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Design of Brushless DC Motor Controller Based on Adaptive RBF Neural Network

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Abstract

Brushless DC motor (BLDCM) has been widely used in industries because of its advantages. BLDCM control system is a nonlinear, multi-variable, strong-coupling system. It is difficult to get satisfied control performance with conventional PID controller. By using self-learning and adaptive ability of neural network to unknown information, an intelligent PID control method based on adaptive radial basis function (RBF) neural network is proposed. Connection weight of neural network is updated according to the motor speed and phase current. The duty ratio of pulse width modulation (PWM) is adjusted to regulate the speed of BLDCM. The effectiveness of the proposed control method was validated with simulation and experiment. Simulation and experiment results showed that compared with the conventional PID controller, the proposed controller has less overshoot, faster response speed, stronger ability of anti-disturbance.

Keywords*: Brushless DC Motor (BLDCM); Radial Basis Function (RBF) Neural Network; Adaptive ability; Pulse Width Modulation (PWM)*

1. Introduction

Brushless DC motor (BLDCM) has been widely used in electrical equipment, mining and other industrial application fields due to its advantages of high power density, high efficiency, easy maintenance, silent operation and so on[1-3]. The BLDCM controller plays a vital role to influence the performance of BLDCM. BLDCM control system is a multi-variable, nonlinear, strong-coupling system. The high performance control strategy should be robust and adaptive. The conventional proportional-integral-derivative (PID) controller has shortcomings when controlling nonlinear and uncertain target. The interest in emerging intelligent controller for BLDCM has been increased significantly.

Some intelligent control methods have been applied in the BLDCM controller[4-11]. A fuzzy logic based soft switching resonant inverter was developed to overcome over voltage and over current problems existing in resonant converter for speed control of brushless DC motor [4]. In [5], a genetic algorithm was adopted, the optimum tuning parameters of PID controller was found by taking integral absolute error. A model for BLDCM drive with PID controller and hybrid fuzzy logic controller (HFLC) was designed to obtain the BLDCM speed control in [6]. Document [7] presented a PID self-tuning method based on relay feedback technique. In [8], the adaptive fuzzy controller was capable of improving the tracking performance under external disturbances than non-adaptive fuzzy controller. An adaptive fuzzy logic algorithm to control the speed of BLDCM was implemented in [9]. Speed control was obtained by tuning the PID value with adaptive fuzzy logic algorithm. An observer based on direct adaptive fuzzy-neural network controller was employed for a high order unknown nonlinear systems in [10]. In [11], an adaptive tuning of PID controller was proposed in order to deal with the control

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problem for a class of uncertain chaotic systems. Although previous researches presented robust in motor control, the controllers were complex and difficult to implement.

Neural network is suitable for the control of nonlinear systems. A special network structure is obtained with the radial basis function (RBF) neural network. It has remarkable advantages over other type neural networks. The advantages include better approximation capability, simpler network structure and faster learning speed [12-14]. RBF neural network controller has good application prospect in controlling area of nonlinear and uncertain targets. RBF neural network has been widely applied in different scientific areas such as pattern recognition, optimization and motor driver [15-18].

In order to obtain control schemes that have good dynamic responses, a PID control method based on adaptive RBF neural network is proposed in this paper. RBF neural network and the PID control method are combined. RBF Neural network PID controller was adopted to tune PID parameters in BLDCM control system. Thereby an adaptive PID controller with more stability and stronger ability is constructed. The proposed controller can meet the requirements of stability, rapidity, accuracy and robustness in BLDCM drivers.

2. PID Controller Design Based on RBF Neural Network

2.1. Adaptive RBF Neural Network Model

The neural network is a kind of intelligent control algorithm. It is known for its strong capacity of self-learning, self-adapting and self-organization. RBF neural network was first proposed by J. Moody and C. Darken [19]. It is a kind of feed-forward neural network with good performance. The neural network has not only global approximation ability but also the better approximation property [20].

RBF network is a feed-forward network with three layers. It consists of input layer, hidden layer, and output layer. The nodes within each layer connect to the forward layer. The input nodes are connected to the hidden layer neurons directly. The mapping from input layer to hidden layer is nonlinear while the mapping from hidden layer to output layer is linear. Output of neural network can be changed by adjusting the weight coefficient to accelerate the learning speed and avoid local minimum problem. The structure of multi-input and single-output RBF neural network is shown as Figure 1.

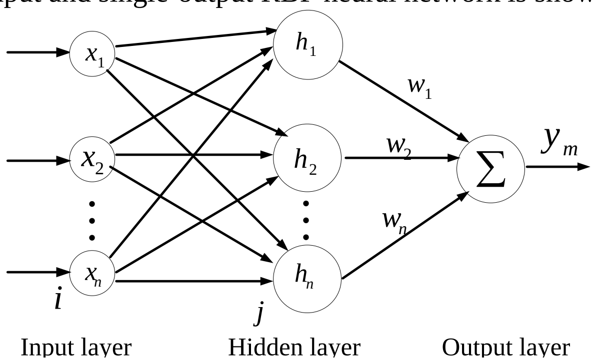

Figure 1. The Structure of RBF Neural Network

The input vector of input layer in RBF neural network can be expressed as $\mathbf{X}=[x_1,x_2,\cdots,x_n]^{\mathrm{T}}$. Radial basis vector of hidden layer can be expressed $\mathbf{H}=[h_1,h_2,\cdots,h_n]^{\mathrm{T}}$. h_i is radial basis function. Different algorithms can be chosen in Radial basis function in its application. Gauss function is selected in this paper, namely the equation,

$$h_j = \exp(-\frac{\| \mathbf{X} - c_j^2 \|}{2b_j^2}), j = 1, 2, \cdots n \quad (1)$$

Where c_j is the center vector of j node, $j = 1, 2, \cdots m$. b_j is the base-width parameter of the hidden layer, it is larger than zero. Gaussian transfer function is used for the hidden neurons. The weight from input layer to hidden layer is 1. The weight vector from hidden layer to output layer is $W = [w_1, w_2, \cdots, w_m]^{\mathrm{T}}$.

The output of the identification network is

$$y_m = \sum_{j=1}^{m} w_j h_j \quad (2)$$

To realize the RBF network automatic adjustment of weight, center vector and base-width, performance index of identifier network is

$$J = \frac{1}{2}(y(k) - y_m(k))^2 \quad (3)$$

Node center, output weights and node base-width parameters are calculated according to the gradient descent method, they are shown as the follows:

$$\left.\begin{aligned}
&\Delta w_j(k) = \eta(y(k) - y_m(k))h_j \\
&w_j(k) = w_j(k-1) + \Delta w_j(k) + \alpha(w_j(k-1) - w_j(k-2)) \\
&\Delta b_j(k) = \eta(y(k) - y_m(k))w_j h_j \frac{\left\| \mathbf{X} - c_j \right\|^2}{b_j^3} \\
&b_j(k) = b_j(k-1) + \Delta b_j(k) + \alpha(b_j(k-1) - b_j(k-2)) \\
&\Delta c_j(k) = \eta(y(k) - y_m(k))w_j \frac{x_j - c_{ji}}{b_j^2} \\
&c_{ji}(k) = c_{ji}(k-1) + \Delta\eta c_{ji}(k) + \alpha(c_{ji}(k-1) - c_{ji}(k-2))
\end{aligned}\right\} \quad (4)$$

Where $i = 1, 2, 3$, η is the learning rate, α is inertial coefficient.

There is a high accuracy and an acceptable speed of computation in the approximating characteristics of the RBF network. However, the relatively small number of nodes in the RBF hidden layer normally has a low accuracy, and hence one may not be able to minimize the root-mean-square error of function. So the adaptive RBF network is proposed. The structure of adaptive RBF Neural Network is shown as Figure 2.

J is the root-mean-square error function, J^d is the maximum value of J. The block P refers to the process of getting the function. The block $< ? >$ is the process of comparing J with J^d to make the following decisions.

(1) If $J > J^d$, then $n = n + 1$. The number of nodes in the hidden layer increased.

(2)If $J > J^d$ and $T = 0$, then $T = T + 1$ and $n = n + 1$. The initial state of the counter is $T = 0$ and the number of nodes in the hidden layer increased.

(3)If $J < J^d$ and $T > 0$, then $n = n + 1$. The number of nodes in the hidden layer is reduced. And the adaptive process of RBF neural network is completed.

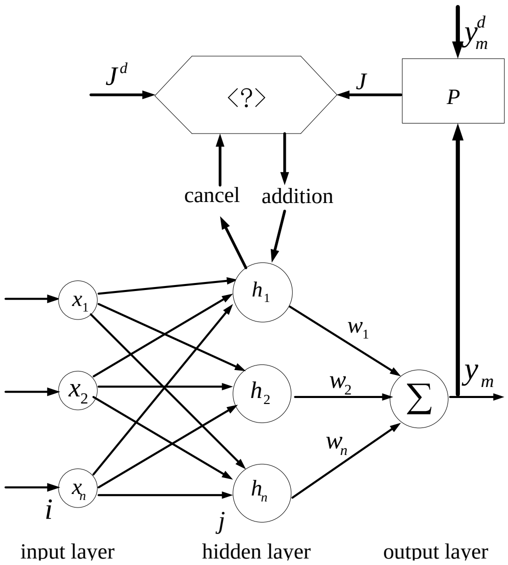

Figure 2. The Structure of Adaptive RBF Neural Network

Consequently, the number of nodes in the hidden layer is dependent on the error function. It can vary from a specific minimum to a maximum. As the network with adaptive structure is always designed to satisfy a specific accuracy, such algorithm is commonly employed to in neural network.

2.2. Adaptive RBF Neural Network PID Tuning Principle

According to the introduction of the above adaptive RBF neural network, tuning principle based on adaptive RBF neural network PID is shown as Figure 3.

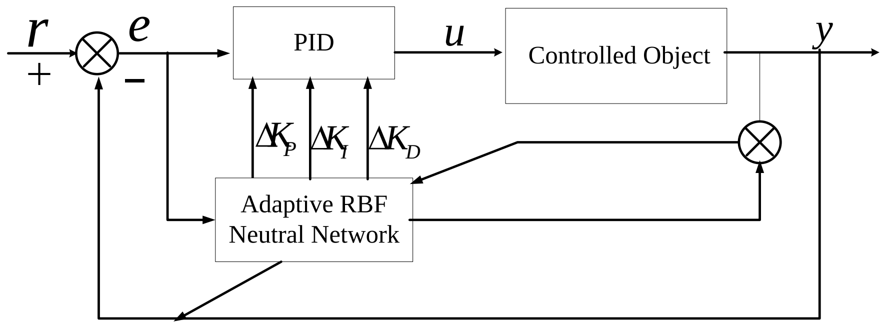

Figure 3. Tuning Principle Based on RBF Neural Network PID

Set r as the system input, y as the system output, u as the controller output. The control error is :

$$e(k) = r(k) - y(k) \tag{5}$$

The incremental PID controller is adopted in this paper. PID parameters are:

$$\left.\begin{aligned} x_c(1) &= e(k) - e(k-1) \\ x_c(2) &= e(k) \\ x_c(3) &= e(k) - 2e(k-1) + e(k-2) \end{aligned}\right\} \tag{6}$$

Where $x_c(1)$ is the proportional term, $x_c(2)$ is the integral term, $x_c(3)$ is the differential term.

Neural network tuning index is:

$$E(k)=\frac{1}{2}e(k)^2 \tag{7}$$

PID control algorithm is

$$u(k)=u(k-1)+K_P x_c(1)+K_I x_c(2)+K_D x_c(3) \tag{8}$$

The parameter K_P、 K_I、 K_D can be adjusted with the gradient descent method. The calculation process is as follows:

$$\left.\begin{aligned}
\Delta K_P &= -\eta\frac{\partial E}{\partial K_P} = -\eta\frac{\partial E}{\partial y}\frac{\partial y}{\partial \Delta u}\frac{\partial \Delta u}{\partial K_P} = \eta e(k)\frac{\partial y}{\partial \Delta u}x_c(1)\\
\Delta K_I &= -\eta\frac{\partial E}{\partial K_I} = -\eta\frac{\partial E}{\partial y}\frac{\partial y}{\partial \Delta u}\frac{\partial \Delta u}{\partial K_I} = \eta e(k)\frac{\partial y}{\partial \Delta u}x_c(2)\\
\Delta K_D &= -\eta\frac{\partial E}{\partial K_D} = -\eta\frac{\partial E}{\partial y}\frac{\partial y}{\partial \Delta u}\frac{\partial \Delta u}{\partial K_D} = \eta e(k)\frac{\partial y}{\partial \Delta u}x_c(3)
\end{aligned}\right\} \tag{9}$$

Where $\frac{\partial y}{\partial \Delta u}$ is the Jacobian information of the controlled object. It can be obtained by identification of the neural network.

3. Design of BLDCM Controller Based on Adaptive RBF Neural Network

3.1. Mathematical Model of BLDCM

The typical BLDCM system and the other related equations for obtaining the mathematical model is taken from [18]. The typical mathematical model of BLDCM is described in the following equations:

$$\begin{bmatrix}u_a\\u_b\\u_c\end{bmatrix}=\begin{bmatrix}R&0&0\\0&R&0\\0&0&R\end{bmatrix}\begin{bmatrix}i_a\\i_b\\i_c\end{bmatrix}+\begin{bmatrix}L-M&0&0\\0&L-M&0\\0&0&L-M\end{bmatrix}\frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix}i_a\\i_b\\i_c\end{bmatrix}+\begin{bmatrix}e_a\\e_b\\e_c\end{bmatrix} \tag{10}$$

Where R is the stator resistance. L and M is self-inductance and mutual inductance. u_a , u_b , u_c is the phase voltage. i_a , i_b , i_c is phase current. e_a , e_b , e_c is back EMF.

The electromagnetic torque developed by the motor can be expressed as,

$$T_e = e_a i_a + e_b i_b + e_c i_c / \omega \tag{11}$$

Where T_e is the electromagnetic torque of motor. ω is the rotor velocity in radians per second.

Electromagnetic torque is utilized to overcome the opposing torque of the load. The torque balance equation is expressed as,

$$T_e = T_L + J\frac{\mathrm{d}\omega}{\mathrm{d}t}+B\omega \tag{12}$$

Where T_L is the load torque. J is the inertia. B is the friction constant of the motor.

3.2. Design of BLDCM Controller Based on Adaptive RBF Neural Network

The speed of BLDCM is accurately regulated by controlling PWM duty ratio D. Phase current and speed are input parameter of RBF neural network, duty ratio D is output parameter. The control parameters can be changed on-line. Neural network layers and number of neuron selection are designed according to the system requirements. The network weight vector is revised by the neural network. The accurate duty ratio D can be obtained according to the operation state of the system. Structure of BLDCM controller based on adaptive RBF neural network is shown in Figure 4. The double closed loop control is adopted in system. The inner loop and outer loop is current loop and speed loop respectively.

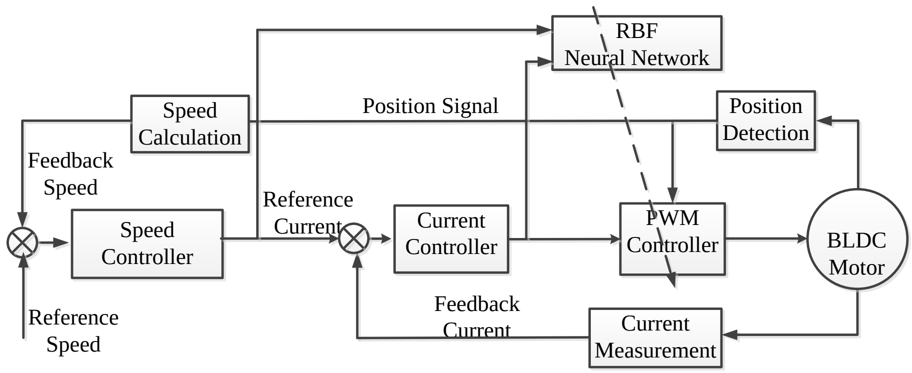

Figure 4. BLDCM Controller Based on Adaptive RBF Neural Network

The calculation flow of the proposed BLDCM controller is as follows:

(1) Initialize the parameters of RBF neural network according to the initialization process. Set the connection weight to a random number between [-0.5, 0.5]. Set the threshold value of duty ratio D is [0, 1], the duty ratio error threshold is 0.02.

(2) Start the system, sample the phase current and motor speed.

(3) Send the sampled phase current i_a , i_b , i_c and speed n to RBF neural network. Correct the network weight vector in real time according to the operation state of the motor.

(4) In accordance with the phase current, speed and output D of neural network, PWM duty ratio D is regulated in real time to regulate the motor speed. Compare actual value of duty ratio D with threshold value. If error e_k is less or equal to error threshold value e_k^*, then speed control signal is outputted and the algorithm ends. Otherwise Return to step (1).

Input signals are sent to network during the whole control process. The weight vector of RBF neural network is updated in real-time until the output duty ratio D is ideal and the reference speed is achieved.

4. Simulation and Experiment Results

4.1. Simulation Results and Analysis

A simulation model of BLDCM controller was established with MATLAB to test performance of proposed control method. The simulation adopted conventional PID controller and adaptive RBF neural network PID controller respectively. The BLDCM parameters are given in Tab.1.

Table 1. BLDCM Parameters

Parameters	Value
Stator phase resistance R (ohm)	0.5
Stator phase inductance L (H)	0.01
Voltage Constant (V/rpm)	0.16
Torque Constant (N.m / A)	0.7
Moment of Inertia (kg.m2/rad)	0.001
Pole pairs	4

The simulation results of BLDCM speed response using conventional PID controller and the proposed RBF neural network PID controller is shown in Figure 5 and Figure 6 respectively. The reference speed was 3000 r/min in simulation. The load torque was $2\,\mathrm{N \cdot m}$ at the beginning and changed to $4\,\mathrm{N \cdot m}$ at 0.2 s.

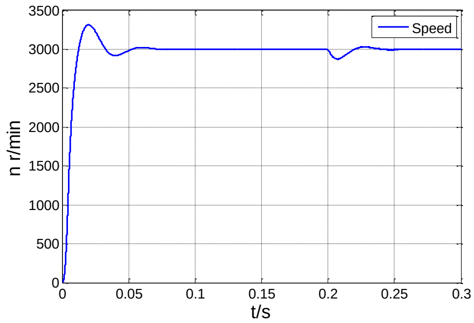

Figure 5. Speed Response with Conventional Neural PID Controller

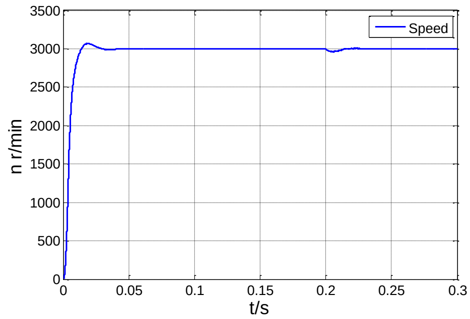

Figure 6. Speed Response with RBF Network PID Controller

When using conventional PID controller, the reference speed was attained in 0.02s. The overshoot was about 8%. The adjustment time was 0.08s. The steady-state error was about 2r/min. When using RBF neural network PID controller, reference speed was reached in 0.02s. The overshoot was 2.5%. The adjustment time was 0.04s. The steady-state error was 2r/min. It can be seen that steady-state error and rising time is same for both controllers. There are superior in overshoot and adjustment time characteristics with the proposed controller in the drive system.

The simulation results were obtained when the load varies. The load of motor changed from 2 N·m to 4 N·m when the simulation time at 0.2s. The response under varying load conditions is shown in Figure 5 and Figure 6. If conventional PID controller is used, the speed was decreased 2.4%. The recovery time was about 0.04s. While the proposed controller is used, speed was decreased 1% and the recovery time was 0.02s. There are less undershoot and recovery time in proposed controller with the load changed. The proposed RBF neural network PID controller for the BLDCM was more superior than conventional PID controller in all aspects from the above results.

4.2. Experimental Results and Analysis

The experiment was carried out to test performance of proposed control method. A BLDCM controller with DSP TMS320F28335 was established. The hardware structure of experiment is shown in Figure 7. All functions including data acquisition, processing and control are achieved by DSP. The circuits consist of power driver, inverter circuit, Hall signal circuit, current sampling and CAN communication circuit and so on. The real photo of control system is given in Figure 8.

The PC and BLDCM controller communicate each other with CAN bus. BLDCM controller can sample the speed, current by itself. The experimental data is transferred to the PC. The data is saved in PC and can be drawn as waveform. Waveform of current and PWM signals are shown in Figure 9.

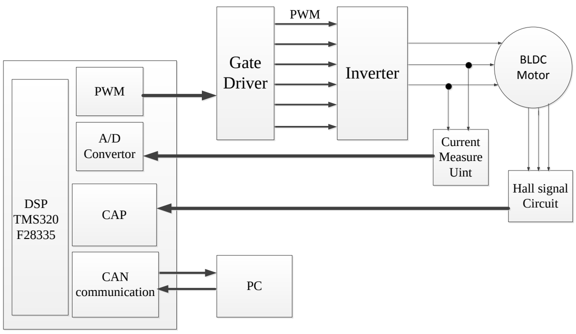

Figure 7. Hardware Structure of BLDCM Controller

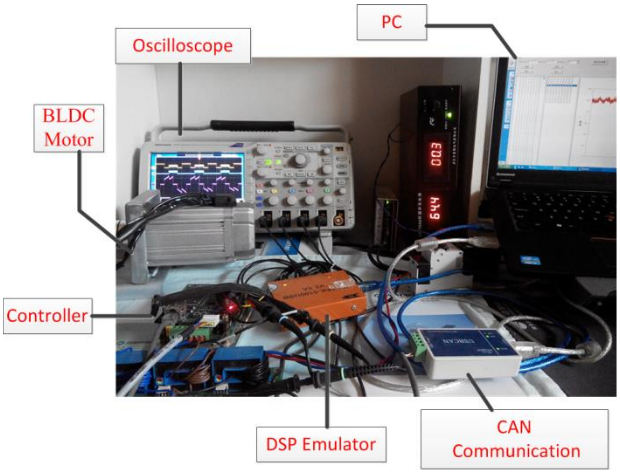

Figure 8. BLDCM Control System

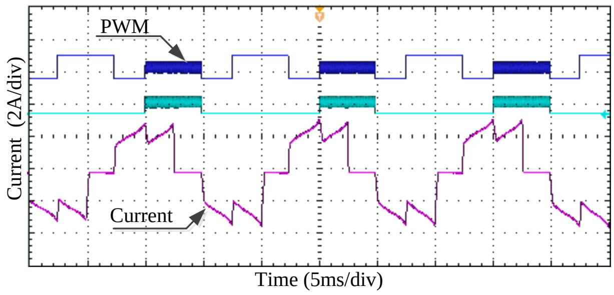

Figure 9. Waveform of Current and PWM Signals

The experiment that BLDC motor speed varies with constant load was carried out firstly. Initially the reference speed is 0 r/min. The constant load is $2\,\mathrm{N \cdot m}$. Then the reference speed is 3000r/min. speed response is obtained for both the controllers. The performance of both controllers is summarized.

Figure 10 and 11 show the comparison of motor speed using two kind controllers. If the conventional PID controller is used, the settling time was 0.28 s, the overshoot was 4%, the adjusting time was about 0.35s, the steady-state error was 10 r/min. If the proposed controller is used, the settling time was 0.25 s, the overshoot was 1%, the adjusting time was 0.28 s, the steady-state error was 4 r/min. From the above verification and comparison, it is proved that proposed controller has better performance than conventional PID controller.

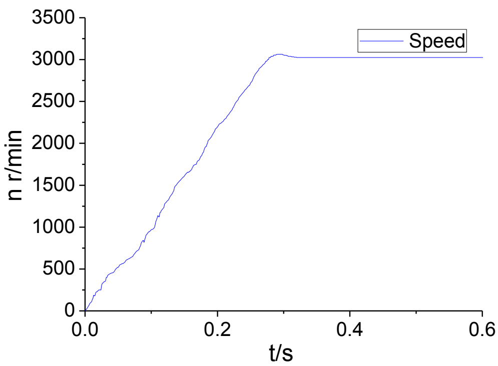

Figure 10. Speed Response with Constant Load using Conventional PID Controller

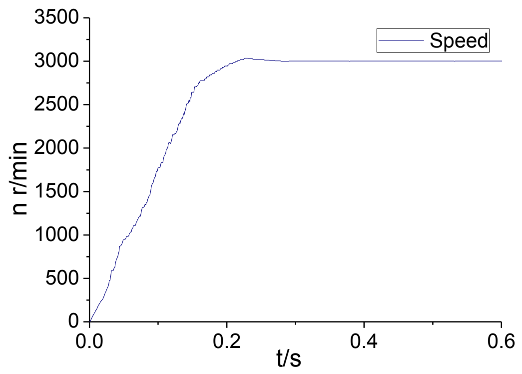

Figure 11. Speed Response with Constant Load using RBF Neural Network PID Controller

Then the experiment that the load changed suddenly at constant speed was carried out. The motor speed maintains constant and the load varies. Initially, 2 $N \cdot m$ load is applied to the motor. Then the load change from 2 $N \cdot m$ to 4 $N \cdot m$. The speed response is shown in Figure 12 and Figure 13. If conventional PID controller is used when the load is changed, the speed decrease 4%, recovery time is about 0.1 s. If the RBF neural network PID controller is used, the speed decrease 1.5%, recovery time is 0.06 s. From the above comparison of the experimental results, it further validate the proposed RBF neural network PID controller can improve the system dynamic performance. The improvement is validated from the above experimental results comparison.

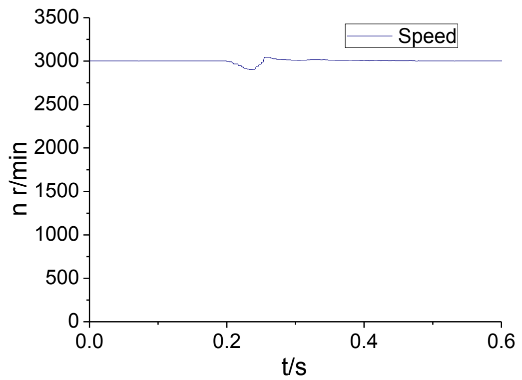

Figure 12. Speed Response with Changed Load using Conventional PID Controller

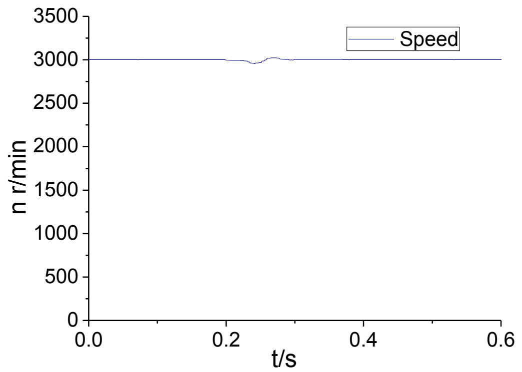

Figure 13. Speed Response with Changed Load using RBF Neural Network PID Controller

5. Conclusions

BLDCM control system is a complex, strong-coupling, nonlinear system. Conventional PID controller is difficult to meet the high performance requirements of BLDCM. A new controller based on adaptive RBF neural network is proposed. The PID parameters are adjusted online. The network weight vector is corrected real-time according to the motor condition. Thus BLDCM speed control strategy is implemented. The performance of proposed method has been investigated by experimental and simulation results. Simulation and experimental results showed that the RBF neural network controller has faster response and smaller overshoot than conventional PID controller. It has stronger anti-interference, more adaptive and robustness ability. The feasibility and superiority of the proposed control method is validated.

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