ROTOR POSITION CONTROL OF BLDC MOTOR USING ANFIS CONTROLLER TRAINED BY PSO TECHNIQUE

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Abstract - *This paper develops a methodology of Particle Swarm Optimization (PSO) based ANFIS controller for position control of a brushless DC motor. The PSO has been used for the selection of the training inputs of the ANFIS in order to minimize the training result error. In order to improve the system performance and large amount of uncertainties present in such systems, the PSO is used to regulate all the parameters of ANFIS controller. The rotor position control of BLDC motor is simulated using MATLAB/Simulink Toolbox. The proposed technique is more proficient in the part of improving the step response characteristics as well as it is reducing the steady-state error, settling time and maximum overshoot.*

Key Words: *ANFIS controller, BLDC Motor, Particle Swarm Optimization, MATLAB/ Simulink.*

1. Introduction

BLDC motors are used extensively in industrial sectors since the architecture is suitable for any safety critical applications. These motors have gained more popularity due to its better characteristics and performance. The precise rotor position and speed control of brushless dc motor is more important in robotics as well as in servo applications [1-5]. Also, rotor position control scheme is used in space crafts and military applications.

In recent years, many controllers have been developed for the brushless dc motor.PID is most preferred controller in the industry and it requires exact mathematical model of the system to be controlled. Also PID controller has uncertainty problem due to set speed variations and load disturbance [6-9]. The problem connected with PID controller has been reduced by employing artificial intelligent techniques [10].

Fuzzy set theory plays an important role in dealing with uncertainty of making decisions in complex or imprecise processes. Effectiveness of fuzzy logic control design depends on knowledge of human expert and it provides response depending on its rule base. It is not robust in relation the topological changes of the system and such changes would demand alterations in the rule base [11-14].

Artificial Neural Networks (ANN) is the general function approximator and is able to include the model based structure of complex and nonlinear systems. But ANN also has some restrictions i.e., impossible interpretation of the functionality and difficulty in determining the number of layers and number of neurons [15-18].

Adaptive neuro-fuzzy inference systems (ANFIS) reduce the problems of both fuzzy and neural networks. It represents a class of ANNs that are based on fuzzy inference systems. As ANFIS incorporate both neural networks and fuzzy logic principle in a single structure [19-21]. But, its output response exhibits high settling time and large steady state error in the system performance.

To overcome this problem, a new model of fuzzy based PID ANFIS controller for rotor position control of BLDC motor was designed [22]. In this method, the overshoot, settling time and THD in torque waveform is reduced compared to other controllers. Due to the complicated selection of the rule base in the fuzzy control strategy, the result was not good. The responses had taken a lot of time to reach the final steady state value.

To avoid the above problems, a sincere attempt is made by designing an efficient controller using ANFIS trained by metaheuristic techniques, which is the main contributory work of this paper.

In recent years, many metaheuristic optimization techniques have gained a wide attention in control applications. Optimization is a method that finds an optimal solution for a problem. Some of the commonly used techniques are genetic algorithm (GA) and particle swarm optimization (PSO).These metaheuristic techniques have proven their superiority over the conventional techniques.

A Genetic Algorithm (GA) is a technique used to find the exact solution in optimization problems. But, GA has some restrictions i.e., optimization process is very complex and expensive computational cost.

The particle swarm optimization (PSO) is a robust population-based optimization technique based on the movement of swarms. Compared with other metaheuristic technique, PSO has a simple concept, easy implementation and good computational efficiency [24-27].So it is more appropriate for the ANFIS tuning task. PSO has been successfully applied in many areas like functions optimization, ANN training and fuzzy system control.

This paper is organized as follows: Introduction is given in section 1. Modeling of the BLDC motor in brief and rotor position controller concept is outlined in section 2.Proposed PSO based Adaptive Neuro-fuzzy inference system based rotor position controller is presented in section 3 and section 4 discusses simulation results. Concluding remarks is outlined in section 5.

2. Modeling of BLDC Motor

It is assumed that the BLDC motor is connected to the output of the inverter, while the inverter input terminals are connected to a constant supply voltage .The mathematical model of the BLDC motor can be represented by the following Equations (1)-(3).

$$V_a = R_a i_a + L_a \frac{di_a}{dt} + M_{ab} \frac{di_b}{dt} + M_{ac} \frac{di_c}{dt} + e_a \quad (1)$$

$$V_b = R_b i_b + L_b \frac{di_b}{dt} + M_{ba} \frac{di_a}{dt} + M_{bc} \frac{di_c}{dt} + e_b \quad (2)$$

$$V_c = R_c i_c + L_c \frac{di_c}{dt} + M_{ca} \frac{di_a}{dt} + M_{cb} \frac{di_b}{dt} + e_c \quad (3)$$

Where V_a, V_b and V_c denotes phase voltages of the motor. R_a, R_b and R_c represent stator winding resistances. Phase currents of the motor are represented by i_a, i_b and i_c. Self inductances of the motor winding are represented by L_a, L_b and L_c and the mutual inductances between stator windings are denoted by M_{ab}, M_{ac}, M_{ba}, M_{bc}, M_{ca} and M_{cb} respectively.

The torque is expressed in Equation (4) as,

$$T_{em} = J \frac{d\omega_r}{dt} + B\omega_r + T_L \quad (4)$$

Where J, ω_r and B represents the moment of inertia, angular velocity and frictional coefficient of the motor respectively. T_L is the load torque. But the torque for this 3-phase BLDC motor is dependent on the speed, current and back-EMF waveforms, so the instantaneous torque can be represented in Equation (5) as,

$$T_{em} = \frac{1}{\omega_m}(e_a i_a + e_b i_b + e_c i_c) \quad (5)$$

3. Proposed Rotor Position Controller

Fig. 1 shows the block diagram of the ANFIS Controller.

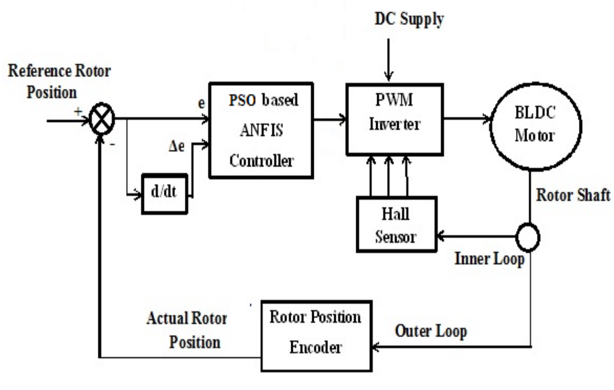

Fig. 1. Block diagram of the proposed ANFIS controller.

The feedback loop has two parts namely inner and outer loop. Inner loop is used for coordinating the gate pulse of the BLDC motor. Outer loop is used to sense the actual rotor position of the rotor using rotor position encoder. The actual rotor position is compared with reference rotor position thereby error (e) and rate of change of error (Δe) are obtained. Error and rate of change of error is processed by the rotor position controller and provides control signal to the switching logic circuit.

4. Overview of ANFIS Structure

ANFIS is a method for tuning an existing rule base with a learning algorithm based on a collection of training data. The structure of ANFIS is shown in Fig. 2.

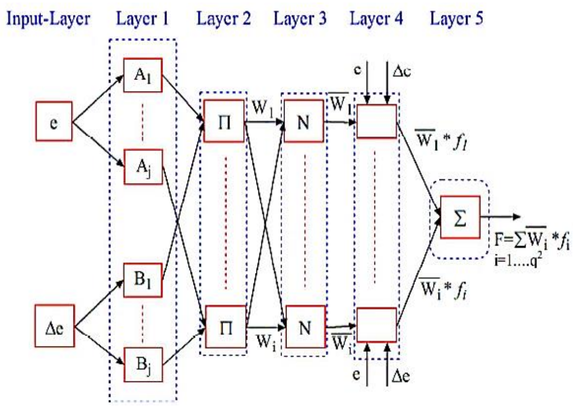

Fig. 2. Structure of Adaptive Neuro Fuzzy Inference System.

Layer 1: (Input Layer) Every node *i* with a node function is given in the Equations (6)-(7) as,

$$L_{1,i} = \mu A_i(e), \text{ for i=1, 2……j} \tag{6}$$

$$L_{1,i} = \mu B_i(\Delta e), \text{ for i=1, 2……j} \tag{7}$$

Where e (or (Δe)) is the input node *i* and *Ai* (or *Bi*) is a linguistic label linked with this node.

Layer 2: (Fuzzification Layer) Output node equation of this layer is given in Equation (8) as,

$$L_{2,i} = W_i = \mu A_i(e) \mu B_i(\Delta e) \quad \text{for i = 1, 2 … } j^2 \tag{8}$$

Layer 3: (Rule Layer) Node equation of this layer is given in Equation (9) as,

$$L_{3,i} = \overline{W_l} = \frac{W_l}{\sum_{l=1}^{j^2} W_l} \tag{9}$$

Layer 4: (Defuzzification Layer) Every node *i* in this layer with a node function is given in Equation (10) as,

$$L_{4,i} = \overline{W_l} f_i = \overline{W_l}(p_i e + q_i \Delta e + r_i) \tag{10}$$

Where W_l is a normalized firing strength from Layer 3 and (p_i, q_i, r_i) is the parameter set of this node.

Layer 5: (Output Layer) The single node in this layer is a fixed node labeled Σ, it is represented in Equation (11) as,

$$L_{5,i} = \sum_{l=1}^{j^2} \overline{W_l} f_i = \frac{\sum_{l=1}^{j^2} W_l f_i}{\sum_{l=1}^{j^2} W_l} \tag{11}$$

Fig. 3 shows Proposed PSO based ANFIS Structure for the rotor position control. The structure consists of five layers. First layer is the input layer, second layer is the input membership function layer. Third layer is the rule layer where the inputs and outputs are linked with AND operator. Fourth layer is the output membership function layer. Last layer is the output layer which sums up all the inputs coming from the previous layer.

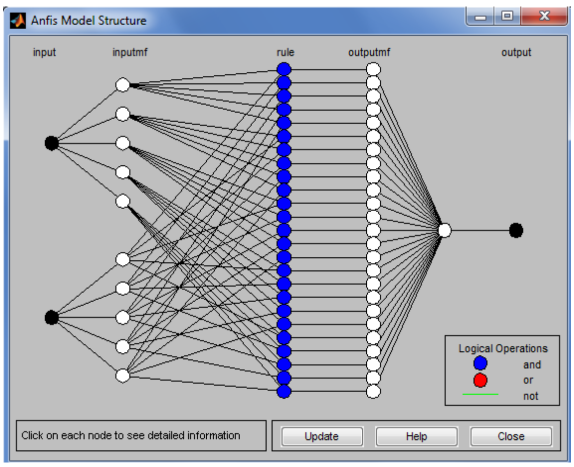

Fig. 3. Proposed PSO based ANFIS Structure for the rotor position control.

5. Proposed PSO ANFIS Controller

PSO algorithms are applied to search the parameters of ANFIS controller. The optimal range and shape of membership functions obtained with ANFIS are adjusted using PSO technique.

A swarm is collected of m particles flying in the D-dimension in a certain velocity. Every particle changes its position on the basis of considering its own and other particles historical best position. The position for the i^{th} particle is x_i = (x_{i1}, x_{i2},…x_{iD}), where $1 \leq i \leq m$ and m is the size of the particle swarm. The value of particle *i* is stored as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ and it is represented by pbest. Also the PSO technique gives the best value gbest . Then it generates the velocity of each particle near its pbest and gbest. The velocity is expressed as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$.

The position of each particle is modernized by the following Equation (12),

$$v_{id}(t+1) = \omega \times v_{id}(t) + c_1 r_1 (P_{id}(t) - \chi_{id}(t)) + c_2 r_2 (P_{gd}(t) - \chi_{id}(t))$$
$$\chi_{id}(t+1) = \chi_{id}(t) + v_{id}(t+1) \tag{12}$$

where, *Pid* and *Pgd* are *pbest* and *gbest*. Also c_1 and c_2 are learning factors and x_{id} (t) is the position vector for the i^{th} particle, v_{id} (t) is the connected with velocity vector. Because of the learning factor, the particle could be close to its own historical best position. Then ω is the inertia weight, the value of which gives the quantity inherited from the current velocity of the particle. If it is selected accurately, then the particle will have the balanced operation and development. The basic steps for PSO are given in the flowchart as shown in Fig. 4.

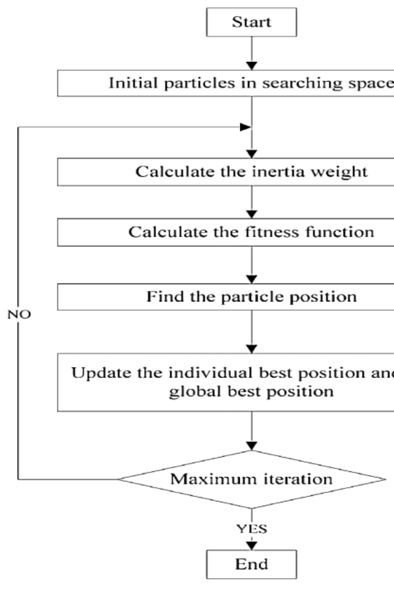

Fig. 4. Flowchart for Particle Swarm optimization.

The proposed Particle Swarm Optimization procedure to tune the ANFIS parameter is reviewed in the following points:

Step 1: Assume the parameters in searching space.

Step 2: Initialize the population, velocity, pbest, and gbest with the scaling factors for the ANFIS controller.

Step 3: Evaluate each function with its inertia weight.

Step 4: Estimate the fitness function for all individual.

Step 5: Adjust both the velocity and the member function. Then find the particle position.

Step 6: Update both individual and global best position.

Step 7: Stop if the maximum number of iterations is reached, otherwise increase the iteration counter by one and go back to step 3.

6. Training Process

The training processes were performed by using hybrid learning methods with 20,000 data points and Grid partition clustering methods are used for generating the primary membership function. Fig. 5(a) and 5(b) shows the primary membership functions for both error and rate of error. Fig. 5 (c) shows the primary fuzzy rules for the ANFIS controller.

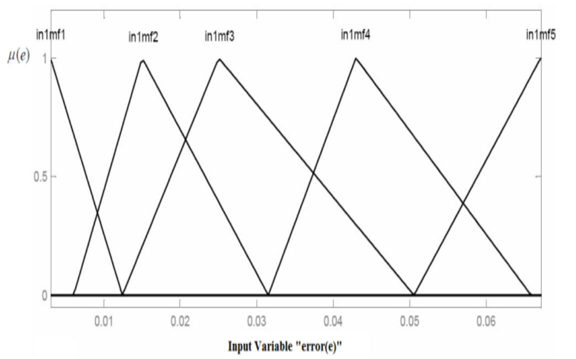

Fig. 5(a). Primary membership functions for error (e).

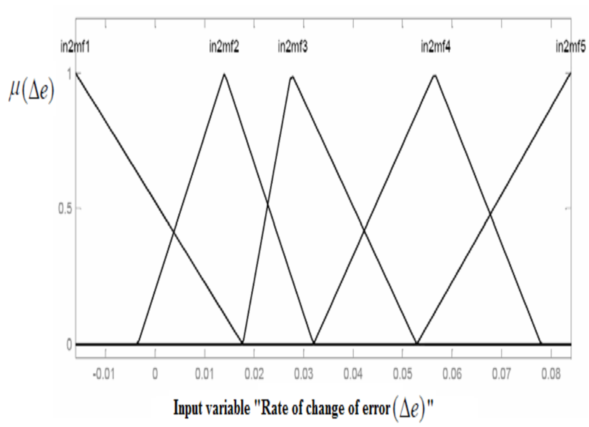

Fig. 5(b). Primary membership functions for rate of error (Δe)

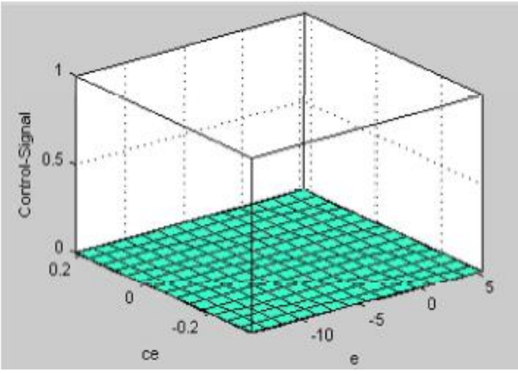

Fig.5 (c) Primary rule base for the ANFIS Controller

After initialization of membership functions, the training process is started. Ten iterations are considered for training process and at the end of last iteration, root mean square error is 0.0471. It is evident that, training data is well trained in the ANFIS controller. Fig. 6(a) shows the error plot for training process and fig. 6(b) shows the final rule base for the proposed PSO based ANFIS controller.

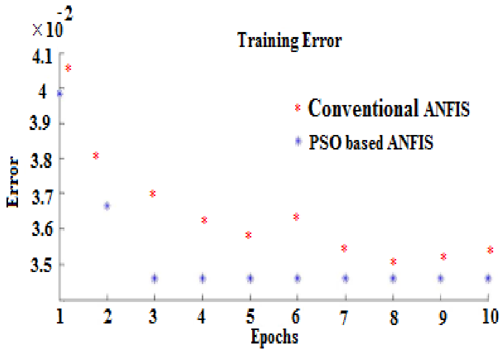

Figure.6 (a) Training error plot for the ANFIS controller

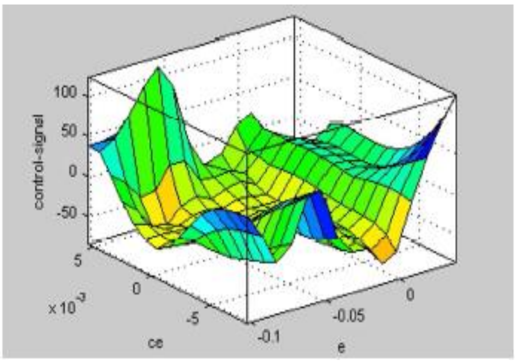

Fig.6 (b) Final rule base for the ANFIS Controller

After the completion of training process, ANFIS controller is ready for testing with training data and checking of data. The same size of testing and checking data were collected from the step reference input of the system. Examination of training data with test data and checking data are shown in fig. 6(c).

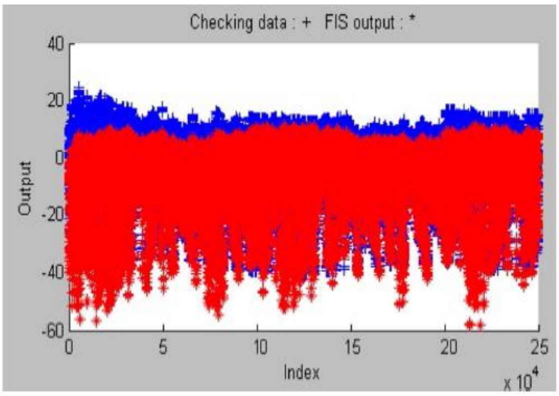

Fig. 6(c) Testing with checking data

7. Simulation Results and Discussion

Rotor position, error and torque characteristics of the brushless motor are measured and analyzed by using proposed and conventional ANFIS controller. The BLDC motor performance is obtained by simulation using MATLAB/SIMULINK 10. The ratings of the BLDC motor drive system are: Output Power-40 Watts, Current-2.5 Amps, Voltage-30 V DC, Speed-1500 rpm, Torque- 0.5 N-m.

Simulation results of rotor position response of BLDC motor using conventional ANFIS and PSO based ANFIS controllers are shown in fig. 7(a), and 7(b) respectively.

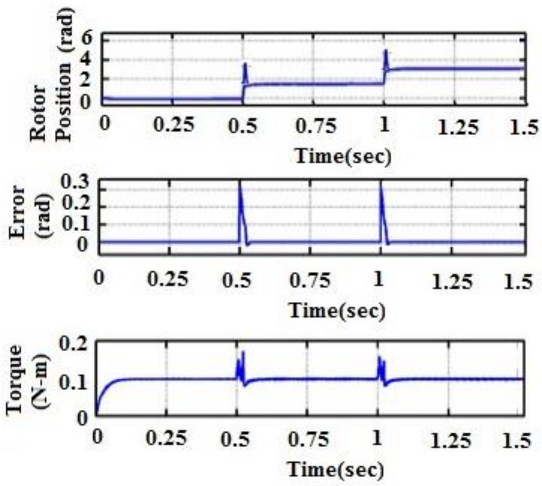

Figure 7(a). Response of the conventional ANFIS controlled BLDC motor

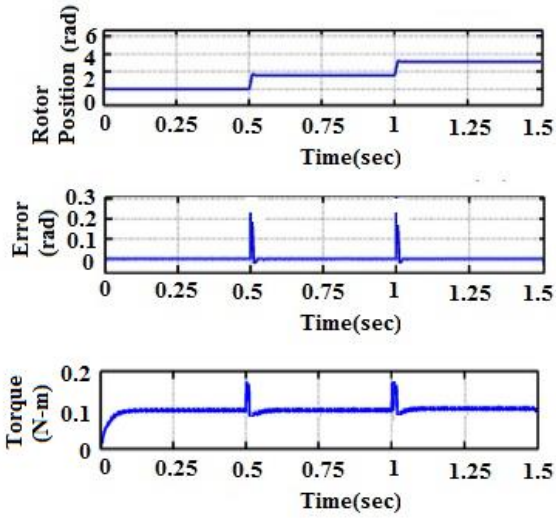

Figure 7(b). Response of the PSO based ANFIS controlled BLDC motor

Conventional ANFIS and PSO based ANFIS controllers has produced a steady error of 0.068 and 0.05 respectively. The torque generated by the PSO based ANFIS controller is very smooth and there are no oscillations when compared with conventional ANFIS controller. From the analysis with standard control system inputs, it has been proved that, the PSO based ANFIS controller has shown improved performance.

Table 1 provides the comparison of conventional and proposed PSO based ANFIS controllers and reveals that the performance of the proposed ANFIS controller is superior to that of the other controllers.

Table 1 Comparison of conventional and proposed ANFIS controller

S.No	Controllers	Settling Time (Sec)	Overshoot (%)	Steady State Error	Average Time		THD in Torque Waveform (%)
					Average Training Time (Sec)	Average Testing Time (Sec)	
1.	Fuzzy based PID ANFIS	0.1654	1.116	0.068	0.1739	0.1047	6.5
2.	PSO based ANFIS	0.0562	0.002	0.05	0.1638	0.0815	1.2

8. Conclusions

PSO trained ANFIS based rotor position controller has been proposed for BLDC motor. The excellence of the proposed controller has been observed and discussed through simulation results. The parameters of the brushless motor are measured and analyzed with the proposed PSO based ANFIS and conventional ANFIS controllers. By assessment of the dynamic response, it can be understood that, great reduction of torque ripple is obtained and the settling time, peak overshoot, steady state error and convergence time are reduced with the proposed rotor position controller. From the MATLAB simulation, the proposed controller clearly outperforms the other considered controllers.

References

1. Bhim Singh and Sanjeev Singh, “*State of the art on Permanent Magnet Brushless DC Motor Drives*” – Journal of Power Electronics, Vol. 9, No.1, January 2009.
2. N.Hemati, J. Thorp and M.C. Leu, “*Robust nonlinear control of brushless dc motors for direct drive robotic applications*,” IEEE Transactions on Industrial. Electronics, vol. 3, pp. 562-575, June 1990.
3. C. SheebaJoice, S. R. Paranjothi, and V. JawaharSenthil Kumar“, *Digital Control Strategy for Four Quadrant Operation of Three Phase BLDC Motor With Load Variations*”, IEEE Transctions on Industrial Informatics, vol. 9, no. 2, May 2013.

4. Alin ¸ Stirban, Ion Boldeaand Gheorghe-Daniel Andreescu, "*Motion-Sensorless Control of BLDC-PM Motor With Offline FEM-Information-Assisted Position and Speed Observer*", IEEE Transactions on Industry Applications, Vol. 48, No. 6, 2012.
5. Varatharaju, V.M., Mathur, B.L., and Udhyakumar, K. "*Speed control of PMBLDC motor using MATLAB/Simulink and effects of load and inertia changes*", Proc. of 2010 2nd International Conf. on Mechanical and Electrical Technology (ICMET), Singapore, pp. 543 – 548, Sept. 2010.
6. Fabrizio Padula, Antonio Visioli, *"Tuning rules for optimal PID and fractional-order PID controllers"* Journal of Process Control, Vol. 21, No. 1, pp. 69–81 , January 2011.
7. Vinod KR Singh Patel, A.K.Pandey. *Modeling and Performance Analysis of PID Controlled BLDC Motor and Different Schemes of PWM Controlled BLDC Motor*, International Journal of Scientific and Research Publications, Vol.3, No.4, pp.1-14, April 2013.
8. Mohamed S. Zaky, "*A self-tuning PI controller for the speed control of electrical motor drives*", Electric Power Systems Research, Vol. 119, pp. 293-303, February 2015.
9. AtefSaleh Othman Al-Mashakbeh," *Proportional Integral and Derivative Control of Brushless DC Motor*", European Journal of Scientific Research, Vol.35 No.2, pp.198-203,2009.
10. 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.
11. R. E. Precup, R. C. David, E. M. Petriu, M.B. Radac, S. Preitl, J. Fodor, "*Evolutionary optimization-based tuning of low-cost fuzzy controllers for servo systems*," Knowledge-Based Systems, vol. 38, pp. 74-84, 2013.
12. Mehmet Cunkas and, Omer Aydoğdu, "*Realization of Fuzzy Logic Controlled Brushless DC Motor Drives UsingMatlab/Simulink*", Mathematical and Computational Applications, Vol. 15, No. 2, pp. 218-229, 2010.
13. N.Senthil Kumar, C.Senthil Kumar, "*Design and Implementation of Adaptive Fuzzy Controller for Speed Control of Brushless DC Motors*", International Journal of Computer Applications, Vol. 1,no.27, pp. 36-41, 2010.
14. G. Cheng, "*Brushless DC Motor Speed Control System Based on Fuzzy PID Controller"*, Journal of Communications in Computer and Information Science, No.345, 287-294, 2012.
15. D. T. Pham and X. Liu, "*Identification of linear and nonlinear dynamic systems using recurrent neural networks*," Artificial Intelligent in Engineering, vol. 8, pp. 67–75, 1993.
16. Y. Gao and M. Joo, "*Online adaptive fuzzy neural identification and control of a class of MIMO nonlinear systems*," IEEE Transaction on Fuzzy System, Vol. 11, pp. 462–477, Aug. 2003.
17. Jian Sun, Yi Chai, Chunxiao Su, Zhiqin Zhu, XiankeLuo: "*BLDC motor speed control system fault diagnosis based on LRGF neural network and adaptive lifting scheme*", Applied Soft Computing, Vol.14, pp. 609-622, 2014.
18. M. Gokbulut, B.Dandil, C.Bal, "*A Hybrid Neuro-Fuzzy Controller for Brushless DC Motors*", Artificial Intelligence and Neural Networks, pp.125–132, 2006.
19. Ashok. Kusagur, S.F. Kodad, B V. Sankar Ram, "*Modeling, Design & Simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Speed Control of Induction Motor*", International Journal of Computer Applications, Vol. 6, pp. 29-44, 2010.
20. Sanju Saini and Arvind Kumar "*Speed Control of Separately Excited D.C Motor using Self Tuned ANFIS Techniques*" IJCST, Vol. 3, No. 1, Jan. - March 2012.
21. K. Premkumar, B.V. Manikandan, "*Adaptive Neuro-Fuzzy Inference System based speed controller for brushless DC motor*", Neurocomputing, Vol.38, pp. 260-270, 2014.
22. C.Navaneethakkannan, M.Sudha," *Analysis and Implementation of ANFIS-based Rotor Position Controller for BLDC Motors*", Journal of Power Electronics, vol.16,No.2, pp.564-571,March 2016
23. S. Nara, P. Khatri, and J. Garg, "*Proportional integral derative controller tuning of temperature control system using genetic algorithm*," International Journal of Electronics, Information and Systems, Vol. 12, No. 2, pp. 37–42, 2010.
24. S. Panda, B.K. Sahu, P.K. Mohanty *"Design and performance analysis of PID controller for an automatic voltage regulator system using simplified particle swarm optimization*" Journal of the Franklin Institute, Vol. 349, No. 8, pp. 2609–2625, October 2012.
25. Z. Cui and X. Gao, "*Theory and applications of swarm intelligence*", Neural Computing and Applications, Vol. 21, No. 2, pp. 205–206, 2012.
26. Juing-Shian Chiou, Shun-Hung Tsai, Ming-Tang Liu, "*A PSO-based adaptive fuzzy PID-controllers*", Simulation Modelling Practice and Theory, Vol. 26, pp. 49-59, August 2012.
27. Sakuntala Mahapatra, Raju Daniel, Deep Narayan Dey, Santanu Kumar Nayak,

"*Induction Motor Control Using PSO-ANFIS*", Procedia Computer Science, Vol. 48, pp. 753-768, 2015.