Chapter 136
Online Fuzzy Supervised Learning of Radial Basis Function Neural Network Based Speed Controller for Brushless DC Motor

K. Premkumar and B.V. Manikandan

Abstract In this paper, Online Fuzzy Logic Supervised Learning of Radial Basis Function Neural Network (RBFNN) based speed controller for Brushless DC (BLDC) motor is presented. The Fuzzy PID controller is acting as supervisor for RBFNN controller. Dynamic speed response is analyzed for BLDC motor with conventional PID controller and proposed controller. Rise time, peak overshoot, recovery time and steady state error are measured and analyzed for above controller. From the results, the proposed controller outperforms than PID controller.

Keywords BLDC motor · PID controller · Fuzzy PID controller · Online radial basis function neural network controller

136.1 Introduction

Brushless DC motor becomes a replacement for DC motor because it overcomes the limitation of a brushed DC motor. They incorporate high efficiency, high torque per weight, increased reliability, reduced noise, a lower susceptibility of the commutator assembly to mechanical wear and longer lifetime. It has come to govern countless applications, particularly in transport, heating and ventilations, motion control systems, positioning and actuation systems, model engineering and radio controlled cars [1, 2]. In the last two decades, many numbers of intelligent controllers was developed based non linear model of BLDC motor [3–12]. In [3], Proportional Integral (PI)

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based speed controller is designed for three base BLDC motor. Proportional Integral controller based current controller is proposed for BLDC motor [4]. In the speed response, PI controller produces uncertainty due to load variations and set speed variations. Fuzzy logic based speed controller is discussed for brushless AC motor [5]. In [6], hybrid Fuzzy-PID controller is implemented for BLDC motor. As a result, fuzzy logic controller outperforms the PID controller. In [7], adaptive speed controller based on the fuzzy logic system is implemented for BLDC motor. The effectiveness of the fuzzy logic controller is analyzed and superior for variable speed drives. But it required expert, who know the system to be modelled. In [8], educational tool for neural network and it is presented for Brushless DC Motor. In [9], Radial Basis Function Neural Network is used for learning the maximum of system unknown loads and external disturbances for BLDC motor. Genetic algorithm optimized RBFNN based speed controller is presented for BLDC motor in [10]. A neural network approach for the identification and control of a separately excited direct DC motor driving a centrifugal pump load is applied in [11]. In [12], speed control of DC motor of neural network is presented. And neural networks are trained by Levenberg-Marquardt back propagation algorithm. In [3–12], the neural network is trained by off line learning algorithm. In this paper, an online learning algorithm is used to train the RBFNN. The Fuzzy logic controller is used for supervisor to train the RBFNN in online. And it is applied to control the speed of the BLDC motor. Dynamic speed response is analyzed and compared with the conventional PID controller. Control system parameter, i.e., Rise time, peak overshoot, recovery time and steady state error for speed response is measured and compared to both PID controller and proposed controller.

136.2 The Design Approach of Online Fuzzy Supervised Learning of Radial Basis Function Neural Network Controller

In this section, the design approach of online fuzzy supervised learning of neural network is presented for BLDC motor. Figure 136.1 shows the online fuzzy supervised learning of RBFNN based speed controller for BLDC motor.

Rotor position sensor and speed sensor used to measure the actual rotor position and the speed of the motor. The speed error (e) is obtained by comparing reference speed with actual speed. The rate of change of speed error (Δe) is produced by differentiating the speed error. The e and Δe is the input to the online supervised RBFNN controller. This controller also receives the supervised error (e_s) by comparing the Fuzzy PID supervised algorithm output (U_F) and output of the controller (U_a). Based on this supervised error, the parameter of RBFNN is updated in the network. The switching logic and PWM inverter are receiving the signal from the controller and rotor position sensor. The switching logic circuit provides the PWM signal for inverter based on controller output and rotor position. The speed of

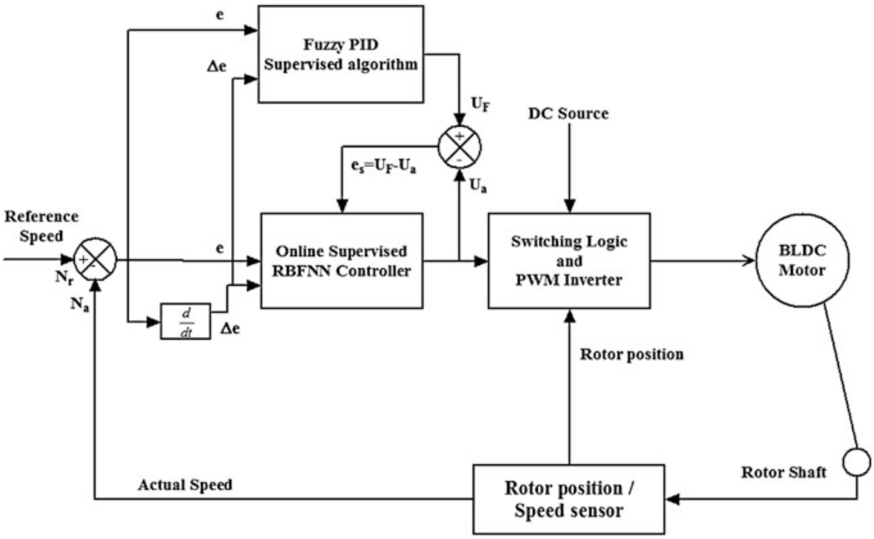


Fig. 136.1 Online Fuzzy supervised learning of RBFNN based speed controller for BLDC motor

the motor is controlled by controlling the DC bus voltage by means of triggering the switches in PWM inverter.

136.2.1 Development of Fuzzy PID Supervised Algorithm

In this section, the development of Fuzzy PID Supervised Algorithm is presented for RBFNN. Figure 136.2 shows the basic block diagram for Fuzzy supervised PID Algorithm.

Fuzzy logic PID controller consists of three main functions that are fuzzification, fuzzy rule base and defuzzification. In fuzzification, the crisp value is converted into a fuzzy variable. It receives the inputs and inputs are distributed by using membership function. In fuzzy rule base, the inputs and outputs are connected with if then rules. It has provided the relation between inputs and outputs. In defuzzification, output fuzzy value is converted into crisp value. The Fuzzy PID supervisor is modeled by Takagi-Sugeno (T-S) type system. Fuzzy PID has two inputs that are e and Δe and output (U_F). Each input has three triangular membership functions and provided in the Eq. (136.1).

$$\begin{aligned}
\mu A_i(e, a_i, b_i, c_i) &= e - a_i/b_i - a_i \quad \text{for } a_i \le e \le b_i; \\
&\quad c_i - e/c_i - b_i \quad \text{for } c_i \le e \le b_i \\
\mu B_i(\Delta e, a_i, b_i, c_i) &= \Delta e - x_i/y_i - x_i \quad \text{for } x_i \le \Delta e \le y_i; \\
&\quad z_i - \Delta e/y_i - z_i \quad \text{for } z_i \le \Delta e \le x_i
\end{aligned} \tag{136.1}$$

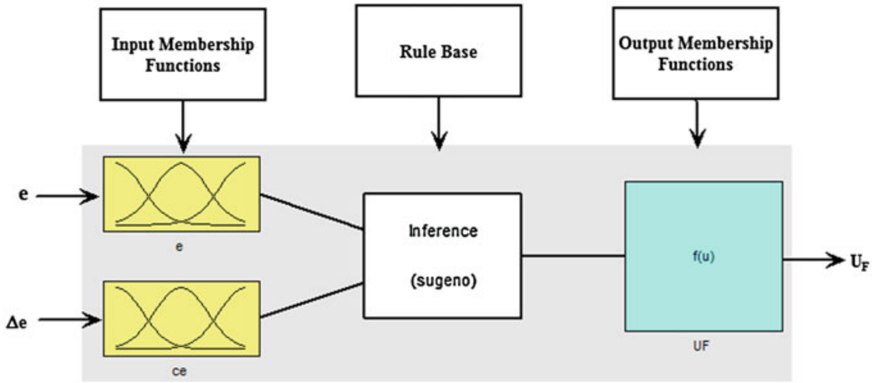


Fig. 136.2 Block diagram for fuzzy PID supervised algorithm

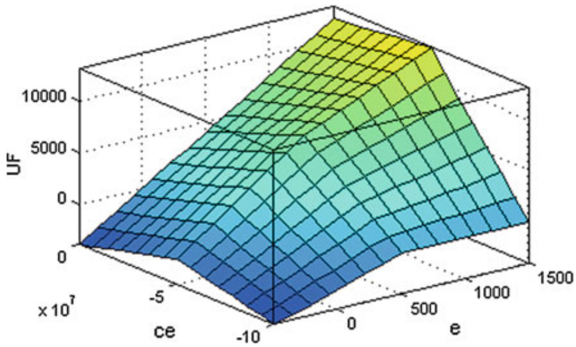
where a, b, c, x, y and z are adjustable location of the triangular membership functions. Output has nine constant values. The if then rules for the T-S system is given in the Eq. (136.2).

$$\begin{aligned}
&\text{Rule 1}: \ \text{IF e is } A_1; \ \Delta e \text{ is } B_1; \quad \text{then } f_1 = s_1\\
&\text{Rule 2}: \ \text{IF e is } A_1; \ \Delta e \text{ is } B_2; \quad \text{then } f_2 = s_2\\
&\vdots\\
&\text{Rule } j-1: \ \text{IF e is } A_i; \ \Delta e \text{ is } B_{i-1}; \quad \text{then } f_{j-1} = s_{j-1}\\
&\text{Rule } j: \ \text{IF e is } A_i; \ \Delta e \text{ is } B_i; \quad \text{then } f_j = s_j
\end{aligned} \tag{136.2}$$

where s is the output constant value of T-S fuzzy inference system. Figure 136.3 shows the rule base for Fuzzy PID supervised algorithm.

The weighted average defuzzification method is used in the fuzzy logic controller and given in the Eq. (136.3). Where W_j is the weight of the output membership functions.

Fig. 136.3 The rule base for fuzzy PID supervised algorithm



$$U_F = W_j * f_j / \Sigma W_j \tag{136.3}$$

136.2.2 Development of Online Supervised Radial Basis Function Neural Network

In this section, development of Radial Basis Function Neural Network is described. Figure 136.4 shows the Architecture of Four Receptive Field Radial Basis Function Neural Network. In general, it combines the interpolation and approximation theory.

Consider a Gaussian basis function of centered u_i with a width parameter σ; the activation level of the ith receptive field unit or hidden layer is given in the Eq. (136.4),

$$W_i = R_i(\|x - u_i\|) = \exp\left(-(x-u_i)^2/2\sigma_i^2\right) \tag{136.4}$$

where x is the input multidimensional vector. Each training input (U_F) from Fuzzy PID supervised algorithm serves as a center for the basis function (R_i), the Gaussian interpolation RBFNN is given in the Eq. (136.5),

$$d(x) = \left(\sum_{i=1\ldots n}\left(c_i \exp\left(-(x-U_F)^2/2\sigma_i^2\right)\right)\right) \Big/ \left(\sum_{i=1\ldots n} W_i\right) \tag{136.5}$$

where c_i is the linear function of the inputs. Center and output of RBFNN are changed based upon supervised error (e_s).

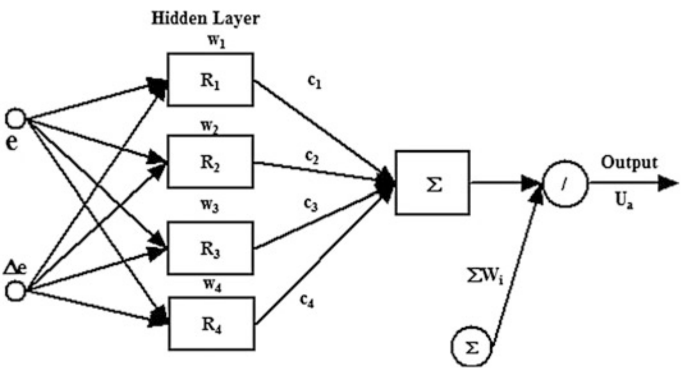


Fig. 136.4 The architecture of four receptive field radial basis function neural network

136.3 Simulink Model and Simulation Results

In order to validate the proposed controller, The Simulink model is created by MATLAB/Simulink Toolbox. And speed response is obtained for varying load conditions and varying set speed conditions. Figure 136.5 shows a Simulink model of proposed controller. The specification for the BLDC motor are follows, Nominal Power-50 Watts, Rated Current-2.5 Amps, Input Voltage-28 V DC, Rated Speed-1,500 rpm, Rated Torque-0.38 N-m.

136.3.1 Speed Response Under Varying Load Condition

Result of simulation of varying load condition under PID and proposed controller is shown in Fig. 136.6. Here, we considered two cases. Case 1, the load is varied from no load to full load at 0.2 s. Case 2, the load is varied from full load to no load at 0.4 s. The control system parameters are measured for speed response and tabulated in Table 136.1. From the results in Table 136.1, it is revealing that the performance index of all vital parameter i.e., Rise time, peak overshoot and steady state error are in favor of proposed controller only.

136.3.2 Speed Response Under Varying Set Speed Conditions

Result of simulation in varying set speed conditions under PID and proposed controller is shown in Fig. 136.7. Here, we considered two cases. Case 1, the set

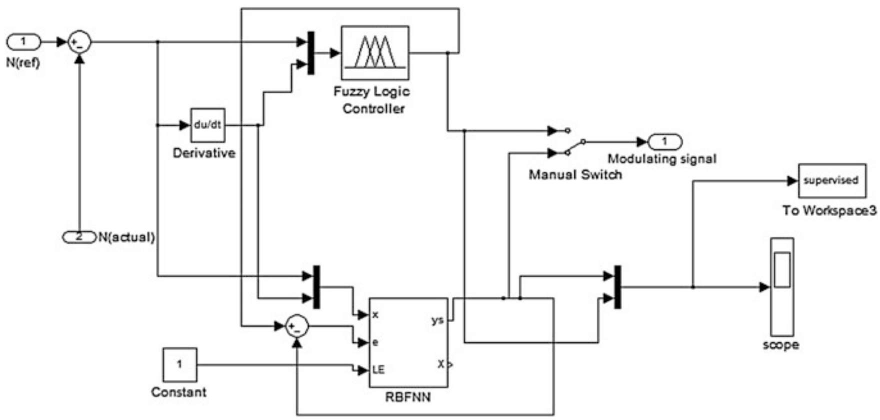


Fig. 136.5 The simulink model of online fuzzy supervised learning of radial basis function neural network

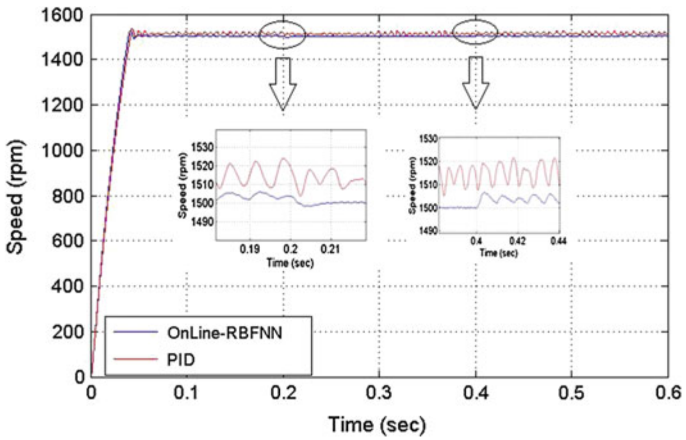


Fig. 136.6 Speed response of BLDC motor under varying load condition with PID and proposed controller

Table 136.1 Control system parameters under varying load conditions

Controller	Rise time (s)		Peak over shoot (%)		Steady state error (rpm)	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
PID	0.04	–	2.6	1.46	12	15
Online RBFNN	0.035	–	1.5	0.33	0.5	3.5

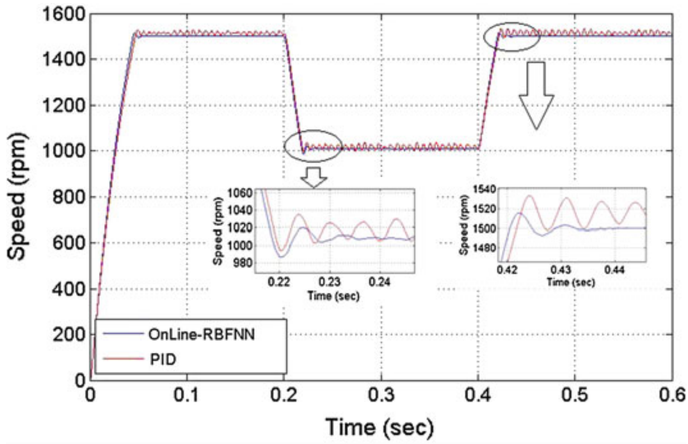


Fig. 136.7 Speed response of BLDC motor under varying set speed condition with PID and proposed controller

Table 136.2 Control system parameters under varying set speed conditions

Controller	Recovery time (s)		Peak over shoot (%)		Steady state error (rpm)	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
PID	0.30	0.50	3.5	3.2	15	17
Online RBFNN	0.22	0.43	2.0	1.5	8	0.5

speed is varied from 1,500 to 1,000 rpm at 0.2 s. Case 2, the set speed is varied from 1,000 to 1,500 rpm at 0.4 s. The control system parameters are measured for speed response and tabulated in Table 136.2.

From the results in Table 136.2, it is revealing that the performance parameters are in favor of proposed controller only.

136.4 Conclusion

An online fuzzy supervised learning of RBFNN is proposed and simulated for BLDC motor. The aim of this paper is to develop an online learning algorithm for RBFNN. The Fuzzy PID supervised algorithm is applied to the RBFNN and it is compared with PID control. In case of PID controller, produces more oscillation in the speed response and has large steady state error. In case of proposed controller, produces less oscillation and has less steady state error when compared to PID control. From the results, proposed controller outperforms than PID controller under varying load and set speed conditions.

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