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(RESEARCH ARTICLE)

Control strategy and experimental study of brushless DC motor based on fuzzy BP neural network

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Abstract

Traditional PID control suffers from issues such as low control accuracy, significant overshooting, and poor disturbance rejection capabilities. This study explores a hybrid control strategy for a brushless DC motor using a combination of fuzzy backpropagation (BP) neural network and proportional-integral-derivative (PID) control. The aim is to enhance the precision and adaptability of the motor control system. The fuzzy BP neural network is employed to address the inherent nonlinearity and uncertainty in the motor system, thereby improving control performance. PID controllers contribute to increased system stability and rapid response capabilities. A simulation control program is constructed in the Matlab/Simulink environment to place the brushless DC motor under various operating conditions. Fuzzy PID control and fuzzy BP neural network PID control methods are applied separately to control the brushless DC motor, evaluating the effectiveness of each control approach. The research results validate that the brushless DC motor controlled by the proposed fuzzy BP neural network algorithm achieves a final speed closer to the target speed, with lower overshooting and speed error, reduced torque fluctuations, and better adaptation to environments with significant disturbances. The control strategy exhibits good disturbance rejection and robustness, effectively improving the overall dynamic performance of the motor control system.

Keywords: Brushless DC motor; PID control; BP neural network; MATLAB/Simulink

1. Introduction

Brushless DC motors (BLDC), compared to traditional permanent magnet DC motors, exhibit significant advantages in various aspects, driving their widespread applications across different fields [1]. Firstly, brushless DC motors eliminate the presence of mechanical brushes in traditional DC motors, thereby avoiding mechanical losses caused by friction and wear. This improvement enhances the reliability and stability of the system [2-4]. This not only reduces maintenance costs but also extends the motor's lifespan, making it more suitable for applications that require prolonged operation and low maintenance. Secondly, brushless DC motors employ advanced electronic control technologies, such as vector control and sensor feedback, making precise control of the motor possible. Compared to traditional permanent magnet DC motors, BLDC motors can achieve higher efficiency and more precise speed/torque control[5]. This makes brushless DC motors excel in applications that require high performance and precise control, such as electric vehicles, unmanned aerial vehicles, and medical devices, among others. Furthermore, due to the absence of mechanical brushes, brushless DC motors have a simplified and compact structure, resulting in higher power density[6]. This allows BLDC motors to deliver greater power output within limited space, providing increased flexibility for motor system integration and design. In applications with strict requirements for volume and weight, such as electric vehicles and portable devices, brushless DC motors are highly favored for their lightweight and compact characteristics[7]. Furthermore, brushless DC motors also exhibit excellent energy efficiency. Due to the highly optimized electronic control systems and the elimination of energy losses associated with mechanical brushes, BLDC motors can more efficiently convert electrical

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energy into mechanical energy, reducing energy waste. This makes brushless DC motors an ideal choice for promoting sustainable and environmentally friendly energy use, especially in today's society that emphasizes green energy and efficiency[8-10]. In general, brushless DC motors, with a range of advantages such as high efficiency, reliability, precise control, and compact structure, are gradually replacing traditional permanent magnet DC motors and playing an increasingly important role in modern industrial and technological applications. This trend is expected to strengthen further with continuous technological innovation and the expansion of application areas, laying a solid foundation for the future development of motor technology.

With the continuous development of technology, numerous control methods for brushless DC motors have emerged. Generally speaking, to control such motors, it is necessary to employ six-step commutation and a three-phase voltage source inverter. The commutation of the inverter components is determined by the state of the Hall effect sensors. In recent years, works have been reported for speed control in this type of engine based on this scheme; such is the case of the work presented by Zhao et al.[11]. Shanmugasundram et al. employed PID control, fuzzy control, and neural network control for the control of brushless DC motors, as described in the literature[12], and compared and analyzed the results. Arulmozhiyal and Kandiban[13] developed a fuzzy PID controller, utilizing fuzzy control rules for PID tuning. In the literature[14], Al-Maliki and Iqbal also employed fuzzy logic control, currently aimed at tuning PID controller parameters. Liu et al.[15] proposed a method, through experiments, utilizing adaptive neural networks for current detection to achieve motor control. Ramya et al. combined particle swarm optimization with neural networks and proposed an adaptive fuzzy control strategy for application in brushless DC motors[16]. Wang et al.[17] also employed fuzzy inference rules for the control of brushless DC motors, enhancing the precision of motor control. Templos-Santos et al.[18] utilized a bio-inspired algorithm to optimize the control parameters of permanent magnet synchronous motors. Potnuru et al.[19] employed a pollination algorithm in the control of numerous DC motors to precisely regulate the motor speed. Merugumalla and Kumar[20] utilized the firefly algorithm to develop a speed control driver for a brushless DC motor. In the aforementioned control methods, there is a greater emphasis on employing novel sensing mechanisms to provide the control system with specific feedback signals, thereby achieving the control of brushless DC motors. However, this approach is relatively complex, and in certain situations, it requires a substantial investment to implement the control of brushless DC motors due to higher costs.

For the control of brushless DC motors, the application of neural networks for adaptive control emerged starting from the work of Yu and his colleagues[21]. This approach utilizes neural networks to achieve adaptive control for driving brushless DC motors. Abed and his collaborators[22] integrated neural networks with a diffusion system for the diagnosis of bearing faults in brushless DC motors. In[23], Luo et al. applied adaptive dynamic surface control techniques using neural network modeling to control brushless DC motors. Saleh et al.[24] developed a speed control system for a brushless DC motor using wavelet neural networks. Naung et al.[25] adjusted the parameters of a PI controller for speed control of a brushless DC motor through neural network tuning. In[26], Kim achieved speed control of a brushless DC motor using dynamic neural networks. Ho et al.[27] implemented a DC brushless motor driver through the use of neural networks. In reference[28], Aguilar et al. developed a speed tracking controller for a permanent magnet synchronous motor based on a second-order sliding mode observer, and conducted tests under load variations. Khadar et al.[29] modeled the five-phase induction of a sensorless control strategy for a DC brushless motor. Wu et al. [30] achieved sensorless speed control of a permanent magnet synchronous motor using terminal sliding mode. Kivanc et al.[31] developed a sensorless speed control system for a spatial vector permanent magnet synchronous motor based on four switches and a three-phase inverter.

Currently, artificial neural networks have been employed to address various tasks, such as pattern recognition[32], parameter estimation[33], prediction of values[34], and they have also been utilized in the control of different types of systems[35-37]. Sreeram[38] achieved speed control of sensorless brushless DC motors using fuzzy logic and a four-switch three-phase inverter. In[39], Shiva et al. implemented a sensorless speed control system for a permanent magnet synchronous motor using a reactive power model reference adaptive system speed estimator and adaptive neural networks. In [40], Saed et al. proposed a sensorless control for improving the speed of a brushless DC motor drive based on the radial displacement of the stator. In[41], Elbeji and colleagues achieved sensorless control of the directional wind energy conversion for a permanent magnet synchronous motor using neural networks. In[42], Verma et al. compared the performance of a PI controller, an anti-windup PI controller, a fuzzy logic-based PI controller, and a fuzzy controller PI to validate the performance of a brushless DC motor under different loads and speeds. In[43], Vanchinathan and colleagues tuned the speed of a sensorless brushless DC motor by controlling the fractional-order PID (Proportional-Integral-Derivative) controller. Rif'an and colleagues[44] utilized a combination of Kalman filter and neural network to predict load variations, and validation was carried out by simulating a brushless DC motor.

This article proposes a control method for Brushless DC Motors (BLDCM) based on a fuzzy BP neural network through the analysis of various control methods. The aim of this method is to reduce dependence on the model and achieve automatic parameter tuning. Its adaptive learning capability can greatly enhance the response speed of the entire motor control system. The mathematical model of the BLDCM is established, and a fuzzy BP neural network PID controller is constructed by analyzing the structure of the control system. Finally, a simulation model based on the fuzzy BP neural network PID control for motor drive is built using simulation software. Comparative analysis of motion simulation under different operating conditions is conducted with a DC brushless motor using a fuzzy PID control method. The control strategy demonstrates good performance under various operating conditions of the BLDCM. Compared to traditional PID control, it exhibits no overshoot, stronger disturbance rejection capability, and effectively improves the control stability of the DC brushless motor.

2. Experimental Details

2.1. Brushless DC Motor Mathematical Model

To facilitate the research of the control method in this paper, a mathematical model for a brushless DC motor is constructed. The control system circuit is shown in Figure 1 for reference.

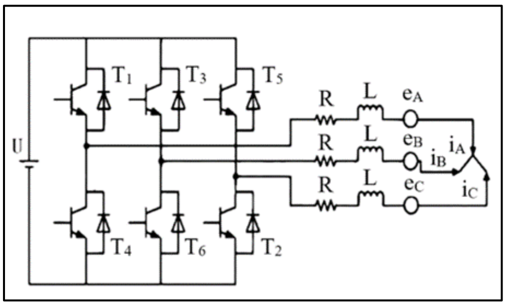


Figure 1 Circuit diagram of the BLDCM control system

To simplify the model and facilitate calculations, the following assumptions are made:

- Assume that the iron core of the BLDCM is unsaturated.
- Assume that the three-phase windings of the BLDCM are perfectly symmetrical.
- Neglect the slot effect and armature reaction of the BLDCM.
- Neglect the switching characteristics interference of electronic devices.

Provided that the above assumptions are valid, the phase voltage equation for a DC brushless motor is:

$$\begin{bmatrix} U_a \\ U_b \\ U_c \end{bmatrix} = \begin{bmatrix} r & 0 & 0 \\ 0 & r & 0 \\ 0 & 0 & r \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L & M & M \\ M & L & M \\ M & M & L \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \quad (1)$$

In equation (1): U_a, U_b, U_c is the three-phase winding phase voltage, V; i_a, i_b, i_c is the three-phase winding current, A; e_a, e_b, e_c is the stator winding counter electromotive force, V; r is the BLDCM three-phase winding resistance, Ω; L is the self-inductance of the three-phase winding of the BLDCM, H; M is the BLDCM three-phase winding mutual inductance, H.

The torque equation of the motor is:

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

In equation (2): T_e is the electromagnetic torque of the motor, Nm ; ω is the mechanical angular velocity when the motor is rotating, rad/s.

The rotor motion balance equation for the motor is:

$$T_e - T_L = J\frac{d\omega}{dt} + B\omega \qquad (3)$$

In equation (3): B is the viscous friction coefficient of the motor; J is the moment of inertia, $kg \cdot m^2$; T_L is the load on the motor, Nm.

2.2. Fuzzy Logic Controller Design

The fuzzy controller is an intelligent control method that integrates fuzzy sets, fuzzy linguistic variables, and fuzzy rules for reasoning. Fuzzy control is highly reliant on expert experience and possesses strong robustness. Typically, a fuzzy controller takes system error (e) and error change rate (ce) as inputs to determine the control signal. By utilizing parameters associated with e and ce, the fuzzy rules define the output magnitude, enabling real-time adjustability of parameters. This characteristic of the fuzzy controller is employed in this paper to achieve PID parameter correction in the brushless DC motor's PI control system, thereby attaining a certain level of adaptability.

$$e(t) = \omega_r - \omega \qquad (4)$$

$$ce(t) = e(t) - e(t-1) \qquad (5)$$

The fuzzy subsets for the parameters e, ce, ΔKP, ΔKI and ΔKD are {NB, NM, NS, ZO, PS, PM, PB}, with a domain ranging from -6 to 6. The membership functions for the fuzzy rules in this paper are represented as shown in Figure 2.

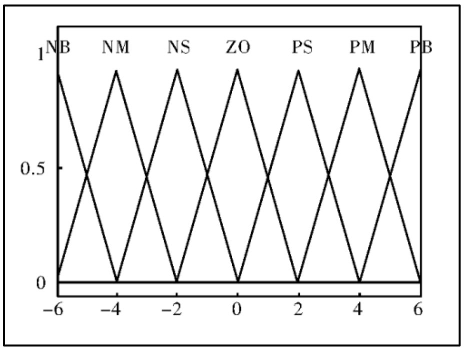


Figure 2 Fuzzy logic controller affiliation function

After the input and output affiliation functions are determined the control rules need to be designed, the fuzzy control rule table design process is mainly based on the expert experience and the characteristics of the object to be controlled, the fuzzy control rule table of this paper is listed in Table 1, Table 2 and Table 3.

Table 1 K_P Fuzzy rule table

e \ ce	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	NM	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NM
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	NM	PS	ZO	NS	NM	NM	NM

PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	NS	NM	NM	NM	NB	NB

Table 2 K_I Fuzzy rule table

ce e	**NB**	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NB	PM	PM	NS	ZO	PS	PS
ZO	PM	PM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	NS	ZO	PS	PS	PM	PB	PB
PB	ZO	PS	PS	PM	PB	PB	PB

Table 3 K_D Fuzzy rule table

ce e	**NB**	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
ZO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

2.3. Fuzzy neural network dual closed-loop speed control system

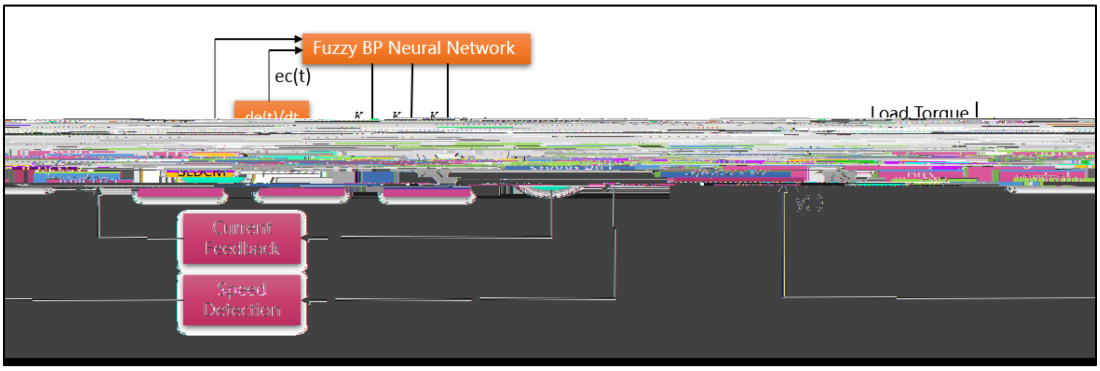


Figure 3 Brushless DC Motor Control System Structure Diagram

Figure 2 illustrates the structure of the brushless DC motor control system. This system integrates both current feedback and speed feedback to achieve a dual-feedback closed-loop control. To enhance the precision of controlling the controlled object, the traditional PID algorithm is employed to control the current loop. Meanwhile, the speed loop adopts the fuzzy backpropagation neural network PID control algorithm proposed in this paper.

In Figure 3: $r(t)$ is the target speed of the brushless DC motor; $y(t)$ is the feedback speed of the control system; $u(t)$ is the voltage control signal output by the speed PID controller; $e(t)$ is the difference between the target speed and the feedback speed.

$$u(t) = f\left(v(t)\right) \quad (6)$$

$$v(t) = P(t) + I(t) + D(t) \qquad (7)$$

In equation (6) and equation (7):

$$\begin{cases} P(t) = k_p\left(\beta r(t) - y(t)\right) \\ \dfrac{dI}{dt} = \dfrac{k_p}{k_i}\left(r(t) - y(t)\right) + \dfrac{1}{T_i}\left(v(t) - u(t)\right) \\ \dfrac{K_d}{N}\dfrac{dD}{dt} = -D - k_c k_d \dfrac{dy}{dt} \end{cases} \quad (8)$$

In equation (8): $\dfrac{dI}{dt}$ is to prevent the integral value from going out of bounds; T_i is a time constant; k_p , k_i and k_d are PID coefficients; N＝10.

To address the low control accuracy and poor disturbance rejection capability issues in the current traditional PID control strategy for brushless DC motor, this paper, based on summarizing previous research, proposes a fuzzy BP neural network structure as shown in Figure 3. $e(t)$ and $ec(t)$ are inputs, while K_p, K_i and K_d are outputs.

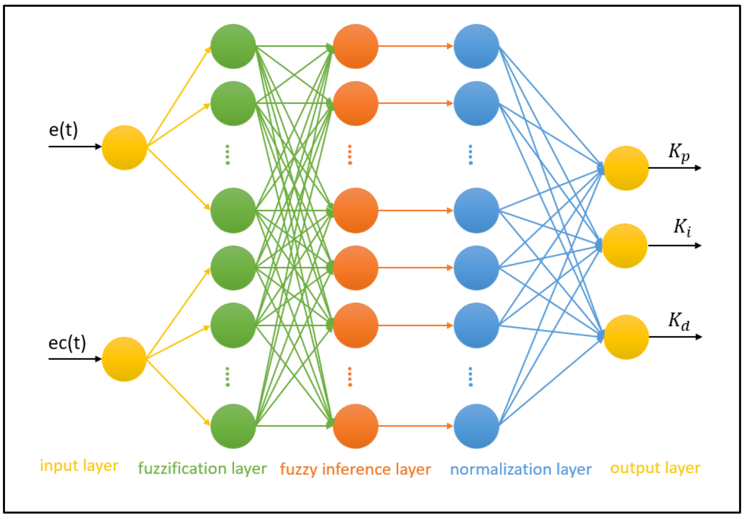


Figure 4 Fuzzy BP neural network structure

(1) Input Layer. The role of the input layer in the fuzzy neural network structure of this paper is to transmit the system error and error rate to the fuzzification layer.

$$f_m^1 = x_m \qquad (9)$$

$$g_{mn}^1 = x_{mn} = x_m \quad (10)$$

In equation (9) and (10): x_m is the m-th input variable; x_{mn} is the degree of affiliation of the m-th input variable on the nth fuzzy subset; f_m^1 is the input value of the first-layer node; g_{mn}^1 is the output value of the first-layer node.

(2) Fuzzification Layer. This layer transforms the values from the input layer into the required fuzzy quantities through fuzzification, thereby generating membership functions for each linguistic variable in the fuzzy BP neural network system. The linguistic variable's domain is [-6, 6], and it can be obtained as follows:

$$f_{mn}^2 = g_{mn}^1 \qquad (11)$$

$$g_{mn}^2 = \exp\left[-\frac{\left(x_m - c_{mn}\right)^2}{\left(\sigma_{mn}\right)^2}\right] = S_m^n\left(x_m\right) \qquad (12)$$

In equation (11) and (12): c_{mn} is the center of the membership function for the m-th input variable in the n-th fuzzy subset; σ_{mn} is the base width of the membership function for the m-th input variable in the n-th fuzzy subset. f_{mn}^2 is the input value of the second-layer node; g_{mn}^2 is the output value of the second-layer node; $S_m^n\left(x_m\right)$ is the linguistic variable value of the m-th input variable corresponding to the n-th fuzzy subset.

(3) Fuzzy Inference Layer. This layer performs fuzzy inference on the fuzzy vector from the previous layer and outputs the result.

$$f_m^3 = g_{mn}^2 \qquad (13)$$

$$g_l^3 = S_1^{n_1}\left(x_1\right) \times S_2^{n_2}\left(x_2\right) \qquad (14)$$

In equation (13) and (14): f_m^3 is the input value of the third-layer node; g_l^3 is the output value of the third-layer node; l is a rule point, l =1,2,...,49; $S_1^{n_1}\left(x_1\right)$ corresponds to the linguistic variable value of the n_1-th fuzzy subset of the first input in the upper layer; $S_2^{n_2}\left(x_2\right)$ corresponds to the linguistic variable value of the n_2-th fuzzy subset of the second input in the upper layer; n_1 ={1,2,...,7}; n_2 ={1,2,...,7}.

（4）Normalization Layer. The purpose of this layer is to perform normalization calculations on the output obtained from the previous layer. Consequently, the following can be derived:

$$f_l^4 = g_l^3 \qquad (15)$$

$$g_l^4 = \frac{g_l^3}{\sum_{l=1}^{49} g_l^3} \qquad (16)$$

In equation (15) and (16): f_l^4 is the input value of the fourth-layer node; g_l^4 is the output value of the fourth-layer node.

（5） Output Layer. This layer processes the output quantity and then outputs K_p , K_i , K_d after clarification. Consequently, the following can be derived:

$$f_l^5 = g_l^4 \qquad (17)$$

$$\mathrm{g}_h^5 = \sum_{l=1}^{49} \omega_{mn} g_l^4 \qquad (18)$$

In equation (17) and (18): f_l^5 is the input value of the fifthly-layer node; g_h^5 is the output value of the fifthly-layer node. ω_{mn} represents the weights in the output layer of the network; h represents the number of nodes in the 5th layer, h = 1， 2， 3.

The output result can be obtained through the above formula:

$$\begin{cases} K_\mathrm{p} = g_1^5 \\ K_\mathrm{i} = g_2^5 \\ K_\mathrm{d} = g_3^5 \end{cases} \qquad (19)$$

To optimize the parameters of the system algorithm, given the system input value as $r(t)$ and the actual system output value as $y(t)$ define the correction error function E:

$$E = \frac{1}{2}\left[r(t) - y(t)\right]^2 \qquad (20)$$

The learning algorithm for the output layer network weights is:

$$\omega_{mn}(k+1) = \omega_{mn}(k) - \eta\frac{\partial E}{\partial \omega_{mn}} + \alpha\left[\omega_{mn}(k-1) - \omega_{mn}(k-2)\right] \qquad (21)$$

In equation (21): $\omega_{mn}(k+1)$ is the corrected value after the iteration of the output layer network weights; α is the inertia factor; η represents the learning rate; k represents the number of iterations.

Use gradient descent algorithm to adjust the centers and widths of membership functions in the fuzzification layer, respectively:

$$c_{mn}(k+1) = c_{mn}(k) - \eta\frac{\partial E}{\partial c_{mn}} + \alpha\left[c_{mn}(k-1) - c_{mn}(k-2)\right] \qquad (22)$$

In equation (22): $c_{mn}(k+1)$ represents the updated values of the centers of membership functions after iteration in the fuzzification layer.

$$\sigma_{mn}(k+1) = \sigma_{mn}(k) - \eta\frac{\partial E}{\partial \sigma_{mn}} + \alpha\left[\sigma_{mn}(k-1) - \sigma_{mn}(k-2)\right] \qquad (23)$$

In equation (23): $\sigma_{mn}(k+1)$ represents the updated values of the widths of membership functions after iteration in the fuzzification layer.

3. Results and Discussion

To verify the distinctiveness of the fuzzy PID and fuzzy backpropagation neural network control algorithms described in this paper. Build a simulation model for the BLDCM control system as shown in Figure 5. Set the stator phase resistance of the brushless DC motor to be 2.85 ohms. The stator phase inductance is 8.4 mH. The moment of inertia is $2.08\times10^3\ \mathrm{kg\cdot m^2}$. The number of motor pole pairs is 4. Motor rated speed 1200r/min. Two control methods, fuzzy PID control and fuzzy BP neural network control, are used to simulate and analyze the motor control under various operating conditions respectively.

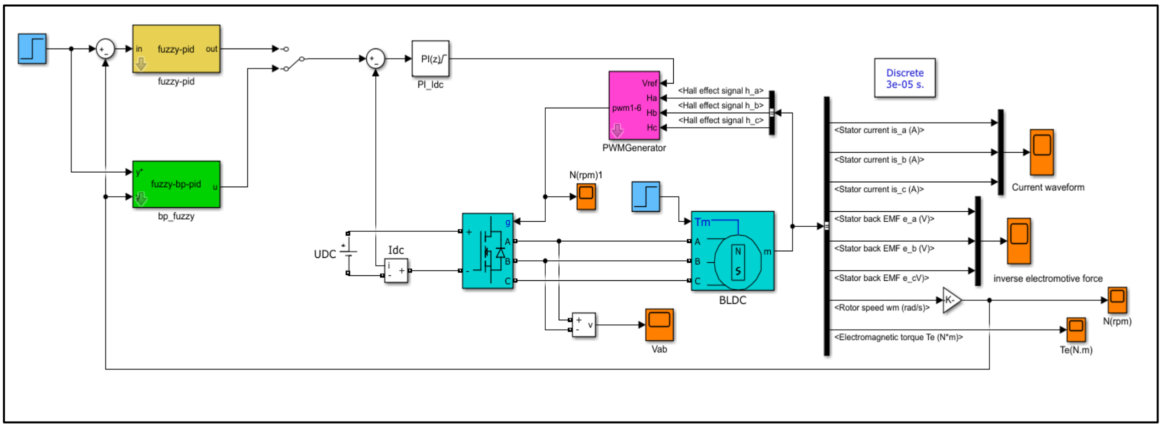
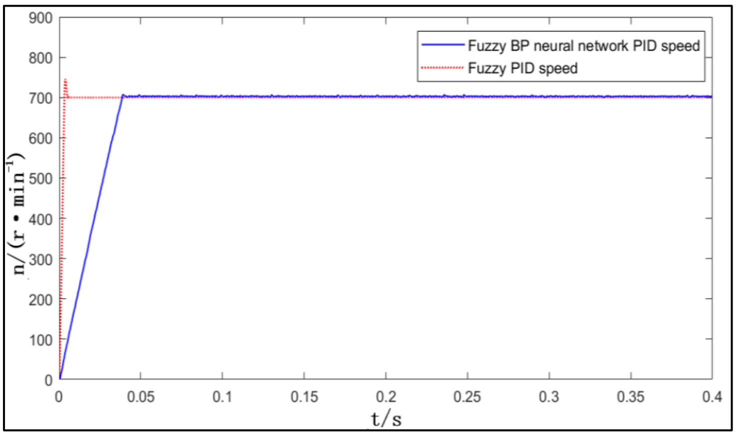
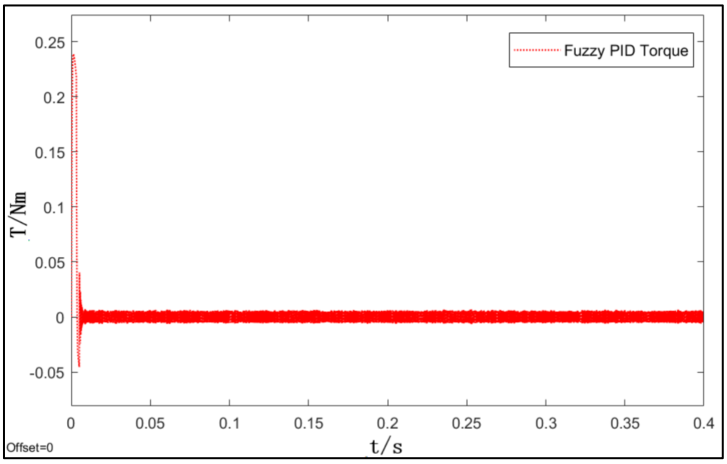


Figure 5 Control system simulation model

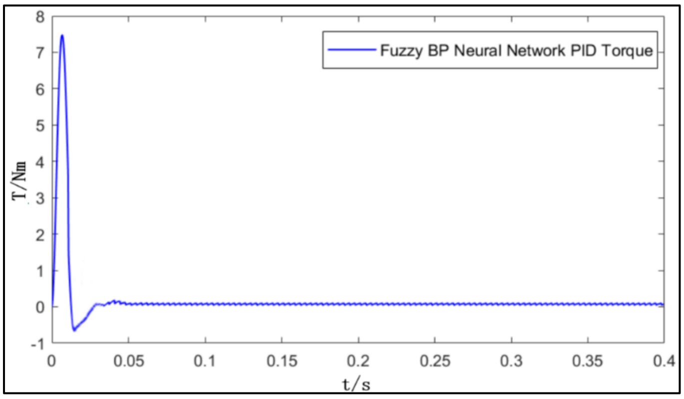
Simulation Case 1: The motor target speed is set to 700r/min for conducting experiments under no-load conditions. Run the simulation model, and compare the motor speeds under two different motor control algorithms as shown in Figure 6(a). The torques are respectively illustrated in Figure 6(b) and Figure 6(c). Through simulation experiments, it is observed that the fuzzy PID control strategy exhibits overshooting, but it has a faster response rate. On the other hand, the fuzzy BP neural network PID algorithm has a slower response speed, but it shows smaller overshoot and speed error, resulting in lower torque fluctuations.



（a）Comparison of RPM



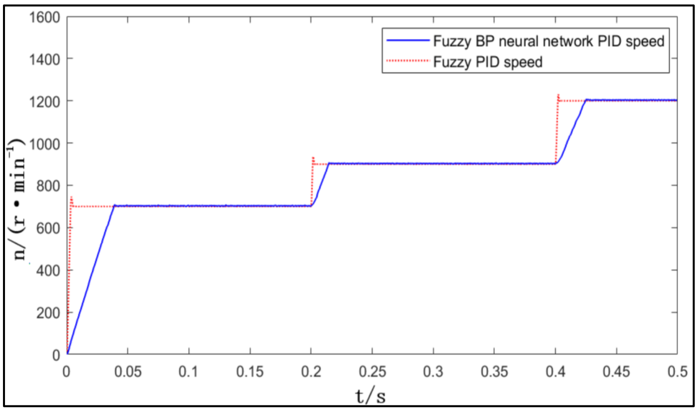
（b）Fuzzy PID Torque



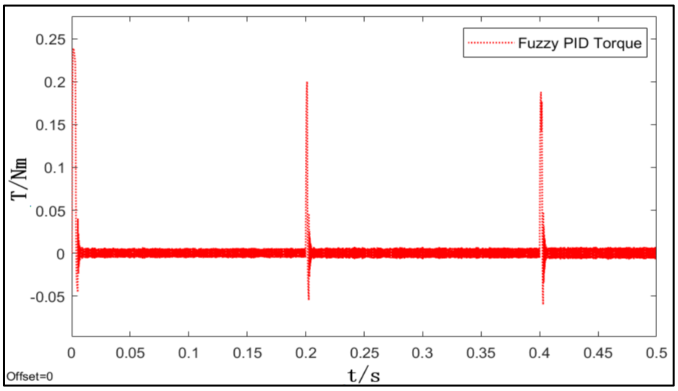
（c）Fuzzy BP Neural Network PID Torque

Figure 6 Simulation results under two control algorithms when the motor is unloaded

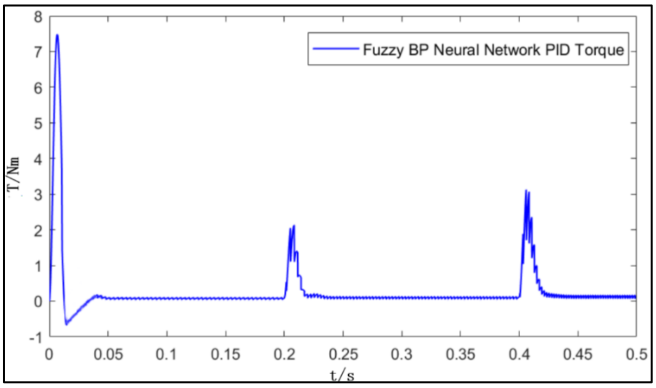
Simulation Case 2: Set the target speeds of the DC brushless motor to 700r/min, 900r/min, and 1200r/min, respectively. The motor starts with a no-load condition at a speed of 700r/min. At t=0.2s, there is an abrupt change to 900r/min, and at t=0.4s, there is another abrupt change to 1200r/min. Motor speed and torque are shown in Figure 7. From Figure 7(a), it can be seen that, under the fuzzy PID control strategy, the DC brushless motor reaches a stable speed at 0.01s, 0.21s, and 0.42s respectively. The adjustment time for the speed to stabilize after a step change is a total of 0.03s, but there is a significant overshoot before reaching stability. Under the fuzzy backpropagation (BP) neural network control strategy, the brushless DC motor reaches a stable speed at 0.03s, 0.22s, and 0.43s, respectively. The adjustment time for the speed to stabilize after a step change is 0.05s, and no overshoot phenomenon is observed. Hence, the fuzzy backpropagation (BP) neural network algorithm proposed in this paper demonstrates smaller overshoot and speed error compared to the fuzzy PID algorithm, as well as lower torque fluctuations.



（a）Comparison of RPM



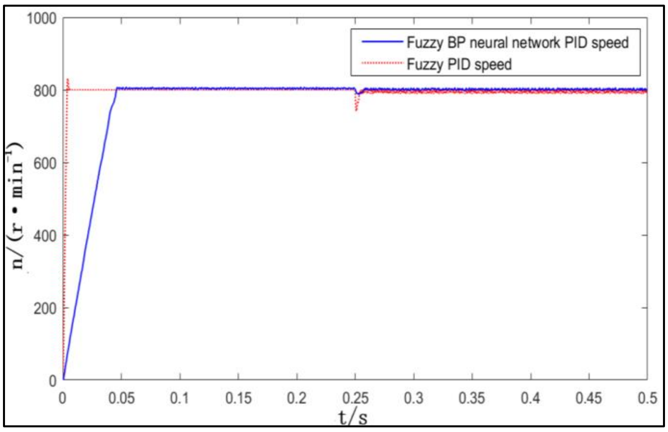
（b）Fuzzy PID Torque



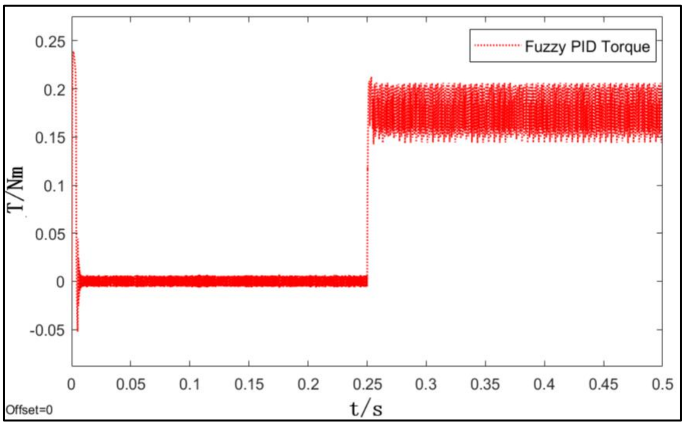
（c）Fuzzy BP Neural Network PID Torque

Figure 7 Simulation results of the two control algorithms at speed step

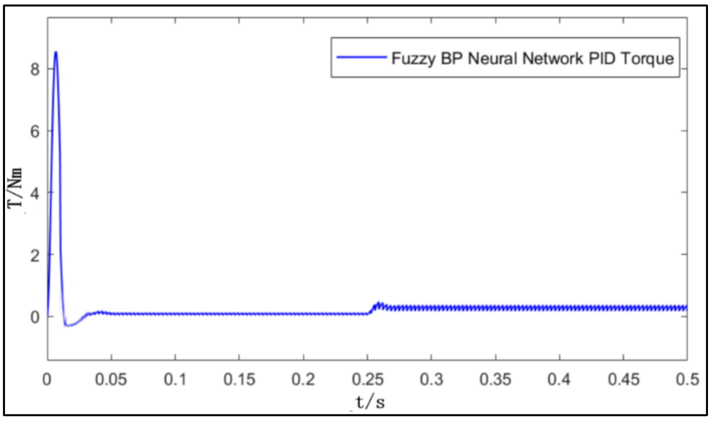
Simulation Case 3: The DC brushless motor was started unloaded with a target speed set at 800 rpm. At 0.25 seconds, a load torque of 0.18 Nm was introduced into the control system of the DC brushless motor. The simulation results of the control system are depicted in Figure 8. According to Figure 8(a), it can be observed that at 0.25 seconds, when the motor load increases, the fuzzy PID algorithm exhibits larger speed fluctuations, but with a faster system response. In contrast, the fuzzy BP neural network algorithm shows smaller fluctuations and greater resistance to disturbances.



（a）Comparison of RPM



（b）Fuzzy PID Torque



（c）Fuzzy BP Neural Network PID Torque

Figure 8 Simulation results under two control algorithms when sudden load is applied

Currently, there have been significant breakthroughs in the research on control strategies for brushless DC motors, and various new control methods have emerged. However, in daily life applications, the motors in most scenarios are controlled using traditional PID control. In some special application scenarios, issues such as low control precision, large overshoot, and poor disturbance rejection ability exist when using traditional PID control for brushless DC motors.

In consideration of these challenges, this paper proposes a control strategy for brushless DC motors based on a fuzzy BP neural network to address the shortcomings observed in traditional PID control, especially in specific situations. It is important to note that for the simplification of the mathematical model of the motor, several assumptions are made in this paper. Firstly, it is assumed that the iron core of the brushless DC motor is completely unsaturated. Secondly, it is assumed that the brushless DC motor does not exhibit slotting effects during commutation. Thirdly, it is assumed that there is no armature reaction during the operation of the motor. Lastly, it is assumed that the switch characteristics of the power conversion devices are free from interference.

The brushless DC motor control strategy proposed in this paper can offer higher system efficiency and energy utilization, aiding in optimizing the relationship between the motor's input current and output speed. This leads to more efficient motor operation, reducing energy losses. Simultaneously, it can provide better dynamic performance and response speed, enabling fast and accurate responses to external load changes and allowing the motor to adapt to diverse working conditions. Additionally, it effectively suppresses the impact of external disturbances on motor performance, enhancing the system's ability to handle various interference factors, such as sudden load variations or power grid fluctuations. This contributes to improved system reliability and stability. Furthermore, the brushless DC motor control strategy described in this paper can also reduce motor noise and vibration. This is particularly crucial for applications that demand low noise and minimal vibration, such as medical equipment or office environments.

4. Conclusions

The motor control system is a nonlinear and complex system. In this paper, a control strategy for brushless DC motors based on a fuzzy BP neural network is proposed to address issues such as low control precision, large overshoot, and poor disturbance rejection ability associated with traditional PID control methods. Firstly, the mathematical model of the brushless DC motor is established, upon which a fuzzy neural network PID controller is constructed. Subsequently, the model of the brushless DC motor control system is built in Matlab/Simulink, and simulations comparing the fuzzy PID control strategy are conducted under three different operating conditions. Simulation results indicate that, under scenarios of motor no-load, motor speed step response, and sudden load disturbance, the brushless DC motor controlled by the fuzzy PID algorithm exhibits faster response speed and shorter settling time. Furthermore, the brushless DC motor controlled by the fuzzy BP neural network algorithm achieves a speed closer to the target speed, with smaller overshoot, speed error, and torque fluctuation. It adapts better to environments with significant disturbances, demonstrating good disturbance rejection and robustness. Overall, the fuzzy BP neural network algorithm effectively enhances the dynamic performance of the entire motor control system.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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