in simulation results. Therefore using the proposed method results in improving the motor performance.

REFERENCES

[1] 1- Thomas G. Habetler , Michele Pastorelli , Leon M. Tolbert " Direct Torque Control of Induction Machines using Space Vector Modulation" IEEE Transactions on Applications , vol. 28, No. 5, September/October 1992 pp: 1045-1053 .

[2] 2- Alnasir, Z.A. , Almarhoon A.H. " Design of Direct Torque Controller of Induction Motor (DTC)" Alnasir, Z.A. et al. / International Journal of Engineering and Technology (IJET) ,2001, pp: 54-70 .

[3] 3- Devender Kumar, Ishan Thakur, Kanika Gupta "Direct Torque Control for Induction Motor using Intelligent Artificial Neural Network Technique" International Journal of Emerging Trends & Technology in Computer Science (IJETTCS) , Volume 3, Issue 4, July-August 2014, pp:44-50.

[4] 4- M. Moghadasian , R. Kianinezhad , F. Betin , G. A. Capolino " Torque Ripple Minimization in Direct Torque Control of Six-Phase Induction Machines Using Fuzzy Inference Systems " ,2010 IEEE .

[5] 5- Rajendra S. Soni , S. S. Dhamal " Direct Torque Control of Three Phase Induction Motor using Fuzzy Logic " Proceedings of International Conference on Electrical, Electronics and Computer Engineering, 25 th August 2013, Bhopal, India :34-38 .

[6] 6- Melvin Koshy , Mrs. Lekshmi A. " Direct Torque Control Schemes for Induction Motor ",2011 .

[7] 7- Riad Toufouti, Salima Meziane, Hocine Benalla " Direct Torque Control Strategy of Induction Motors" Acta Electrotechnica et Informatica No. 1, Vol. 7, 2007 pp:1-7 .

[8] 8- Ahmed Hassan Adel, Amr Refky, Salama Abo-Zaid, Mahmoud Elwany " Torque Ripple Reduction in Direct Torque Control of Induction Motor Drives by Improvement of the Switching Table ", Journal of Multidisciplinary Engineering Science and Technology, Vol. 1 Issue 5, December - 2014, pp:238-243.

[9] 9- Daniel Graupe "Principles of Artificial Neural Networks", Advanced Series on Circuit & Systems -Vol. 6.

[10] 10- Neural Network Toolbox 6 , Matlab User's Guide.

[11] 11- N.Vahdatifar, Ss.Mortazavi, R.Kianinezhad " Neural Network Based Predictive DTC Algorithm for Induction Motors", World Academy of Science, Engineering and Technology 47 2010, pp:771-775.