Mohammad-Reza MOSAVI, Abdoreza RAHMATI, Alireza KHOSHSAADAT

Iran University of Science and Technology

Design of Efficient Adaptive Neuro-Fuzzy Controller Based on Supervisory Learning Capable for Speed and Torque Control of BLDC Motor

***Abstract**. Brushless DC (BLDC) motors have been widely used in many field of drives for their high power/weight, high torque, high efficiency, long operating life, noiseless operation, high speed ranges and ease of control. In this paper, a Neuro-Fuzzy Controller (NFC) based on supervisory learning is presented for the speed and torque control of BLDC motors to enhance high control performance of the drive under transient and steady state conditions. This designed controller is combination of Neural Networks (NNs) and Fuzzy Logic (FL), therefore has parallel processing and learning abilities of NNs and inference capacity of FL. For improvement the performance of leaning algorithm and thereupon increase efficiency of drive, instead of usual Error Back Propagation (EBP) learning technique, a fuzzy based supervisory learning algorithm is employed. The proposed controller has simple structure and also due to its modest fuzzy rule in rule-base is relatively easy for implementation. This controller has high accuracy, suitable performance, high robustness and high tracking efficiency. In order to demonstrate the NFC ability to tracking reference speed and torque and also test of robustness and rejection ability of controller against undesired disturbances or suddenly changes in speed and torque, these designs are simulated with MATLAB/SIMULINK. In some cases, results are compared with that of a conventional PID controller and other designs.*

***Streszczenie.** W artykule zaprezentowane układ sterowania bezszczotkowym silnikiem DC z wykorzystaniem sterownika Neuro-Fuzzy. Dla poprawienia efektywności uczenia sieci zamiast wstecznej propagacji błędu zaproponowano algorytm wykorzystujący logikę rozmytą. Sterownik okazał się być dokładny, odporny i o dużej efektywności śledzenia zmian. Porównano możliwości kontrolera z konwencjonalnym sterownikiem PID. (**Projekt skutecznego sterownika silnika bezszczotkowego DC z wykorzystaniem sieci neuronowych i logiki rozmytej**)*

Keywords: BLDC Motor, Speed, Torque, PID Controller, Adaptive Neuro-Fuzzy Controller, Supervisor
Słowa kluczowe: silnik bezszczotkowy, kontroler, sieci neuronowe.

Nomenclature

BLDC	Brushless Direct Current
PID	Proportional-Integral-Derivative
NN	Neural Network
FL	Fuzzy Logic
NFS	Neuro-Fuzzy System
NFC	Neuro-Fuzzy Controller
FLC	Fuzzy Logic Controller
FIS	Fuzzy Inference System
ANFIS	Adaptive Network-based Fuzzy Inference System
EBP	Error Back-Propagation
ZE	Zero
NB	Negative Big
PB	Positive Big
NS	Negative Small
PS	Positive Small

Introduction

BLDC motors due to their long operating life, high power density, noiseless operation, high speed ranges, high efficiency, high dynamic response and easier control are now widely used in many applications, such as servo drives, computer peripheral equipments and electric vehicles. A brushless DC motor is a synchronous electric motor which is powerdriven by DC electricity and which has an electronically controlled commutation system, instead of a mechanical commutation system based on brushes. In such motors, current and torque, voltage and rpm are linearly related [1-3].

One very simple and robust controller is the PID controllers. The PID controller works very well for linear systems with optimum gain tuning methods. Due to inexpensive maintenance, low cost, simplicity of operation, ease of design and effectiveness for most linear systems, in most of industries the PID controller is still dominantly used and traditional control system for BLDC is usually used this control. However, it has been known that conventional PID controllers generally do not work well for non-linear systems, higher order and time-delayed linear systems, and particularly complex and vague systems that have no precise mathematical models. Also after a long-time operation of the system, plant dynamics may change therefore fixed PID controller gains do not work properly as they did before. In addition due to system parameter variations and external disturbances, the performance of the PID controllers with previously set controller gains is degraded, because PID controllers need to be reconfigured with these changes. However non-linear controllers has good performance, but design of this type of controllers is very difficult. These reasons lead to say that a inteligent controller is so benefit for systems such as BLDC motors drive [4,5].

In this paper, we used ANFIS architectures for implementation of adaptive NFC. The ANFIS implements fuzzy inference system with NN architecture. The proposed controller integrates ideas of the FLC and NN structure into an intelligent control system. The nodes in the hidden layers perform as membership functions and fuzzy rules. Initially, the proposed controller is constructed from the fuzzy IF-THEN rules, which are based on a simple engineering knowledge regarding the controlled BLDC drive system. To learning for the proposed NFC, instead of the traditional EBP through system method, the supervisory learning procedure is used. The proposed controller is used for speed and torque control of a BLDC motor drive. The performance of the designed controller is demonstrated by MATLAB/SIMULINK simulation results [6].

In section II, the types of architecture of the NFS are depicted. In section III, modeling of the three-phase BLDC motor is demonstrated. Section IV, shows NFC design. Learning in NFC is described in section V. Finally in section VI, consequences of simulations of the NFC, in various situations and in comparison are represented.

Neuro-Fuzzy Control Systems

In recent years, scientists have obtained important improvement on various types of control technique. Among these control methods, intelligent control algorithms, which are usually regarded as the combination of FL, NN, genetic algorithm and expert system, have presented special superiorities. The FLC method can be used in systems that have ambiguity or uncertainty. Membership functions with values between 0 and 1 are used in FLC to deal with the control puzzle, such as non-linearity, load disturbance and parameter variation [7]. The advantages of the fuzzy systems are:

. Ability to depict inherent uncertainties of the human knowledge with linguistic variables;

· Simple interaction of the expert of the domain with the engineer designer of the system;

· Easy explanation of the results, because of the natural rules representation;

· Easy extension of the base of knowledge through the addition of new rules;

· Robustness in relation of the possible disturbances in the system [8].

and its disadvantages are:

· Lacking ability to generalize, or either, it only answers to what is written in its rule-base;

· Not robust in relation the topological variations of the system, such changes would demand alterations in the rule-base;

· Depends on the existence of an expert to detect the inference logical rules [8].

The NN is a computation and information processing method that mimics the process found in biological neurons. The basic element of a NN is the neuron. The relationship between two neurons is defined as the weight, which can be tuned or trained off-line, on-line, or combination of both. However, either FLC or NN has its own drawbacks, which cannot be neglected [7]. The advantages of the NNs are:

· Learning ability;
· Parallel processing;
· Generalization capacity;
· Robustness in relation to disturbances [8].

and its disadvantages are:

· Impossible interpretation of the functionality;
· Difficulty in detection of number of layers and neurons [8].

Every intelligent technique has special properties (e.g. ability to learn, explanation of decisions) that make them suited for particular applications. For example, while NNs are suitable at recognizing patterns, they are not capable for explaining how they reach their decisions. FL systems, which can reason with imprecise information, are appropriate at explaining their decisions, but they can not automatically acquire the rules they use to make those decisions. These limitations have been a central driving force behind the creation of combination of inteligent systems where two or more techniques are combined in a manner that overcomes the problems and limitations of individual techniques.

Usually, all the combinations of techniques based on NNs and FL called NFSs. The species combinations of these methods divided in the following classes:

***Cooperative Neuro-Fuzzy System*:** a cooperative system can be considered as a preprocessor wherein NN learning mechanism determines the FIS membership functions or fuzzy rules from the training data. Once the FIS parameters are determined, NN goes to the background. The rule based is usually determined by a clustering approach (self organizing maps) or fuzzy clustering algorithms. Membership functions are usually approximated by NN from the training data. Fig. 1 shows the block diagram of the cooperative NFS [8,9,10].

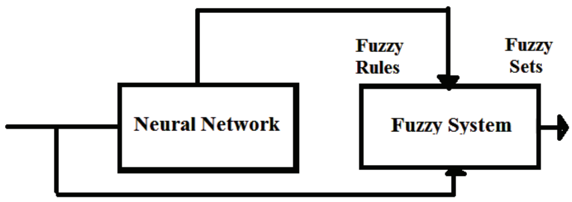


Fig. 1. Block diagram of cooperative NFS

***Concurrent Neuro-Fuzzy System*:** In a concurrent system, NN assists the FIS continuously to determine the required parameters especially if the input variables of the controller cannot be measured directly. In some cases the FIS outputs might not be directly applicable to the process. In that case NN can act as a postprocessor of FIS outputs. Fig. 2 shows the block diagram of the cooperative NFS [8,9,10].

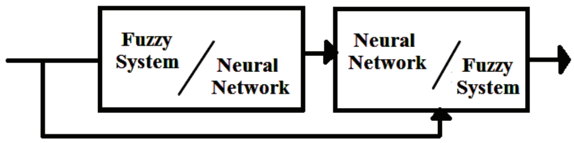


Fig. 2. Block diagraam of concurrent NFS

***Hybrid Neuro-Fuzzy System*:** In this category, a NN architecture with various layers and nodes is used to implement FIS (parameters of the fuzzy sets, fuzzy rule-base and weights of the rules) in an iterative way. This type of the neuro-fuzzy systems is one of the well known and useful method for combination of the NNs and FL. The theory behind the system would indicate that NNs would receive more crisp and meaningful inputs thus improving the overall output and quality of NNs predictions.

There are several architectures for hybrid NFS with various application. Some of these systems are: ANFIS, ANNBFIS, DENFIS, FALCON, GARIC, NEFCLASS, NEFPROX, SANFIS and FLEXNFIS [11].

Modeling of Three-Phased BLDC Motor

The construction of BLDC motor is similar to the AC motor, known as the permanent magnet synchronous motor. The stator windings are similar to those in a poly phase AC motor, and the rotor is composed of one or more permanent magnets. BLDC motors are different from AC synchronous motors in that the former incorporates some means to detect the rotor position (or magnetic poles) to produce signals to control the electronic switches as shown in Fig. 3. The most common position/pole sensor is the Hall element, but some motors use optical sensors [12].

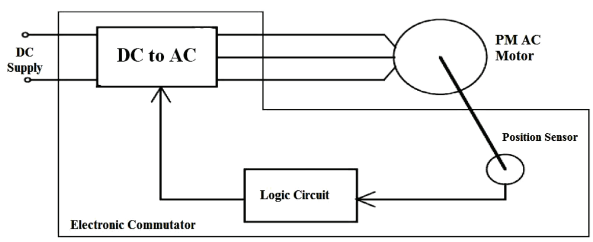


Fig. 3. Brushless DC motor

BLDC motor has characteristics like a DC motor, whereas it is controlled the same as AC motors. In this paper, we used a BLDC motor with trapezoidal back-EMF and 120° electric angle. The equivalent circuit of BLDC motor is shown in Fig. 4. The BLDC motor works according to six states, and in any state, two-phase work principle is completely similar [13].

Fig. 5 shows the commutation procedure of BLDC motor, according to the position of rotor, six MOSFETs work in defined conducting sequence so that the magnetic field generated by three phases A, B, C of BLDC motor can make the rotor circumrotate. The black arrow in Fig. 5 is the direction of the magnetic field. The ideal waveforms of back-EMFs of BLDC motor are represented in Fig. 6 [13].

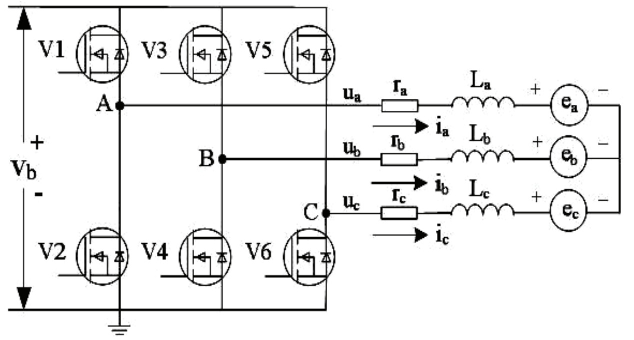


Fig. 4. Equivalent circuit of BLDC motor

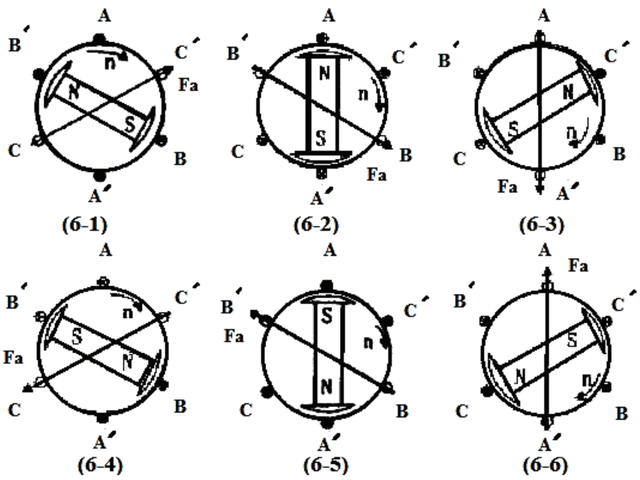


Fig. 5. Commutation procedure of BLDC motor

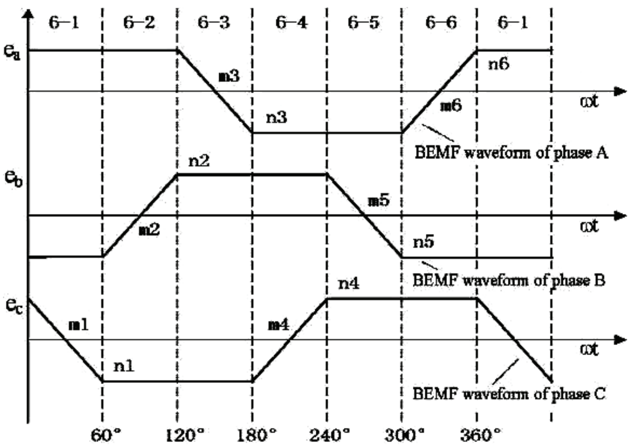


Fig. 6. Ideal waveforms of back-EMFs three phase of BLDC

Because the motor's three phases are similar, we have: $r_a = r_b = r_c = r_m$, $L_a = L_b = L_c = L_m$ and the typical mathematical model of a three-phase BLDC motor is described by the following equations:

$$(1)\quad \begin{bmatrix} u_a \\ u_b \\ u_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \times \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L_m - M & 0 & 0 \\ 0 & L_m - M & 0 \\ 0 & 0 & L_m - M \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix}$$

where r_m, L_m and M are the resistance, inductance and mutual inductance of the stator and u_x, e_x and i_x are phase voltage, back-EMF voltage and phase current of the stator respectively [13]. Electromagnetic torque is expressed as:

$$(2)\quad T_e = \frac{Z_P}{2\omega_e}(e_a i_a + e_b i_b + e_c i_c)$$

where ω_e is the electrical speed of the rotor and Z_P is the number of magnetic poles [14]. The equation of motion can be represented as:

$$(3)\quad T_e = T_L + J\frac{d\omega_r}{dt} + B\omega_r$$

where T_L, J, ω_r and B are load torque, inertial moment, angular velocity and friction constant [15].

Design of Adaptive NFC

For designing of NFC, we spot controller from two spots that explained in the follow:

In the first approach, the controller is depicted as a set of rules, which accepts the input in the form of qualitative variables and gives the output in the form of linguistic qualitative. The main advantages of such a system are:

· Approximate knowledge about the plant is required and exact model of system is not required.

· Knowledge representation and inference is fairly easy.

· Implementation is fairly easy.

The fuzzy controller is one rule-based control system. One of the important advantages of using a fuzzy viewpoint is that the FL provides the best methods for knowledge depiction that could be devised for encoding knowledge about continuous variables. Fig. 7, represnets the model of a fuzzy system, which is composed of four major part [16,17].

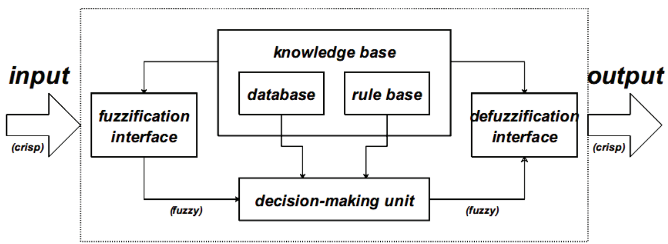


Fig. 7. General model of a fuzzy system

Fig. 8 shows membership function of error and derivative of error between output and reference of the controller which has been used in this paper. "a" for this application is 0.5. The fuzzy inference table is shown in Table 1.

In the second approach, the controller is depiced as a non-linear map among the inputs and outputs. Depending on a specific plant, the map (in the form of a network) can be trained to implement any kind of control plan [17].

NNs with their massive parallelism and ability to learn any type of non-linearity are used to address some of the practical control problems. A NNs based control system performs a particular form of the adaptive control with the controller taking the form of a multi-layer network and the adaptable parameters being defined as the adaptable weights. The main advantages of this controller are:

· Parallel architecture;

· Any type of non-linear mapping is possible;

· Training is feasible for diverse operating situations, therefore it can be adjusted to any favorited condition [17].

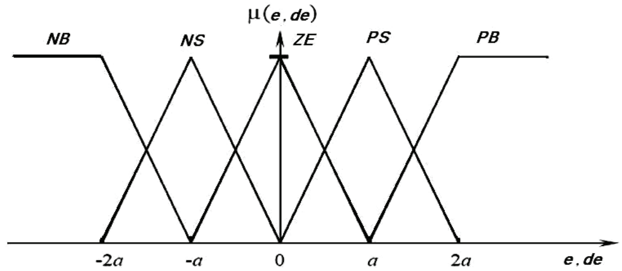


Fig. 8. Membership functions for the error and derivative of error

Table 1. Structure of Fuzzy Critic

e / de	NB	NS	ZE	PS	PB
NB	NB	NB	NS	NS	ZE
NS	NB	NS	NS	ZE	PS
ZE	NS	NS	ZE	PS	PS
PS	NS	ZE	PS	PS	PB
PB	ZE	PS	PS	PB	PB

The simple fuzzy controller demonstrates a suitable non-linear controller; however, it cannot adjust its structure whenever the condition demands. Sometimes the fuzzy controllers with fix structures fail to stabilize the plant under wide variations in the operating conditions. These types of controllers also lack the parallelism of neural controllers. On the other hand, the NNs are very much adjustable to conditions by adapting their weights accordingly. In parallel architecture implementation of the control algorithm is faster. Sometimes in certain neural controller structures the model of the plant is required, but in case of plants whose model becomes uncertain it is difficult to use NNs with fixed structures. To get the advantages of fuzzy and NNs and to overcome their deficiecies, it is wised to use the combination of NN and FL for controling, which leads to an NFC. In this paper we use from ANFIS-based method for implementation of controller [17].

To implement the NFC, we define a general neuron, that its input-output relation is as:

$$O_i^k = a(f(u_1^k, u_2^k, ..., u_n^k, W_1^k, W_2^k, ..., W_n^k)) \quad (4)$$

which a is the node activity function, f is the node input function, u_i^k is $i-th$ input in layer k, W_i^k is $i-th$ weight of node in layer k and O_i^k is the output of $i-th$ node in layer k [18].

Fig. 9 shows the structure of the NFC, which has been used for speed and torque control of BLDC motor. As shown in Fig. 9, architecture of the NFC has four-layers based of four part of fuzzy system as follow:

First layer: is called input layer; every input is scaled in limited range of input membership functions. All weights in this layer are equal to one (W_i^1) and we have:

$$O_i^1 = ku_i^1 \;\; ; \;\; i = 1,2 \quad (5)$$

Second layer: is called fuzzification layer; and convert crisp input to the fuzzy content. Gaussian function is used for nodes of this layer. For output of each node we have:

$$O_i^2 = \mu_{A_j}(u_i^2) \;\; ; \;\; i, j = 1,2,\cdots,5 \quad (6)$$

Third layer: is called inference and decision layer; the output of every node is the product of all input signals. Based on 25 rule in rule-base of fuzzy inference system, there are 25 nodes in this layer with fuction as:

$$O_i^3 = \mu_{A_j}(x)\mu_{B_k}(y) \;\; ; \;\; i = 1,2,...,25 \quad (7)$$

where $j,k = 1,2,\cdots,5$ and x, y are input of $3-th$ layer and represent the firing stenght of $i-th$ rule.

Fourth layer: is called defuzzifier layer; a single node computes the summation of all input signals from third layer. For defuzzification, mass of gravity method is used as:

$$O_1^4 = \frac{\sum_{i=1}^{25} W_i^4 u_i^4}{\sum_{i=1}^{25} W_i^4} \quad (8)$$

where W_i^4 is weight of input variables to fourth layer. They are adaptive and training of NFC equals to adjusting these adaptive weights [18].

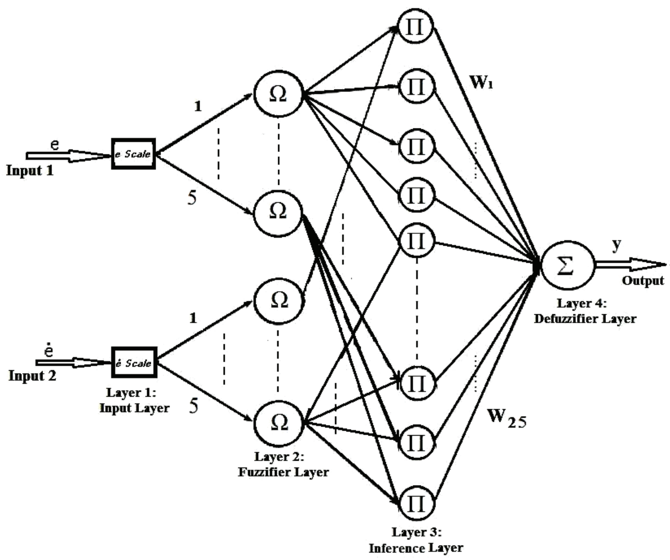


Fig. 9. Neuro-fuzzy network structure

Learning in Adaptive NFC

In some conditions it may be favorable to design a controller, which mimics the action of the human. This has been called supervised control. NNs are suitable for this target. Training the network is similar in principle to learning a system forward model. In this case, however, the network input corresponds to the sensory input information received by the human. The network target outputs used for training correspond to the human control input to the system. Fig. 10 shows the NN-based as a supervisory controller. The EBP algorithm is one of the famous and general method for training NNs [19]. In EBP algorithm, output error of the controller is passed through the system and updating of the weights is obtained. However, this method has some defects, such as sensivity to noise or disturbance and converging in local minimum [17].

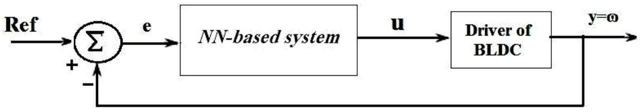


Fig. 10. Supervisory control of system

For improvement of learning capacity, one supervisor (as a critic) can be added to EBP algorithm and reminds its the correct and high perfirmance operation. With this work the weights of network are updated and performance is improved. The error between reference and plant output and those derivatives are used as inputs of supervisor. Fig. 11 shows a NFC controller by using a critic [17].

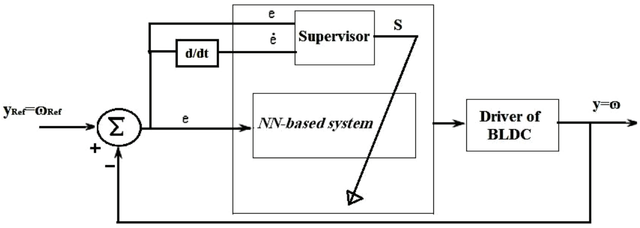


Fig. 11. Block diagram of supervisory controller with critic

Output of critic, named as S signal, can be represented like a PD control system as:

(9) $$S = k_1 e + k_2 \dot{e}$$

where k_1 and k_2 are supervisor coefficients and should be set properly. For training the NFS with PD supervisor, the criterion is selected as:

(10) $$E(W_i) = \frac{1}{2} S^2$$

The parameter W_i should be adapted in the direction of negative gradient of E. Thus, for the last layer, we have:

(11) $$\Delta W_i = -\frac{\partial E}{\partial W_i}$$

By using the chain differential law we have:

(12) $$\Delta W_i \propto -\frac{\partial E}{\partial S}\frac{\partial S}{\partial u}\frac{\partial u}{\partial W_i}$$

or

(13) $$\Delta W_i \propto -S\frac{\partial S}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial W_i}$$

Thus:

(14) $$\Delta W_i \propto -\eta S\frac{\partial u}{\partial W_i}$$

Therefore, the on-line updating law of weights is:

(15) $$W_{i,new} = W_{i,old} + \eta S e \frac{u_i^4}{\sum_{i=1}^{25} u_i^4}$$

where η is the learning rate of the network. It is possible to propagate training to previous layers, but this work causes instability and also more sensitivity and content of calculation. Therefore, learning only for the last layer is adequate [17].

Experimental Result

To display the learning capability and the accuracy of the proposed controller, various simulations were performed under various operating conditions in various speeds and torques. The simulations are performed in two general categories, which including speed response and torque response. In speed's simulations, operations were repeated with the PID controller and the results were compared with those of the NFC.

Fig. 12 shows the implementation of adaptive NFC in SIMULINK simulation. SIMULINK simulation of the BLDC motor drive is represented in the Fig. 13, which this figure consists of three main blocks are the names of current control block, power inverter block and three-phase BLDC motor block.

Table 2. Rated Parameters of BLDC Motor

Parameter	Value	Parameter	Value
K_t	0.21 [N.m/A]	T_n	2 [N.m]
ω_{rated}	3500 [RPM]	K_e	0.011 [V/RPM]
P_{rated}	725 [Watt]	T_L	0.6 [N.m]
L	3.05e-3 [mH]	M	1.2e-3 [mH]
R	0.75 [Ohm]	J	8.2e-5 [Kg.m^2]

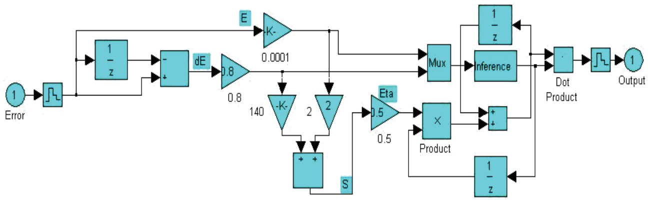


Fig. 12. Implementation of NFC in SIMULINK (with parameters adapted for torque control)

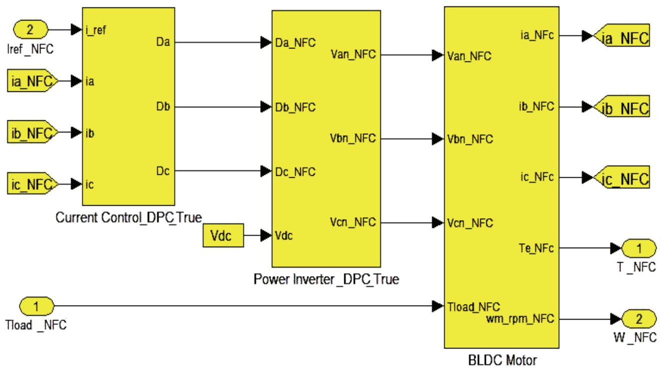


Fig. 13. BLDC motor drive in SIMULINK

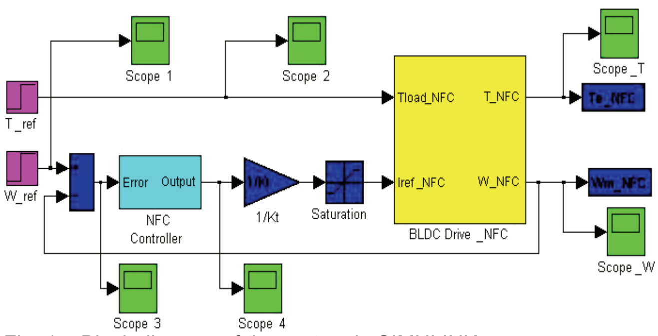


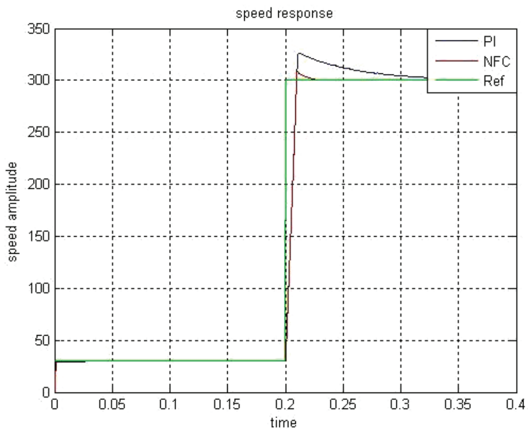
Fig. 14. Block diagram of the system in SIMULINK

Finally, in Fig. 14, all of the systems include adaptive NFC and BLDC plant is shown. Nominal parameters of the BLDC motor are given in the Table 2. The critic in the NFC has been selected as $S = 4e + 10\dot{e}$ for speed cotrol and $S = 0.0002e + 112\dot{e}$ for torque control of motor. The learning rate coefficient is set to $\eta = 0.004$ for speed control and set to $\eta = 0.5$ for torque control of motor. Finally, coefficients of PID controller are assigned by $k_P = 0.8$, $k_I = 9$ and $k_D = 0$ for speed control of BLDC motor sake comparison with result of NFC speed responses. All of the coefficients of critic, learning rate and coefficients of the PID controller, in both speed and torque simulations, were chosen by trial and error. Also currents are controlled via hysteresis current controllers.

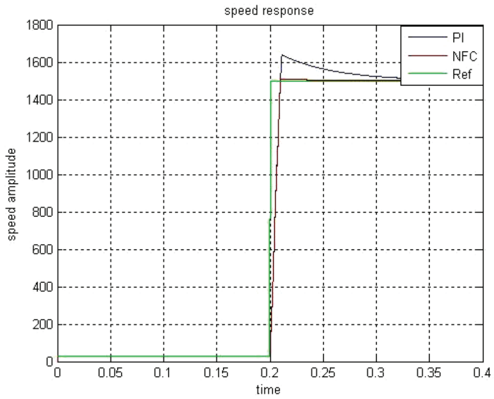
Fig. 15 compares the performance of the BLDC motor drive with NFC and PID controller in various speeds. In this part of simulation, reference speed from 0 to 0.2sec is low and in 0.2sec suddenly raised to another speed. It is clear that speed tracking by using NFC specially in high speeds is better than PID controller. In Fig. 16, NFC and PID controller has rejected load disturbance in various speed. It has be found that NFC has more robustness than PID controller and rejected load disturbance better than PID controller with lower ripple.

For representation of designed controller efficiency in speed response, in some speeds, this work is compared with reference [6,20,21]. In reference [6] overshoot and raise time of controller are 1% and 0.25sec, and in proposed controller overshoot and raise time are 0.8% and 0.2sec, respectively. In reference [20] overshoot and raise time of designed controller are 4% and 0.05sec, and in proposed controller overshoot and raise time are 1% and 0.04sec, respectively. In reference [21] overshoot and raise time of designed controller are 1% and 0.15sec, and in proposed controller overshoot and raise time are 1% and 0.008sec, respectively.

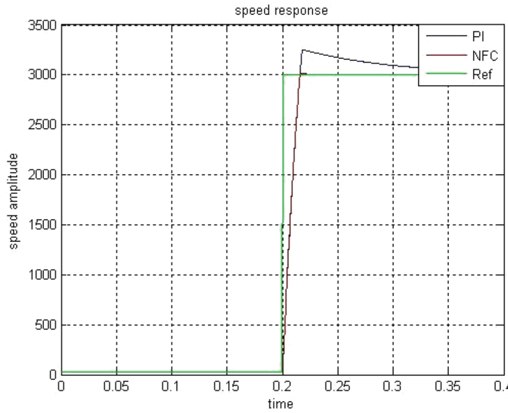
Fig. 17 represent the performance of the BLDC motor drive with NFC controller, at changing reference torque from low to high, in various speeds. From figures, it has be found that torque tracking by using NFC has good response with low ripple. In Fig. 18, the ability of NFC in robustness of torque response in tracking of torque reference, in the case of speed variation suddenly is demonstrated, and simulation results indicate to high robustness and low overshoot of NFC controller response (in moments of sudden change in speed). Finally in Fig. 19, voltages of three phase of the BLDC motor in variable speeds and torques is represented.



(a) 30rpm to 300rpm

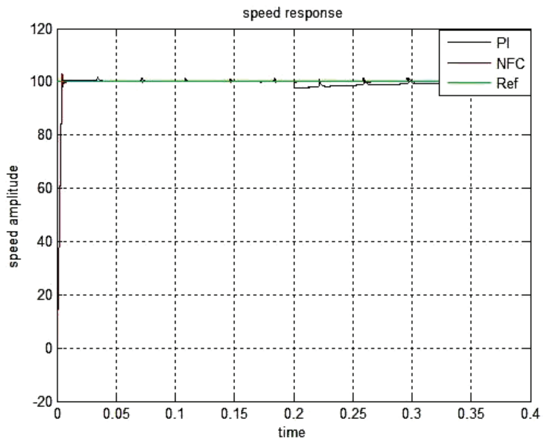


(b) 30rpm to 1500rpm

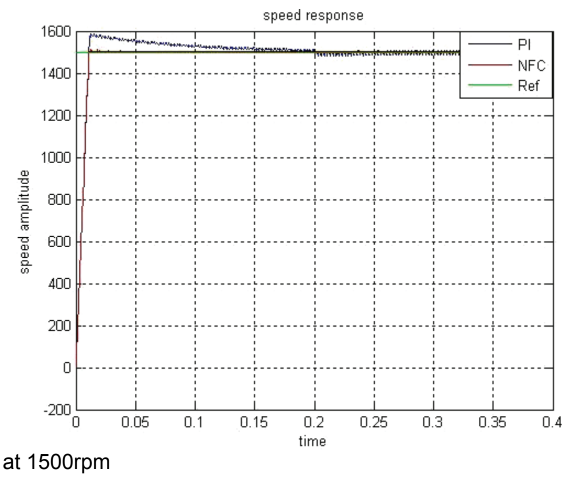


(c) 30rpm to 3000rpm

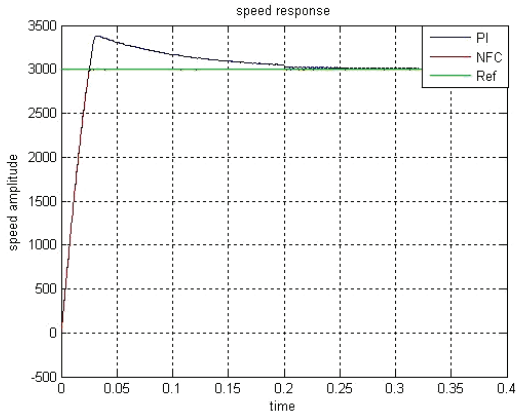
Fig. 15. Comparison of speed tracking of NFC and PID controller at various speeds (red: NFC, blue: PID controller and green: reference speed)



(a) at 100rpm

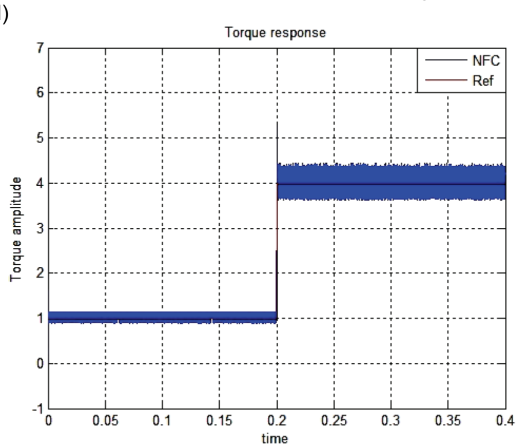


(b) at 1500rpm

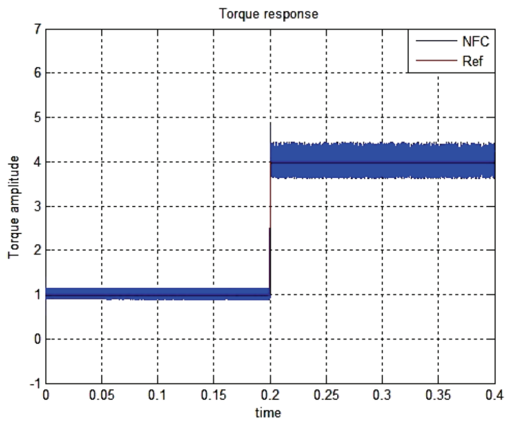


(d) at 3000rpm

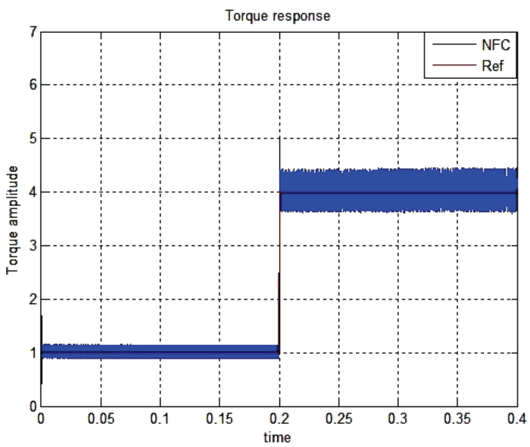
Fig. 16. Comparison of disturbance rejection of NFC and PID controller (red: NFC, blue: PID controller and green: reference speed)



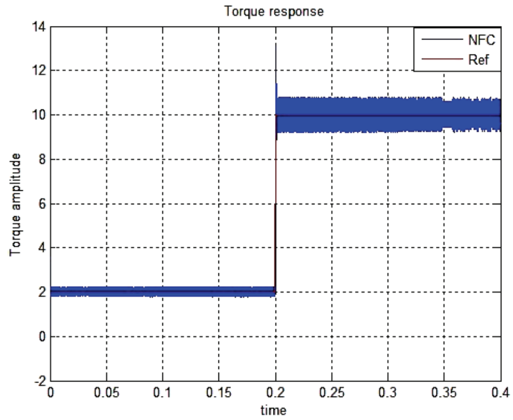
(a) 1N.m to 4N.m (at 100rpm)



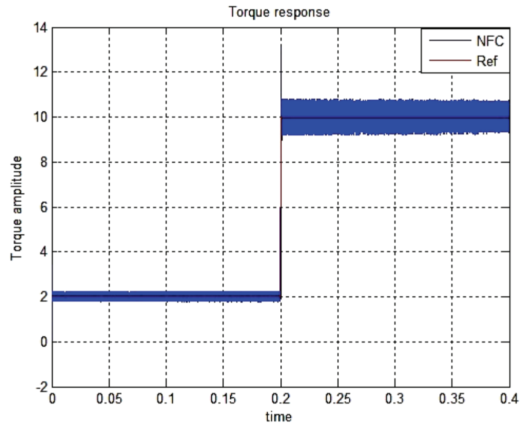
(b) 1N.m to 4N.m (at 1000rpm)



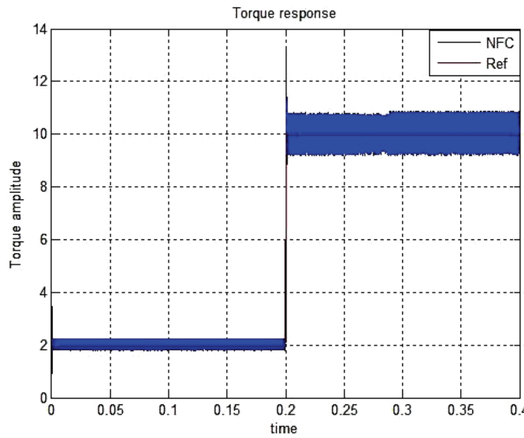
(c) 1N.m to 4N.m (at 3000rpm)



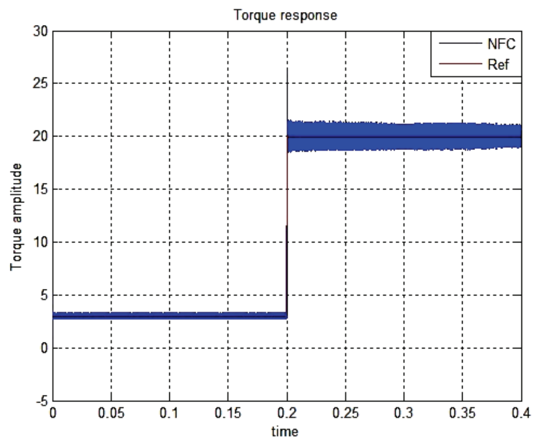
(d) 2N.m to 10N.m (at 100rpm)



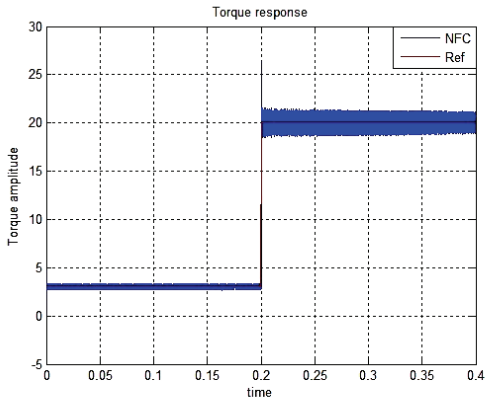
(e) 2N.m to 10N.m (at 1000rpm)



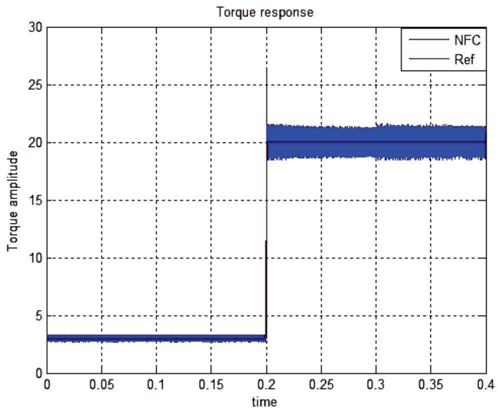
(f) 2N.m to 10N.m (at 3000rpm)



(g) 3N.m to 20N.m (at 100rpm)

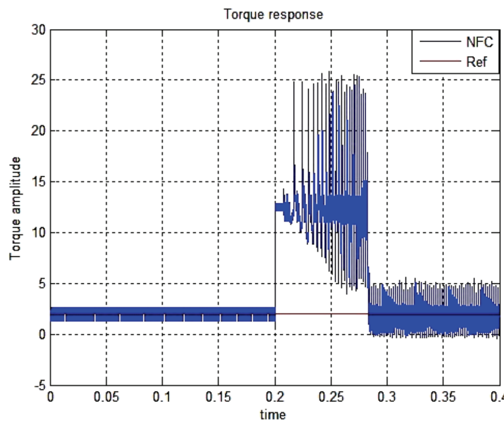


(h) 3N.m to 20N.m (at 1000rpm)

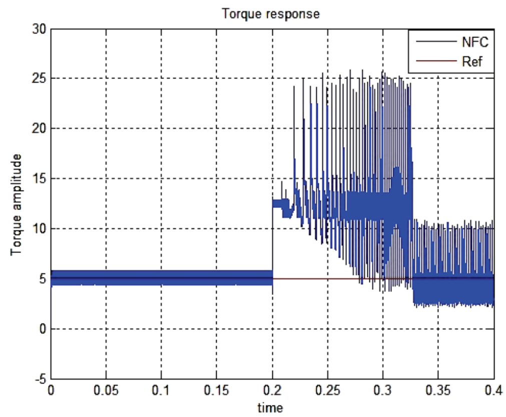


(i) 3N.m to 20N.m (at 3000rpm)

Fig. 17. Torque tracking of NFC at various torques and speeds, sampling time is 5μs (red: NFC, blue: torque reference)

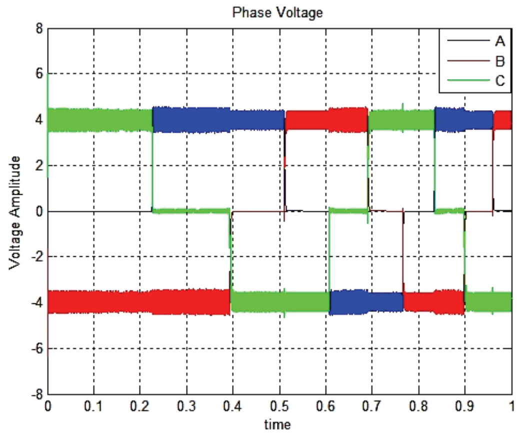


(a) 50rpm to 2000rpm (at 2N.m)

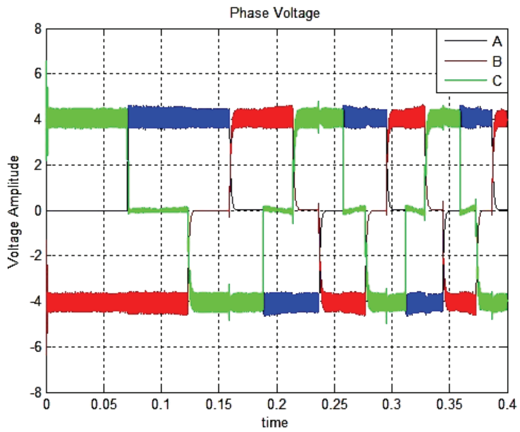


(b) 50rpm to 2000rpm (at 5N.m)

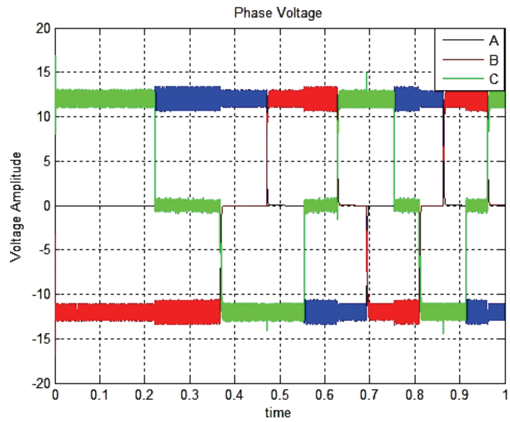
Fig. 18. Robustness and performance in torque reference tracking of NFC against suddenly change at speed in various torque (blue: NFC and red: torque reference)



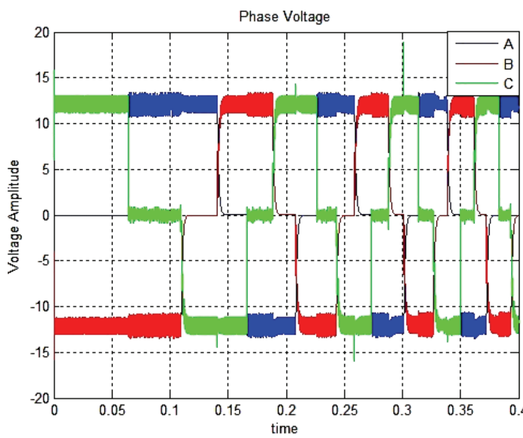
(a) Torque is 5N.m and speed is 100rpm



(b) Torque is 5N.m and speed is 1000rpm



(c) Torque is 15N.m and speed is 100rpm



(d) Torque is 15N.m and speed is 1000rpm

Fig. 19. Voltages of three phase of BLDC motor in variable torques and speeds

Conclusion

In this paper, an adaptive NFC is designed that capable for speed and torque control of three-phase BLDC motor. The four layers of the fuzzy system control is implemented by using a four-layer NN architecture, with two input including error and derivative of error. Decision layer (third layer) of fuzzy system has rule-base with 25 rule and for this reason third layer of network has 25 neuron for processing of inputs from fuzzy inputs of the second layer. The learning of NFC is based on the gradient decent method for only last layer with one PD supervisor that act as a critic for supervision and improvement of controller operation. The designed controller has several advantages, such as, simple structure and learning capability, high robustness against disturbance, high tracking performance of speed and torque, low ripple in torque response, modest nodes at hidden layers, and high accuracy. It does not require an advertent model of the plant. So, this controller, due to its independence to model of plant, can be used for controlling a wide range of complex, non-linear and uncertain systems that have no ditinct mathematical model. Also due to its modest rules of rule-base, construction and implementation is relatively easy. In comparison with the PID controller, the designed NFC has better speed response with better performance of tracking reference speed, lower overshoot, shorter settling time and more robustness in wide range of speed. Simulation results have shown that the proposed controller has good torque response with low ripple and high tracking efficiency.

REFERENCES

[1] H. Lu, L. Zhang and W. Qu, A New Torque Control Method for Torque Ripple Minimization of BLDC Motors With Un-Ideal Back-EMF, *IEEE Transaction on Power Electronics*, Vol.23, No.2, pp.950-958, March 2008.

[2] S. Rajagopalan, Detection of Rotor and Load Faults in Brushless DC Motors Operating under Stationary and Non-stationary Condition, *Dr Thesis, Georgia Institute of Technology*, August 2006.

[3] N. B. Rahman, Neural Network Controller for DC Motor Using MATLAB Application, BS Thesis, University of Malaysia Pahang, November 2008.

[4] S. Jung and S. S. Kim, Hardware Implementation of a Real-Time Neural Network Controller With a DSP and a FPGA for Nonlinear Systems, *IEEE Transactions on Industrial Electronics*, Vol.54, No.1, pp.265-271, February 2007.

[5] K. S. Tang, K. F. Man, G. Chen and S. Kwong, An Optimal Fuzzy PID Controller, *IEEE Transaction on Industrial Electronics*, Vol.48, No.4, pp.757-765, August 2001.

[6] A. Rubaai, D. Ricketts and M. D. Kankam, Development and Implementation of an Adaptive Fuzzy-Neural-Network Controller for Brushless Drives, *IEEE Transaction on Industry Applications,* Vol.38, No.2, pp.441-447, March/April 2002.

[7] S. R. Jalluri and B. V. S Ram, A Neuro Fuzzy Controller for Induction Machines Drives, *Journal of Theoretical and Applied Information Technology,* Vol.19, No.2, September 2010.

[8] J. Vieira, F. M. Dias and A. Mot, Neuro-Fuzzy Systems: A Survey, *WSEAS Transactions on Systems,* Vol.3, No.2, pp.414-419, 2004.

[9] D. Nauck, F. Klawon and R. Kruse, Foundations of Neuro-Fuzzy Systems, *J. Wiley & Sons,* 1997.

[10] A. Abraham, Neuro Fuzzy Systems: State-of-the-Art Modeling Techniques, *Proceedings of the Sixth International Work Conference on Artificial and Natural Neural Networks, Lecture Notes in Computer Science*, Vol.2048, pp.269-276, 2001.

[11] L. Rutkowski and K. Cpalka, Flexible Neuro-Fuzzy Systems, *IEEE Transaction on Neural Networks*, Vol.14, No.3, pp.554-574, May 2003.

[12] K. N. Sujatha, K. Vaisakh and G. Anand, Artificial Intelligence Based Speed Control of Brushless DC Motor, *IEEE Conference on Power and General Meeting,* pp.1-6, July 2010.

[13] J. Cao, B. Cao, P. Xu, S. Zhou, G. Guo and X. Wu, Torque Ripple Control of Position-Sensorless Brushless DC Motor Based on Neural Network Identification, *3rd IEEE Conference on Industrial Electronics and Applications,* pp.752-757, June 2008.

[14] A. H. Niasar, A. Vahedi and H. Moghbelli, Design and Implementation of Sensor less Control for Four-Switch, Three-Phase Brushless DC Motor Drive Based on DSP Technology, *Iranian Journal of Electrical and Computer Engineering,* Vol.8, No.1, pp.1-8, Winter-Spring 2009.

[15] H. Ji and Z. Li, Design of Neural Network PID Controller Based on Brushless DC Motor, *Second International Conference on Intelligent Computation Technology and Automation,* Vol.3, pp.46-49, October 2009.

[16] J. S. R. Jang, ANFIS: Adaptive-Network-Based Fuzzy Inference System, *IEEE Transactions on System, Man, and Cybernetics*, Vol.23, No.5, pp.665-685, May 1993.

[17] A. H. Niasar, M. A. S. Masoum and H. Moghbeli, Adaptive Neuro-Fuzzy Intelligent Controller via Emotional Learning for Indirect Vector Control (IVC) of Induction Motor Drives, *12th Iranian Conference on Electrical Engineering,* 11-13 May 2004.

[18] A. H. Niasar, A. Vahedi and H. Moghbelli, ANFIS-Based Controller with Fuzzy Supervisory Learning for Speed Control of 4-Switch Inverter Brushless DC Motor Drive, *37th IEEE Conference on Power Electronics,* pp.1-5, 18-22 June 2006.

[19] C. Lin and Y. Lu, A Neural Fuzzy System with Fuzzy Supervised Learning, *IEEE Transaction on Systems, Man and Cybernetics,* Vol.26, No.5, October 1996.

[20] N. Sujatha, K. Vaisakh and K. Anand, Artificial Intelligence Based Speed Control of Brushless DC Motor, *IEEE Conference* on *Power and Energy Society General Meeting,* pp.1-6, July 2010.

[21] G. Qin, W. Yao and W. Zhang, Design of Nonlinear Optimization PID Controller for BLDCM Based on Neuro-Fuzzy, *Proceedings of the 8th International Conference on Electrical Machines and Systems,* Vol.2, pp.1524-1527, September 2006.

Authors:

Mohammad-Reza Mosavi (Corresponding Author) *received his B.S., M.S., and Ph.D. degrees in Electronic Engineering from Department of Electrical Engineering, Iran University of Science and Technology (IUST), Tehran, Iran in 1997, 1998, and 2004, respectively. He is currently faculty member of Department of Electrical Engineering of IUST as associate professor. He is the author of about 120 scientific publications on journals and international conferences. His research interests include Artificial Intelligent Systems, Global Positioning Systems, Geographic Information Systems and Remote Sensing. Email: M_Mosavi@iust.ac.ir*

Abdoreza Rahmati *received his B.S. in Electronic Engineering from Department of Electrical Engineering, Iran University of Science and Technology (IUST), Tehran, Iran in 1978, his M.S. in instrumentation from University of Bradford, England in 1985, his Ph.D. in medical instrumentation from University of Bradford, England in 1990. He is currently faculty member of Department of Electrical Engineering of IUST as associate professor. His research interests include Power Electronics.*

Alireza Khoshsaadat *received his B.S. degree in Electronic Engineering from Department of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran in 2009. He is currently master science student of Department of Electrical Engineering of IUST. His research interests include Intelligent Control Systems and Digital Control with FPGA.*