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Hybrid Adaptive Neuro Fuzzy based speed Controller for Brushless DC Motor

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Abstract

This paper presents a Hybrid Adaptive Neuro Fuzzy Control technique for speed control of BLDC motor drives. The proposed controller is an integration of adaptive neuro fuzzy, fuzzy PID and PD controllers. The objective is to utilize the best attribute of fuzzy PID and PD controllers, which exhibits a better response than the neuro fuzzy controllers. The error back propagation learning algorithm (EBPA) is used to train the data to minimize learning error. To validate the performance of proposed controller, simulations are done in MATLAB and comparison is made with PI, PD and fuzzy PID controllers. In addition, the performance of proposed controller is benchmarked with other controllers reported in the literature. The results of the proposed controller are promising in terms of quick settling time, zero peak overshoot and zero steady state error.

1. INTRODUCTION

The Brushless DC (BLDC) Motor is a permanent magnet synchronous motor (PMSM) with trapezoidal Back EMF, and requires no mechanical commutators. It would have certain advantages like high efficiency, high power density, required torque, speed characteristics, and easier control [1-3]. Speed control of BLDC motor drives is a key topic in the field of the control theory. Ziegler- Nichols [4] first implemented the PI/PID controller tuning. The conventional controllers like proportional Integral controller (PI), Proportional Derivative/Proportional Integral Derivative controller (PD/PID) are widely used in electrical applications, chemical processes and various industrial control applications, etc., over a few decades because of their simple design, acceptable control effect and robustness.

In [5-10], discussed the different types of PI controllers like anti-windup PI, self-tuned, offline, gain scheduled PI Controllers to control the speed in the Motors. But these controllers have a certain disadvantages like larger rise time, settling time and more oscillations in steady state. The optimal PI controller gains are obtained in [11-13] using neural networks, algorithms like Practical Swarm Optimization (PSO) and Bacterial Forging (BF) optimization to achieve the optimal performances. The drawbacks of these methods are larger steady state error under sudden load disturbances. The phase locked loop (PLL) assisted internal model (IM) controller to control the speed of BLDC motors is proposed in [14]. This controller has an adjustable speed module structure and integrated with IM control strategy. The conventional controllers are not quite suitable for the drives, which exhibit parameters uncertainty and un-modelled dynamics.

To improve the performance in industrial applications the researchers found out fuzzy logic controllers to be more suitable. In [15] a fuzzy logic controller for achieving improved speed performance of a BLDC servo motor drive is made. In this fuzzy logic controller is implemented in the digital form. The presented controller is effective in dealing with uncertainties and parameter variations when compared with normal PID controllers. In [16], to improve the fuzzy controller performance researches done the optimization of the fuzzy membership functions. The advantages of optimal FLC controller are that it avoids trial and error method for obtaining the membership function.

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In [17] the extended kalman filter (EKF) filter to control the speed of BLDC motor. Here EKF is employed to find the state variables by using stator line voltages and currents. The EKF is used to estimate the speed of BLDC motor in both steady state and dynamic conditions. In [18-22] developed the different types of fuzzy PID controllers, in [23-26] describes the optimal Fuzzy PID controllers and in [26-28] developed the fractional order fuzzy PID controllers to achieve the optimal performances. The extension of the fuzzy PID controller are neural network is used to train the fuzzy outputs. In [29] dealt about the PI/PD fuzzy neural network controller based on EKF to control BLDC motor drives. In the controller, EKF is used to train the fuzzy neural network type PI/PD controller. The fuzzy neural network has two parallel PI/PD controllers with four internal layers.

A prominent technique called adaptive neuro fuzzy controller is used in various applications. Some of the important applications are maximum power extraction and inertia control of wind turbines [30] & [31], estimation of mechanical properties for conductive silicone rubber [32], control of robotic gripper [33], human musculoskeletal arm [34], antilock braking system [35], underwater vehicles [36], control of non linear industrial process and batch process [37] & [38], estimation of system forecasting [39], estimation of open lens system parameters [40]. For electrical applications, adaptive neuro fuzzy system is used to control the speed of electrical motors. In [41] the adaptive neuro fuzzy controller to control the speed in permanent magnet excitation transverse flux linear motor. This controller has two fuzzy inputs and one fuzzy output. The scaling factors of the fuzzy logic controller are trained by artificial neural network.

In [42], a technique for speed control of BLDC motor using the adaptive neuro fuzzy interface methodology. The error and change in error are inputs and controller output data is used to train the adaptive neuro fuzzy system. This adaptive neuro fuzzy controller gives better performance under different load conditions.

In [43] a fuzzy PID supervised ANFIS controller to control the speed of BLDC motor. The Recursive least square back propagation algorithm is used to train the neuro fuzzy system. As we observe the above literature the existing controllers having disadvantages like more settling time, steady state errors and undesired response under varying load conditions. So we proposed a controller to improve the further better settling time, desired response when load varying conditions and zero steady state errors.

In this article, a hybrid adaptive neuro fuzzy controller is proposed to control the speed of the brushless DC motor. The proposed controller is a combination of adaptive neuro fuzzy, fuzzy PID and PD controller. The training data of proposed controller is taken from the input, error and output data of fuzzy PID plus PD controller. The block diagrams of the existing adaptive neuro fuzzy controller are shown in Fig. 1.The organization of the paper is as follows. Section 1 deals the Introduction of the paper. Section 2 describes mathematical modeling and methodology for speed control of brushless DC motor. Section 3 explains the design of proposed controller. Section 4 gives the results and discussions. Finally, the conclusions of proposed controller are discussed in section 5.

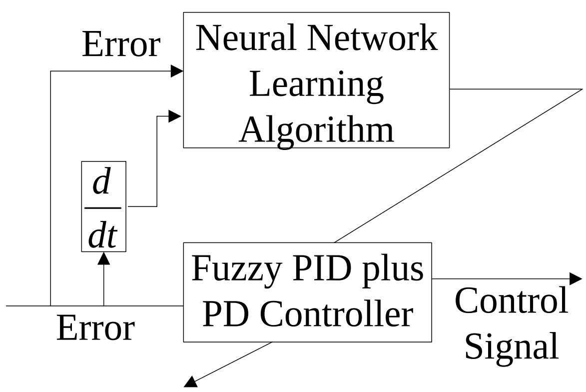

Figure 1. *Block diagram of adaptive neuro fuzzy Controller*

2. METHODOLOGY TO CONTROL THE SPEED OF BLDC MOTOR

The merits of the BLDC motor, when compared to the DC motor, have higher reliability, lower electromagnetic interference (EMI) and lower maintenance costs [1] & [2]. The various fields of applications of BLDC Motor are aerospace applications, domestic applications, industrial automation sector, medical, textile industry and digital control machine tools. Generally, the BLDC Motor consists of three stator windings and permanent magnets on the rotor. BLDC Motor is stated as the trapezoidal back EMF permanent magnet synchronous motor [3], [15] & [44]. The line to line voltage equations is expressed in Eq. (1).

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \begin{bmatrix} \frac{di_a}{dt} \\ \frac{di_b}{dt} \\ \frac{di_c}{dt} \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \quad (1)$$

Where, V_a, V_b, V_c represents the phase voltages of BLDC Motor in Volts,

R represents the resistance of stator Windings in ohms,

i_a, i_b, i_c represents phase currents of the motor in amperes,

L represents the Self Inductance in Henry,

M represents the mutual inductance.

e_a, e_b, e_c denotes the trapezoidal back EMF of each phase in volts.

The electromechanical torque of the BLDC motor is given in Eq.(2)

$$T_a = \frac{(e_a i_a + e_b i_c + e_c i_c)}{w_1}, w_1 = \frac{d\theta_r}{dt} \quad (2)$$

The terms w_1, θ_r represents the rotor position, angular velocity (rad/s). The electromagnetic torque is utilized to overcome the opposing torques of inertia and load, it can be expressed as Eq. (3).

$$T_a = T_L + J_n \frac{dw}{dt} + B_n w_1; w_e = \frac{p}{2} * w_1 \quad (3)$$

Then the terms T_L represents load torque (NM/A), J_n is Momentum of Inertia (J or kg/m^2), B_n indicates Friction coefficient, w_e are rotor frequency and p represents the number of poles in the rotor. To analyze and verify the performance of the proposed controller architecture, simulations were performed in MATLAB/Simulink. The basic building blocks of closed loop control system for this article are BLDC motor**,** DC power supply, three-phase voltage inverter, three phase V-I Measurement block and switching logic circuits**.** The reference signal speed 1200 rpm is given as input signal and output speed signal of the BLDC Motor is given to the proposed controller as feedback. The switching logic is developed by using three hall signals H_1, H_2, H_3, and controller signal, switching logic is given as gating signal to three phase voltage inverter. The Fig.2 shows the Simulink diagram for speed control of BLDC Motor.

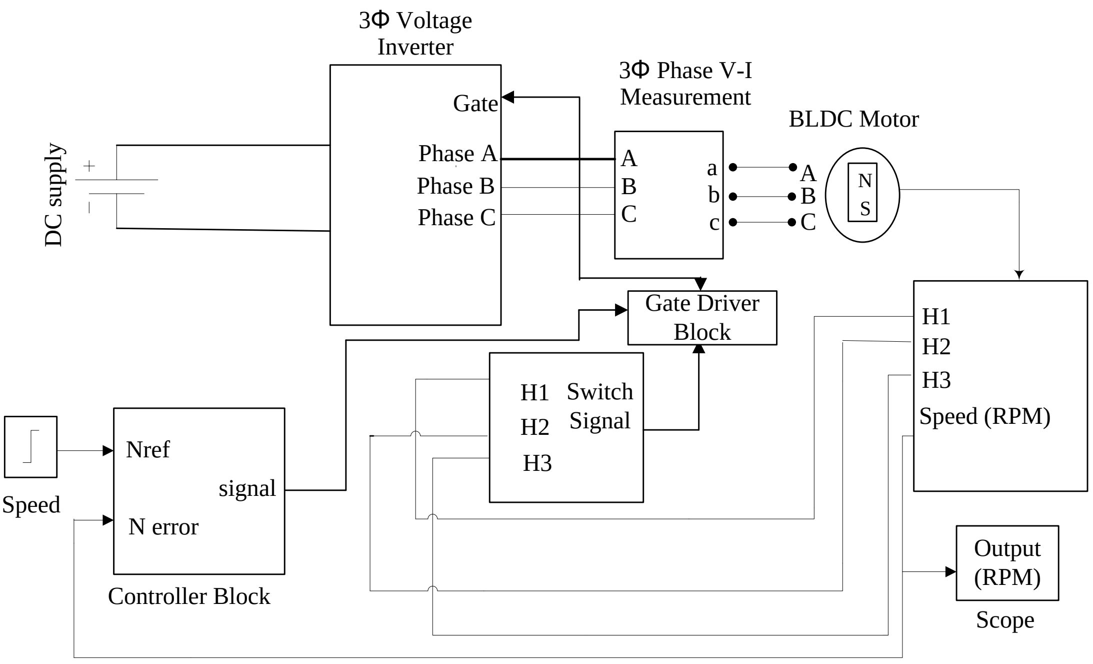

Figure 2. *Simulink Model diagram of Speed Control of BLDC Motor*

3. PROPOSED CONTROLLER FOR SPEED CONTROL OF BLDC MOTOR

The proposed controller for speed control of BLDC Motor is given by the integration of adaptive neuro fuzzy controller, fuzzy PID and PD controller. Initially, the fuzzy PID controller was tuned by using the error signal. The output and input data of fuzzy PID and PD is taken to train the adaptive neuro fuzzy interface system (ANFIS) to tune the adaptive neuro fuzzy controller. Finally, the outputs of the ANFIS, fuzzy PID controller, and PD controller are added parallel named as hybrid adaptive neuro fuzzy controller. The Fig.3 shows the block diagram of the proposed controller.

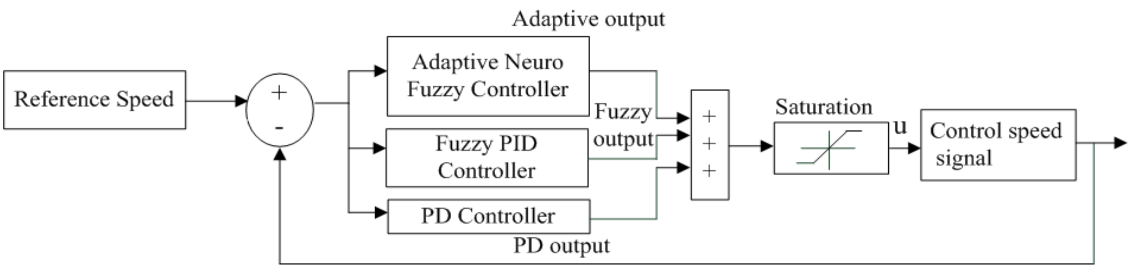

Figure 3. *Block Diagram of the proposed hybrid adaptive neuro fuzzy controller*

The main advantage of the fuzzy inference system is, it controls the complex systems, nonlinear systems, and the time varying dynamic processes systems in several industrial control loops. It can be used as the online gain tuner for developing the fuzzy PID controller. The fuzzy PI and fuzzy PD controller are combined to form fuzzy PID controller [20]. As shown in the Fig.3, a PD controller runs parallel to fuzzy PID controller and adaptive neuro fuzzy controller.

3.1 Adaptive neuro fuzzy Controller

The adaptive neuro fuzzy controller is a combination of artificial neural network with fuzzy interface system. The Takagi- Sugeno model is used in this proposed work [45]. ANFIS is a very good learning technique to take over an issue on uncertainties in any system. This controller is based on constructing a set of fuzzy IF-Then rules with an appropriate membership function to generate the specify input- outputs.

The ANFIS is a taking a Fuzzy Inference System (FIS) and tuning with back propagation algorithm based on the collection of output and input data. The components of ANFIS are first is rule base, the second one is data base which is membership functions. The Third one is reasoning mechanism, which gives the reasonable output [30] & [32-33].

Consider the set of fuzzy rules

Let R_j = If x_1 is $A_1(x_1)$ and x_2 is $A_{2j}(x_2)$ and .... x_n is A_{nj} (x_n) THEN y is c_j

Where x_1 = change in error given as $w_{ref} - w_{r.}$

x_2 = derivative of change in error given as $d(w_{ref} - w_r)/dt$.

y = output given as $P_i x_1 + R_i x_2 + S_i$

$A_1(x_1)$ and A_{nj} (x_n)......... A_{nj} (x_n) are input linguistic labels and c_j is constant consequent labels.

In TS Fuzzy model, the inference procedure used to find the conclusion for input X consists of the two main steps.

The weight of w_j each rule is calculated as

$$w_j = \prod_{i=1}^{n} \mu_{ij}(x_i^0) \tag{4}$$

The output inference result y is obtained by means of the weighted average of the consequents

$$y = \frac{\sum_{j=1}^{m} w_j c_j}{\sum_{j=1}^{m} w_j} \tag{5}$$

Eq.(4) and (5) provides the complete representation of the inference model.

The Architecture of ANFIS network consists of different types of inference models as adaptive networks. The adaptive network consists of following layers as shown in Fig. 4.

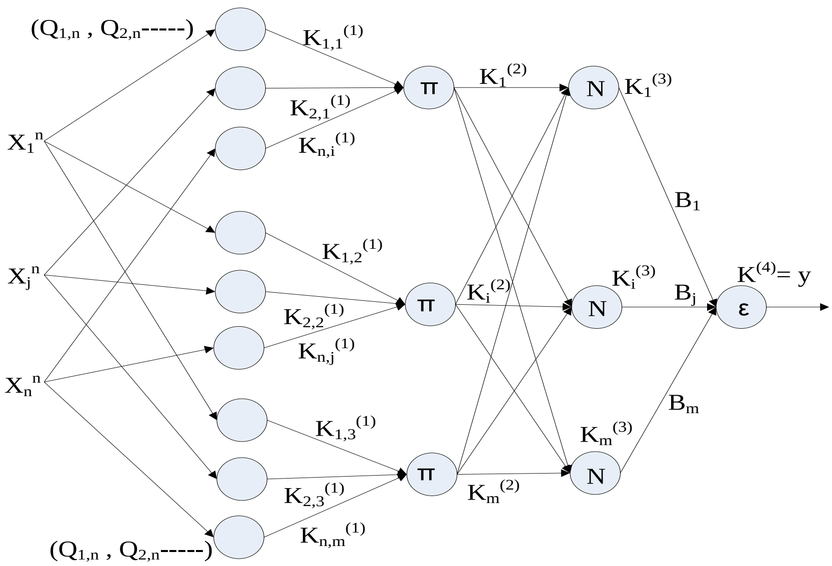

Figure 4. *Architecture of an n – input adaptive neuro fuzzy controller*

The layer 1 having m groups and having n nodes of each one. Every single node generates output $k_{ij}^{(1)}$ by solving each membership function.

$$k_{ij}^{(1)} = \mu_{ij}(x_i^0) = f(x_i^0; p_{1ij}, p_{2j}.....) \tag{6}$$

The layer 2 having m nodes with outputs $k_j^{(2)}$ node j in this layer generates the strength the j^{th} rule by solving the algebraic product of all inputs.

$$k_j^{(2)} = \prod_{i=1}^{n} k_{ij}^{(1)} = w_j \tag{7}$$

The layer 3 consists of an m – nodes normalization layer. The output of the j^{th} node $k_j^{(3)}$ is the ratio of the j^{th} rules of weight to the sum of the all the rules.

$$k_j^{(3)} = \frac{w_j}{\sum_{j=1}^{m} w_j} \tag{8}$$

The layer 4 consists of only one node. The node output $k_j^{(4)}$ is the sum of the weighted consequents. This node is an adaptive node whose parameters c_j, are the set of consequent parameters.

$$k_j^{(4)} = \sum_{j=1}^{m} k_j^{(3)} c_j = y \tag{9}$$

Adaptive neuro fuzzy constructs a fuzzy interface system FIS whose membership function values are tuned using EBPA.

3.1.1 Learning Algorithm: Error Back Propagation Algorithm (EBPA)

In this proposed controller, the neuro fuzzy interface system was trained by using the error backpropagation learning algorithm. In this method weight updating is mostly performed based on gradient descent method [46] & [47]. The standard back propagation learning algorithm is given by

$$\Delta W_{p,ij}^{i,(i+1)} = \alpha \frac{\partial E_p}{\partial W_{p,ij}^{I,(i+1)}} \quad . \tag{10}$$

$$\Delta b_{p,i}^{l} = -\alpha \frac{\partial E_p}{\partial b_{p,i}^{l}} \tag{11}$$

Where W_{ij} is the weights between i^{th} and j^{th} neuron of two connected neurons of two connected layers. The b_i and α represents the bias of neuron and learning rate. The notation p is the weight and biases of each input learning pattern.

Training of weights (E_p)is given by the following eq. (12)

$$E_p = \sum_{k=1}^{nl} (t_{p,k} - o_{p,k})^2 \tag{12}$$

The training is continued up to the sum of squares for all the input pattern (E), reached to the minimum value given in eq. (13)

$$E = \sum_{p=1}^{p} \sum_{k=1}^{N1_l} (t_{p,k} - o_{p,k})^2 \tag{13}$$

Where $t_{p,k}$ is defined as desired target. $o_{p,k}$ defined as network output of K^{th} neuron for input pattern respectively. The N_l is the number of neurons in layer L. Adaptive neuro fuzzy constructs a fuzzy interface system FIS whose membership function values are tuned using EBPA. For the proposed controller the data of error and change error of fuzzy PID plus PD controller data set is used it having the 4000 sets are present. The linear equation of the data sets to train the adaptive neuro fuzzy is given in eq. (14).

$$y = 2E + 0.7x - 5E + 09 \tag{14}$$

The grid partition method is used to generate the adaptive fuzzy controller. The 3 input and 3 output member functions are taken to generate the controller. The Fig.5 and Fig.6 show the input and train data for adaptive neuro fuzzy controller.

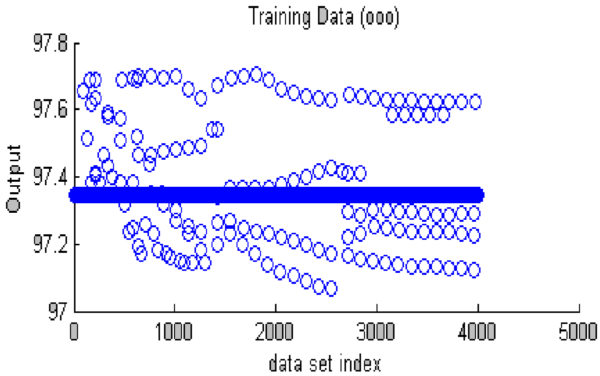

Figure 5. *Training Dataset of adaptive neuro fuzzy controller*

The Structure of adaptive fuzzy controller, generated by the MATLAB code is a five layer network as shown in Fig. 7. It has two inputs given as error and change in error, one output, three membership functions for each. The training error of the proposed controller is shown in Fig 8.

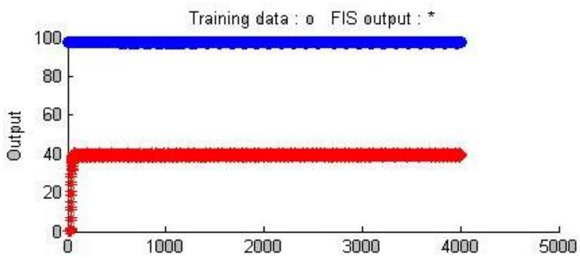

Figure 6. *Adaptive neuro fuzzy output data*

The membership functions for each input, which is trained by the grid partition method as shown in Fig.9. The Fig.10 shows the output of fuzzy rule for a specific value of error and change in error. The adaptive neuro fuzzy controller generated for Fuzzy PID plus PD Controller surface, 3–dimensional plot between two inputs error and change in error and output is shown in Fig.11

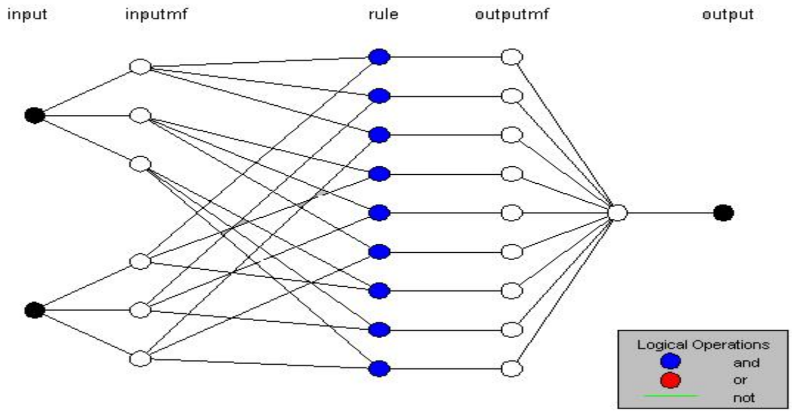

Figure 7. *Structure for adaptive neuro fuzzy controller*

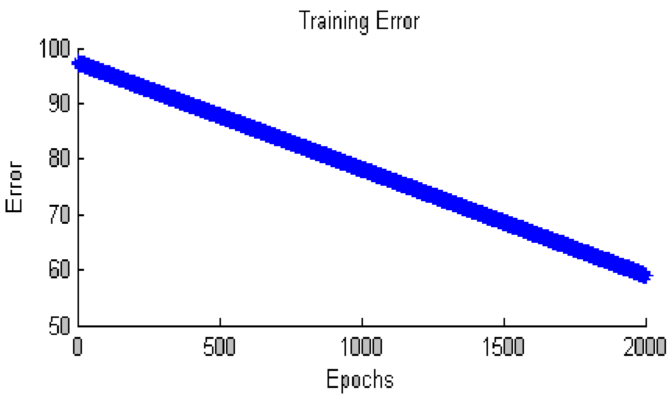

Figure 8. *Training error Plot*

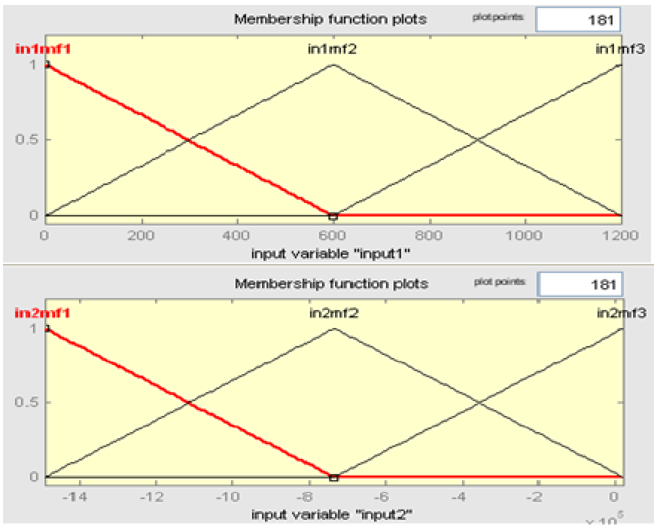

Figure 9. *Input Membership Functions*

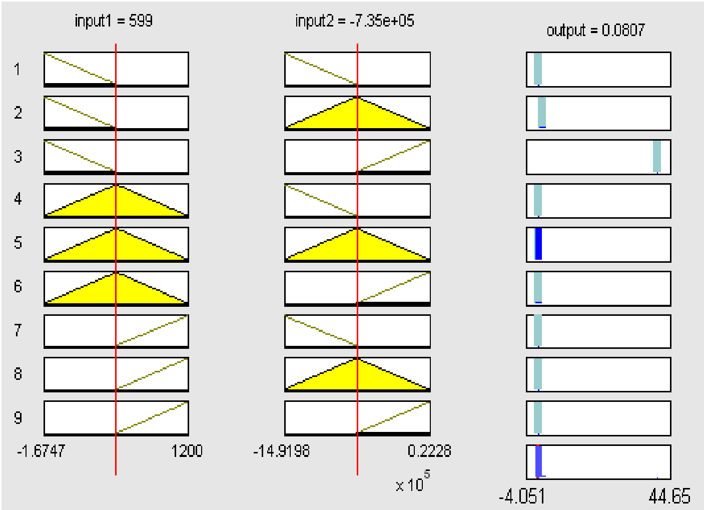

Figure 10. *Adaptive neuro fuzzy controller rules*

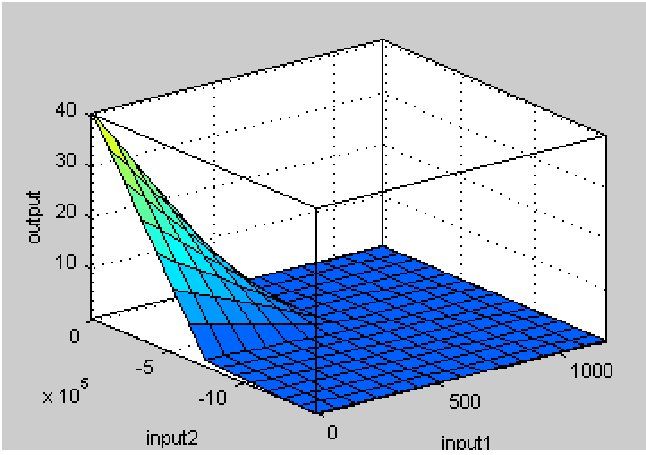

Figure 11. *Surface plot between two inputs and one output.*

3.2 Fuzzy PID Controller

The fuzzy systems are universal approximators. Fuzzy systems are used in situations involving highly complex systems, and for the system, whose behaviour is not clean [18] &, [21]. Both inputs and outputs have 7 triangular membership functions. The input range for both inputs and outputs is between [0.5 to 0.5].The distribution of the membership functions has even functions**,** negative big, negative medium, negative small, zero, positive small, positive medium and positive big. The distribution of the membership functions as shown in the Fig. 12. The defuzzification of these fuzzy sets is given by the centroid method. The centroid method is also called as the centre of area or the centre of gravity. The formula governing the defuzzification is represented in Eq.(11).

$$z = \frac{\int V_c(z)dz}{\int V_c(z)dz} \qquad (11)$$

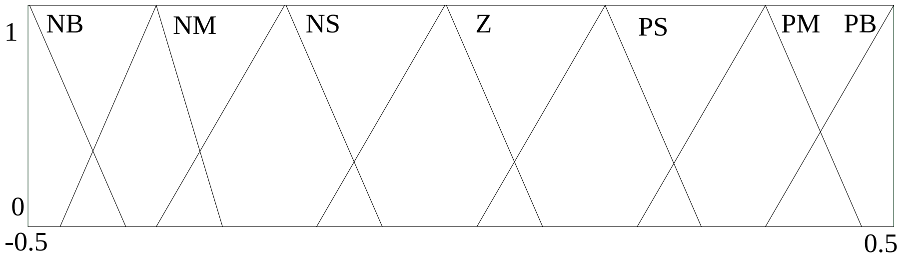

Figure 12. *Membership functions of inputs and outputs for Fuzzy PID Controller*

4. RESULTS AND DISCUSSIONS

Speed response of the BLDC motor is analyzed under the constant speed, varying speed, set point tracking. The control system parameters such as rise time, peak time, settling time, steady state error, peak overshoot, integral absolute error, are used to compare the speed response of a proposed controller with fuzzy PID controller and PI controller. The specifications of the BLDC motor are shown in Table.1

Table.1. *Specifications of BLDC Motor*

Specifications	Value
Rated Voltage (V)	500
Rated Current (A)	8
Rated Speed (rpm)	1200
Stator phase Resistance, R (Ω)	14.56
Stator phase Inductance, I (H)	0.0025
Flux Linkage Established in Magnets (V.s)	0.106
Voltage Constant (V/rpm)	146.6
Torque Constant (N.M/A)	0.74
Back EMF flat Area (Degrees)	120
Moment of Inertia (J(kg/m^2)	0.0008
Friction factor (N m/(rad/s))	0.001
Pole Pairs	4

The Fig.13(a) and Fig.13(b) shows simulation results of the phase voltages with phase different of 120^0 and phase currents having 3.7 Amp of BLDC motor.

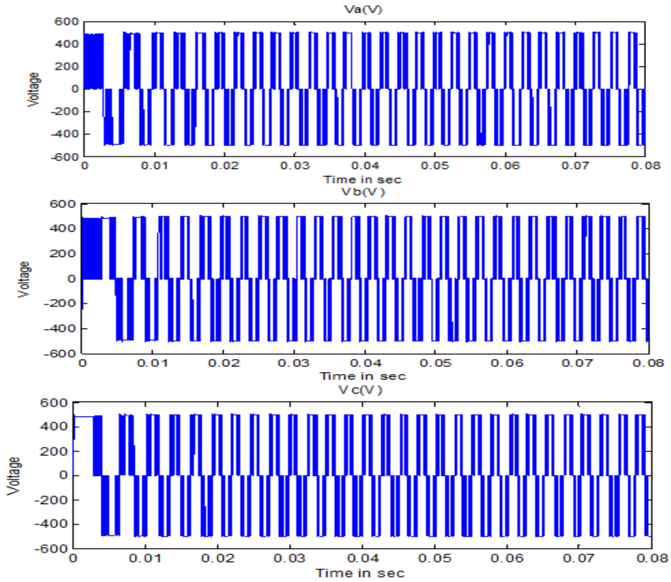

Figure 13 (a). *Phase voltage waveforms*

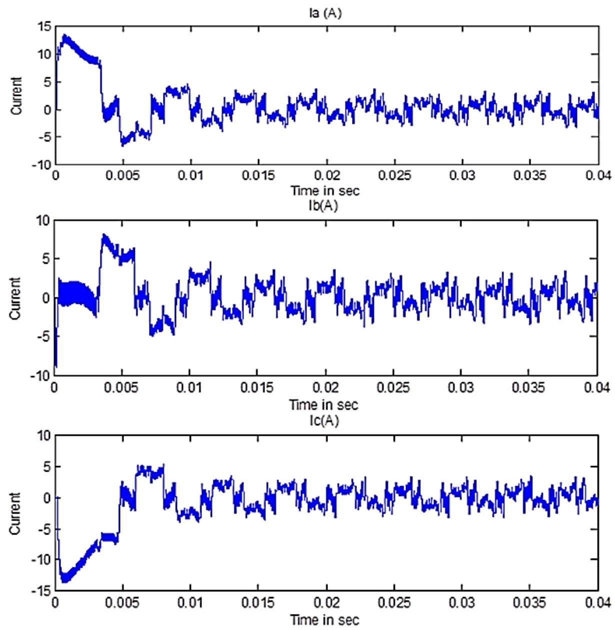

Figure13 (b). *Phase current waveforms*

4.1 Result for Constant speed condition at 1200 RPM under constant load condition 20 Nm

The simulation results for speed control of Brushless DC motor at constant speed condition with constant load condition 20 Nm are shown in Fig .14. The set point of the speed is 1200 RPM. The time domain specifications of the output response are shown in Table 2 as Case .A. The steady state error of PI, Fuzzy PID is 0 and 0.2. The steady state error of proposed Hybrid adaptive neuro fuzzy controller is zero. The settling time for PI and fuzzy PID are 0.07sec, 0.052 sec.The settling time for proposed controller is 0.0045sec. The Integral absolute error (IAE) for PI, Fuzzy PID and proposed adaptive neuro fuzzy controller is 8.127, 5.8521 and 0.70 respectively. The peak over shoot of the PI controller is 1345 rpm, but the fuzzy PID and the proposed hybrid adaptive neuro fuzzy controller exhibits zero overshoot. As in Fig.14, the PI controller fluctuates more while compared with proposed controller The time specifications of the system is better for the proposed hybrid adaptive neuro fuzzy controller.

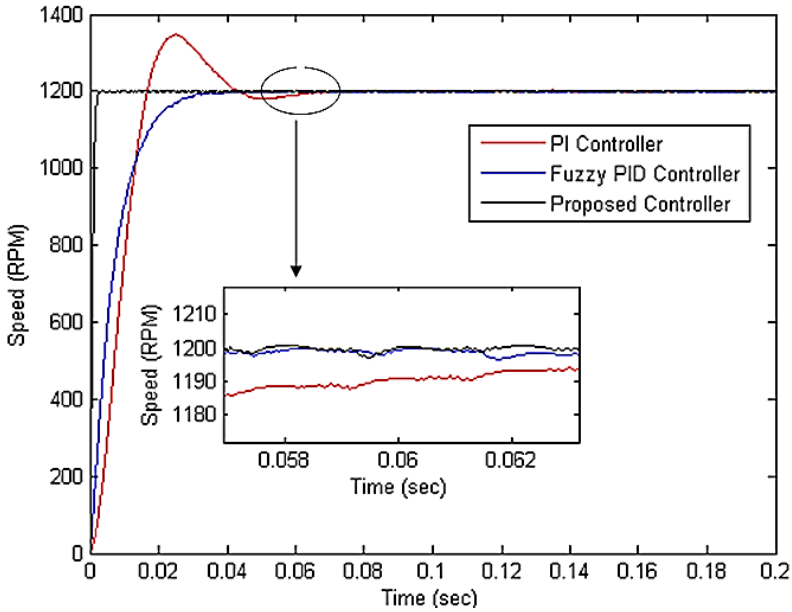

Figure 14. *Performance of Controllers at constant load condition, 20NM*

4.2 Result for Speed at 1200 RPM under varying load condition 1NM to 20NM

The simulation results for speed control of BLDC motor at constant speed condition with varying load condition 1Nm to 20Nm are shown in Fig.15. The set point of the speed is 1200 RPM. The time domain specifications of the output response are shown in Table 2 as Case B. The steady state error of PI and Fuzzy PID are 0, 0.2.

Table 2. *Comparisons of controllers under constant load condition 20 Nm and varying load 1Nm to 20 Nm Condition*

Type of Controller		Control system Parameters						
		Rise Time(t_r) Sec	Peak Time(t_p) Sec	Peak Value (RPM)	Peak Overshoot (%)	Settling Time (t_s) Sec	SteadyState Error (RPM)	IAE
PI	Case A (constant load)	0.015	0.025	1345	12	0.07	0	8.127
	Case B (Varying load)	0.165	0.025	1345	12	0.075	0	8.61
Fuzzy PID	Case A	0.016	-	-	-	0.052	0.2	5.852
	Case B	0.016	-	-	-	0.06	0.2	6.23
Proposed Controller	Case A	0.0015	-	-	-	0.0045	-	0.70
	Case B	0.0018	-	-	-	0.0045	-	1.126

The steady state error of proposed adaptive neuro fuzzy controller is zero. The settling time for PI, fuzzy PID controllers are 0.075sec and 0.06sec respectively. The settling time for proposed controller is 0.0045sec. The Integral absolute error (IAE) for PI, Fuzzy PID and proposed adaptive neuro fuzzy controller is 8.61, 5.862 and 1.126 respectively. By observing the time domain specifications the proposed controller gives the better response for speed control of BLDC motor. As found in the Fig. 15, the proposed controller has little fluctuations when compared to the other controllers. The steady state error is zero.

4.3 Result for setpoint speed at 1200 RPM to 600 RPM under constant load condition 20 Nm

The simulation results for speed control of BLDC motor under varying speed condition under load condition are shown in Fig.16. The set point tracking of the speed is varied between 1200 RPM to 600 RPM at 20 Nm. The time domain specifications of the output response are shown in Table 3. The steady state error of PI, Fuzzy PID controllers is 0 and 0.7 respectively. The steady state error of proposed adaptive neuro fuzzy controller is 0. The recovery time for PI and Fuzzy PID are 0.22sec and 0.2sec. The recovery time for proposed controller is 0.145sec. The Integral absolute error (IAE) for PI, fuzzy PID and adaptive neuro fuzzy controller is 18.94, 13.35 and 2.211 respectively. The peak overshoot for PI, fuzzy PID and proposed adaptive neuro fuzzy controller is 16.6, 0 and 0 respectively. By observing the time domain specifications, the proposed controller tackles the setpoint better while compared with other controllers.

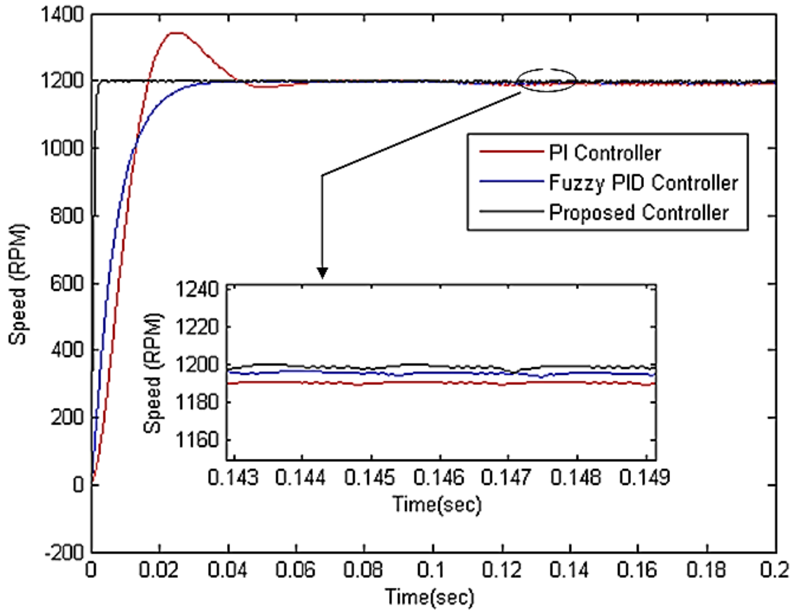

Figure 15. *Speed Response for different conditions under varying load conditions*

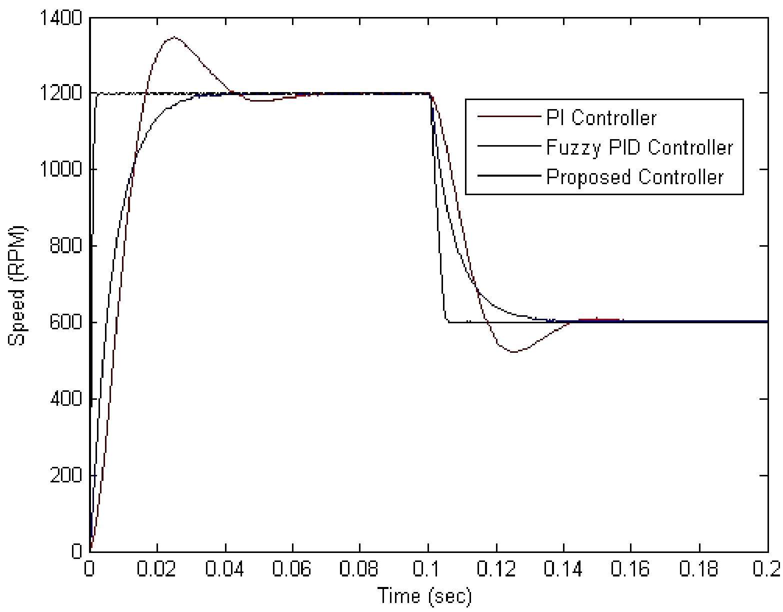

Figure 16. *Speed Response varying speed condition under load condition 20 Nm*

As seen in the Fig. 16, the proposed controller gives the very less oscillations under varying speed conditions. The proposed hybrid adaptive neuro fuzzy controller has zero steady state error.

Table 3. *Comparisons of controllers under constant load condition 20 Nm with Speed Variation 1200 RPM to 600 RPM*

Type of Controller	Control system Parameters			
	Peak Overshoot	Recovery time (sec)	Steady state Error	IAE
PI Controller	16.6	0.22	-	18.9
Fuzzy PID Controller	-	0.2	0.7	13.35
Proposed Controller	-	0.145	-	2.211

Fig.17. Shows set point response for the proposed controller under no load condition. It shows the proposed controller settles in a very low time than the other existing controllers. Also it is observed that, the proposed hybrid adaptive neuro fuzzy controller takes less control energy than PI and Fuzzy PID controllers for all cases.

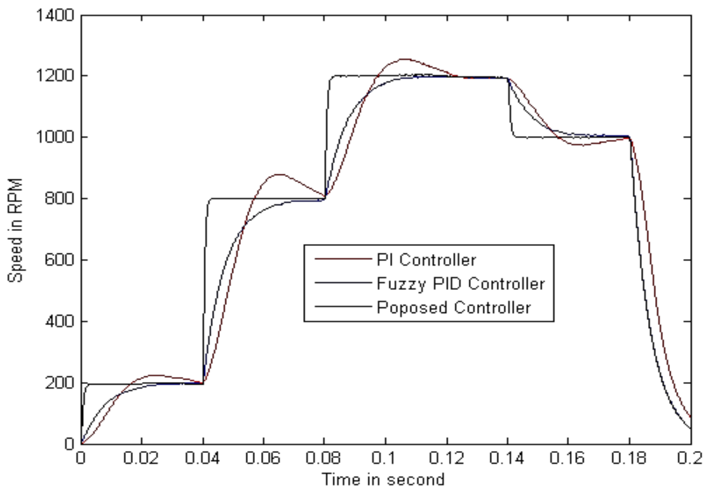

Figure 17. *Comparison of controllers performance at no load condition*

Table 4. *BLDC Motor specifications of Ref-[26], [42] & [43]*

Sl. No	**Motor Parameters**	**Ref-[26]**	**Ref-[42]&[43]**
1.	Rated Voltage (V)	24	470
2.	Rated Current (A)	7	50
3.	Rated Speed (rpm)	4000	1500
4.	Stator phase Resistance, R (Ω)	1.4	3
5.	Stator phase Inductance , I (H)	0.0066	0.001
6.	Flux Linkage Established in Magnets (V.s)	-	0.175
7.	Voltage Constant (V/rpm)	0.1546	0.1466
8.	Torque Constant (N.M/A)	0.02	0.74
9.	Moment of Inertia (J(kg/m^2))	0.00176	0.0008
10.	Friction factor (N m/(rad/s))	0.0003816	0.001
11.	Pole Pairs	4	4

To validate the proposed controller method, we compared with the other existing controllers presented in the literature. The motor specifications of ref [26], [42] and [43], were tabulated in Table.4. In [26], the motor specifications are vector control on a 24 V, 100 W, 7 A, rated speed is 4000 rpm and torque load is 0.02 Nm. Using these motor specifications the proposed controller is simulated and plotted the output shown in Fig 18. Table. 5 shows a comparison of settling time with other techniques available in the literature. The motor parameters specified in the cited literature were used in the proposed controller. In [26] results, hybrid fuzzy PI controller settling time is 0.19 sec. The proposed controller settles at 0.06 sec. Using these motor specifications the proposed controller is simulated and output is shown in Fig 19. From the Table.5, in [42] ANFIS controller settles at 0.0611sec. In [43] ANFIS supervised controller settles a 0.036 sec. The proposed hybrid neuro fuzzy controller gives better settling time i.e 0.02 sec than above existing controllers.

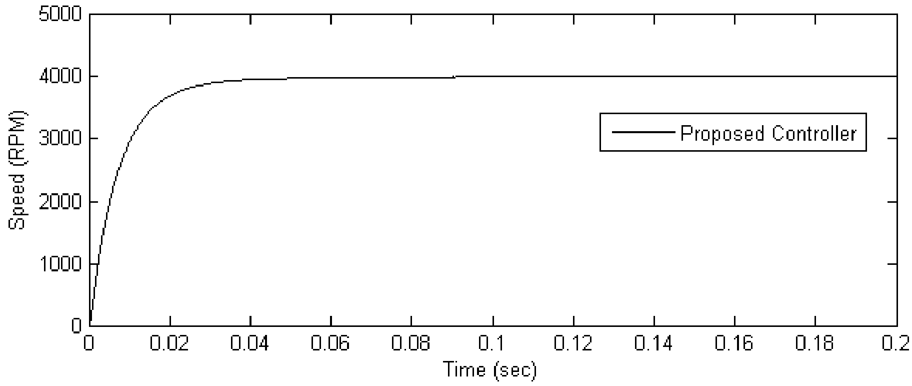

***Figure 18.** Output of proposed controller for motor specifications in [26]*

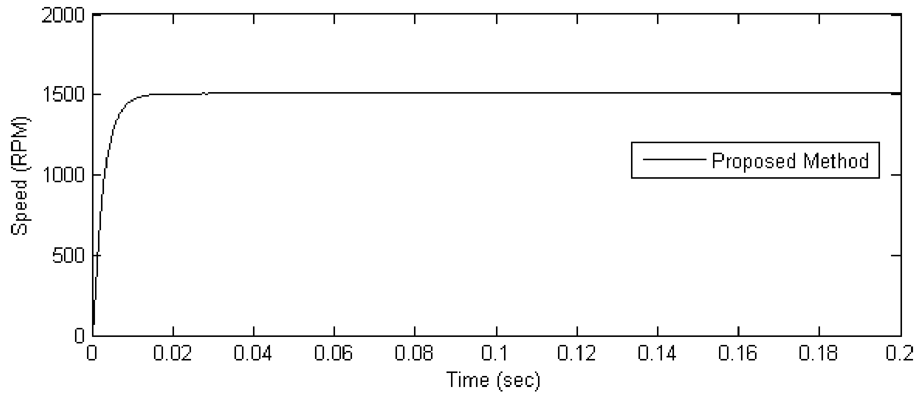

***Figure 19**. Output of proposed controller for motor specifications in [42, 43]*

***Table 5.** Comparison of settling time between proposed Controller with other existing speed Controllers.*

S.No.	**Type of Controller**	**Reference Article**	**Settling Time (sec)**	
			Reference Article	**Proposed Method**
1.	Hybrid Fuzzy-PI Controller	[26]	0.19	0.06
2.	ANFIS Controller	[42]	0.0611	0.02
3.	Fuzzy PID Supervised online ANFIS Controller	[43]	0.036	0.02

5. CONCLUSIONS

The adaptive neuro fuzzy controller is trained and tuned in such a way that it suits for the speed control of the BLDC motor drives. It exposes prominent and satisfactory responses under various operating conditions. Simulation results are shown to demonstrate the performance of BLDC motor drive. The proposed controller gives good performance in comparison with classical controllers under different operating conditions like set point speed tracking, change in phase resistance, full load, no load, and varying load conditions. Further, it can be noticed that the proposed controller settles very faster, at 0.0045 secs with negligible steady state error, better rise time and very low integral absolute error compared to the traditional controllers.

CONFLICT OF INTEREST

No conflict of interest was declared by the authors

REFERENCES

[1] Ozturk, SalihBaris, and Hamid A. Toliyat. "Direct torque and indirect flux control of brushless DC motor." IEEE-ASME T Mech, 16.2 (2011) 351-360.

[2] Lai, Yen-Shin, and Yong-Kai Lin. "A unified approach to zero-crossing point detection of back EMF for brushless DC motor drives without current and hall sensors." IEEE T Power Electr. 26.6 (2011) 1704-1713.

[3] Pillay, Pragasen, and Ramu Krishnan. "Modeling, simulation, and analysis of permanent-magnet motor drives: The permanent-magnet synchronous motor drive." IEEE T Ind Appl. 25.2 (1989) 265-273.

[4] Ziegler, John G., and Nathaniel B. Nichols. "Optimum settings for automatic controllers." trans. ASME. 64.11 (1942).

[5] Shyam, Arundhathi, and Febin JL Daya. "A comparative study on the speed response of BLDC motor using conventional PI controller, anti-windup PI controller and fuzzy controller", Control Communication and Computing (ICCC), 2013 International Conference on. IEEE, 2013.

[6] Shin, Hwi-Beom. "New antiwindup PI controller for variable-speed motor drives", IEEE T Ind Electron. 45.3(1998) 445-450.

[7] Choi, Jong-Woo, and Sang-Cheol Lee. "Antiwindup strategy for PI-type speed controller", IEEE T Ind Electron. 56.6 (2009) 2039-2046.

[8] Demirtas, Metin. "Off-line tuning of a PI speed controller for a permanent magnet brushless DC motor using DSP", Energ Convers Manage. 52.1 (2011) 264-273.

[9] Panda, Sanjib K., et al. "Gain-scheduled PI speed controller for PMSM drive." Industrial Electronics, Control and Instrumentation, 1997.IECON 97.23rd International Conference on.Vol. 2.IEEE, 1997.

[10] Zaky, Mohamed S. "A self-tuning PI controller for the speed control of electrical motor drives", Electr Pow Syst Res 119 (2015) 293-303.

[11] Niapour, SA KH Mozaffari, et al. "Brushless DC motor drives supplied by PV power system based on Z-source inverter and FL-IC MPPT controller", Energ Convers Manage.52.8 (2011) 3043-3059.

[12] Ibrahim, H. E. A., F. N. Hassan, and Anas O. Shomer. "Optimal PID control of a brushless DC motor using PSO and BF techniques." Ain Shams Engineering Journal 5.2 (2014) 391-398.

[13] Kumar, Vikas, Prerna Gaur, and A. P. Mittal. "ANN based self tuned PID like adaptive controller design for high performance PMSM position control", Expert Syst Appl. 41.17 (2014) 7995-8002.

[14] Pan, Ching-Tsai, and Emily Fang. "A phase-locked-loop-assisted internal model adjustable-speed controller for BLDC motors", IEEE T Ind Electron. 55.9 (2008) 3415-3425.

[15] Shanmugasundram, R., K. Muhammad Zakariah, and NarriYadaiah. "Implementation and performance analysis of digital controllers for brushless DC motor drives." IEEE-ASME T Mech. 19.1 (2014) 213-224.

[16] Ali, Jamal Abd, et al. "Fuzzy logic speed controller optimization approach for induction motor drive using backtracking search algorithm", Measurement. 78 (2016) 49-62.

[17] Terzic, Bozo, and Martin Jadric. "Design and implementation of the extended Kalman filter for the speed and rotor position estimation of brushless DC motor." IEEE T Ind Electron. 48.6 (2001) 1065-1073.

[18] Xu, Jian-Xin, Chang-Chieh Hang, and Chen Liu. "Parallel structure and tuning of a fuzzy PID controller", Automatica 36.5 (2000) 673-684.

[19] Reznik, Leonid, Omar Ghanayem, and Anna Bourmistrov. "PID plus fuzzy controller structures as a design base for industrial applications", Eng Appl Artif Intel. 13.4 (2000) 419-430.

[20] Mohan, B. M., and Arpita Sinha. "Analytical structure and stability analysis of a fuzzy PID controller", Appl Soft Comput 8.1 (2008) 749-758.

[21] Ahmed Rubaai, A.; Castro-Sitiriche, M.J.; Ofoli, A.R., "Design and Implementation of Parallel Fuzzy PID Controller for High-Performance Brushless Motor Drives: An Integrated Environment for Rapid Control Prototyping", IEEE T Ind Appl vol.44, no.4, pp.1090-1098, July-Aug. 2008.

[22] Fereidouni, Alireza, Mohammad AS Masoum, and Moayed Moghbel. "A new adaptive configuration of PID type fuzzy logic controller", ISA T. 56 (2015) 222-240.

[23] Chiou, Juing-Shian, Shun-Hung Tsai, and Ming-Tang Liu. "A PSO-based adaptive fuzzy PID-controllers", Simul Model Pract Th 26 (2012) 49-59.

[24] Al Gizi, Abdullah JH, M. W. Mustafa, and Hamid H. Jebur. "A novel design of high-sensitive fuzzy PID controller." Applied Soft Computing. 24 (2014) 794-805.

[25] Beirami, Hamed, Ali ZargarShabestari, and Mohammad Mahdi Zerafat. "Optimal PID plus fuzzy controller design for a PEM fuel cell air feed system using the self-adaptive differential evolution algorithm", Int J Hydrogen Energ. 40.30 (2015) 9422-9434.

[26] Sant, Amit Vilas, and K. R. Rajagopal. "PM synchronous motor speed control using hybrid fuzzy-PI with novel switching functions." IEEE T Magn 45.10 (2009) 4672-4675.

[27] Mishra, Puneet, Vineet Kumar, and K. P. S. Rana. "A fractional order fuzzy PID controller for binary distillation column control", Expert Syst Appl 42.22 (2015) 8533-8549.

[28] Xu, Yanhe, et al. "An adaptively fast fuzzy fractional order PID control for pumped storage hydro unit using improved gravitational search algorithm." Energ Convers Manage. 111 (2016) 67-78.

[29] Rubaai, Ahmed, and Paul Young. "EKF-based PI-/PD-like fuzzy-neural-network controller for brushless drives", IEEE T Ind Appl 47.6 (2011) 2391-2401.

[30] Petković, Dalibor, et al. "Adaptive neuro-fuzzy maximal power extraction of wind turbine with continuously variable transmission", Energy 64 (2014) 868-874.

[31] Hafiz, Faizal, and Adel Abdennour. "An adaptive neuro-fuzzy inertia controller for variable-speed wind turbines", Renew Energ 92 (2016) 136-146

[32] Petković, Dalibor, et al. "Adaptive neuro-fuzzy estimation of conductive silicone rubber mechanical properties", Expert Syst Appl 39.10 (2012) 9477-9482.

[33] Petković, Dalibor, et al. "Adaptive neuro fuzzy controller for adaptive compliant robotic gripper." Expert Syst Appl 39.18 (2012) 13295-13304.

[34] Vatankhah, Ramin, Mehrdad Broushaki, and Aria Alasty. "Adaptive optimal multi-critic based neuro-fuzzy control of MIMO human musculoskeletal arm model", NeuroComputing. 173 (2016) 1529-1537.

[35] Topalov, Andon V.,et al. "Neuro-fuzzy control of antilock braking system using sliding mode incremental learning algorithm", NeuroComputing. 74.11 (2011) 1883-1893.

[36] Liu, Yan-Cheng, Si-Yuan Liu, and Ning Wang. "Fully-tuned fuzzy neural network based robust adaptive tracking control of unmanned underwater vehicle with thruster dynamics", NeuroComputing.196 (2016) 1-13.

[37] Sarhadi, Pouria, Behrooz Rezaie, and Zahra Rahmani. "Adaptive predictive control based on adaptive neuro-fuzzy inference system for a class of nonlinear industrial processes", Journal of the Taiwan Institute of Chemical Engineers. (2015) 132-137.

[38] Jia, Li, and Kai Yuan. "The probability density function based neuro-fuzzy model and its application in batch processes", NeuroComputing. 148 (2015) 216-221.

[39] Wang, Wilson, De Z. Li, and Joe Vrbanek. "An evolving neuro-fuzzy technique for system state forecasting", NeuroComputing. 87 (2012) 111-119.

[40] Petković, Dalibor, et al. "Adaptive neuro-fuzzy estimation of optimal lens system parameters", Opt Laser Eng 55 (2014) 84-93.

[41] Hasanien, Hany M., S. M. Muyeen, and Junji Tamura. "Speed control of permanent magnet excitation transverse flux linear motor by using adaptive neuro-fuzzy controller." Energ Convers Manage 51.12 (2010) 2762-2768.

[42] Premkumar, K., and B. V. Manikandan. "Adaptive Neuro-Fuzzy Inference System based speed controller for brushless DC motor", Neurocomputing. 138 (2014) 260-270.

[43] Premkumar, K., and B. V. Manikandan. "Fuzzy PID supervised online ANFIS based speed controller for brushless dc motor", Neurocomputing 157 (2015)76-90.

[44] Kapun, Aljaz, et al. "Identifying dynamic model parameters of a BLDC motor", ", Simul Model Pract Th 16.9 (2008) 1254-1265.

[45] Del Campo, Inés, et al. "Efficient hardware/software implementation of an adaptive neuro-fuzzy system." IEEE T Fuzzy Syst. 16.3 (2008) 761-778.

[46] Moshkbar-Bakhshayesh, Khalil, and Mohammad B. Ghofrani. "Development of an efficient identifier for nuclear power plant transients based on latest advances of error back-propagation learning algorithm", IEEE T Nucl Sci. 61.1 (2014) 602-610.

[47] Fausett, Laurene. Fundamentals of neural networks: architectures, algorithms, and applications. Prentice-Hall, Inc., 1994.