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RESEARCH ARTICLE

PID Adaptive Feedback Motor System Based on Neural Network

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ABSTRACT This paper presents a neural network-based feedback control method for enhancing the control precision and tracking speed of a permanent magnet brushless motor under command control. The proposed method involves real-time adjustment of the PID controller parameters using electromechanical output signals, enabling adaptive feedback control based on motor output. Experimental results demonstrate that this approach enhances real-time performance and dynamic load response capability, resulting in a current waveform with excellent tracking and low distortion. Overall, this method effectively improves and enhances control effectiveness. Furthermore, the developed control method is successfully applied to the development of tangible products.

INDEX TERMS BP neural network, motor system, PID control, PMSM.

I. INTRODUCTION

In recent years, due to the permanent magnet brushless motor for its excellent performance, it is widely used in many fields such as household appliances, automobiles, pumping units and so on. Alone with the application range of PMBM continues to expand, People have higher requirements on the control performance of permanent magnet brushless motor [1], [2], [3]. The permanent magnet brushless motor model is usually a nonlinear time-varying system, There are uncertainties and nonlinearities in the system. For the mechanical model uncertainty of the motor system, The PID control method is a very classical method. Conventional PID control rules are limited to proportion, integration and differentiation, manual experience control is required for setting parameters, there are some defects in the design, such as blindness and the parameters cannot be modified automatically [4].

In the study of controlling motor speed, method to improve the traditional PID control is found [5], [6]. In paper [6], [7], the fuzzy PID control method of DC motor speed is studied, the control principle of speed of brushless DC motor is analyzed, and the traditional PID control strategy is given. The fuzzy PID control system is designed by fuzzy rules, and the simulation diagram of fuzzy PID control system is constructed. These studies shorten the steady-state response time and improve the stability of the motor governing system. In paper [8], [9], the sliding mode control method of motor speed is studied, and the mathematical model of motor coordinate system is established. In paper [10], [11], a sliding mode controller is designed to compensate the motor speed control. By comparing and analyzing the system simulation, the response speed of control system is improved and the output error of motor speed is reduced. Under the condition of signal mutation, Many research methods of motor control in the past lead to instantaneous instability of control system, and increase the motor speed jitter range. Because few control methods can adjust the control gain of PID algorithm flexibly and effectively depend on the running condition of the motor, the stability of motor speed regulation is hard to guarantee.

The motivation of this paper is to design a high-precision motor control that can improve the dynamic characteristics of PMSM time-varying systems and reduce motor overshoot as well as torque pulsation. a PID adaptive feedback motor method based on neural network is proposed [12], [13], which

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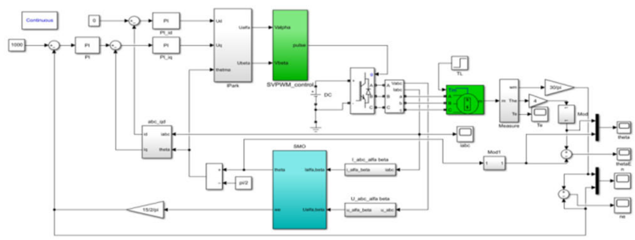


FIGURE 1. Control system structure of PMBM.

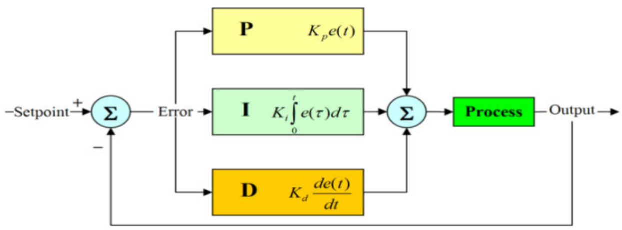


FIGURE 2. PID controller diagram.

dynamically estimate the optimal PID control gain and adjust the relevant parameters of electromechanical system in time. This can not only enhance the anti-interference of the motor control system and attenuate the jitter phenomenon of the motor, but also effectively reduce the speed overshoot, and reduce the speed and motor tracking error, which has good practical application capability.

The structure of this paper is as follows: the first part introduces the basic knowledge and related model; The second part explains the algorithm design based on BP neural network; The third part shows the experiment and application; The fourth part is the summary.

II. PRELIMINARIES

A. PERMANENT MAGNET BRUSHLESS MOTOR AND ITS SPEED CONTROL SYSTEM STRUCTURE

According to the output signal of the rotor position sensor, the rotation of PMBM can determine the rotor position. Through the obtained rotor position information, the reversing signal can be obtained. According to the reversing signal through the drive circuit, provide switching signal for the power tube, and realize stator three-phase winding feed in turn, finally realize the rotation of the motor in one cycle. The structure principle of permanent magnet brushless DC motor speed control system is shown in the Figure 1: Main circuit, permanent magnet brushless DC motor main body (Including a position sensor and a speed transmitter mounted on a rotating shaft)and the speed control system consists of three parts of the computer control system.

B. PID CONTROL

PID controller(Proportion Integration Differentiation, proportional-integral-differential controller), it is composed of proportional element (P), integral element (I) and differential element (D) (see Figure 2). The output status of the controller is as follows:

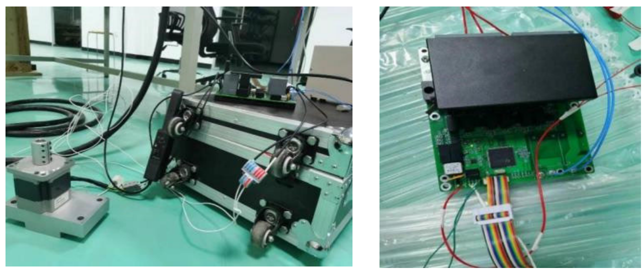
$$u(t) = K_p e(t) + K_i \int_0^t e(t)\,dt + K_d \frac{de(t)}{dt}, \tag{1}$$

where u(t) is the output value, e(t) is equal to the difference between the reference and the output; K_p represents the proportionality coefficient, K_i represents the integral coefficient, K_d represents the differential coefficient.

III. PID ADAPTIVE FEEDBACK MOTOR SYSTEM OF NEURAL NETWORK

A. PERMANENT MAGNET BRUSHLESS MOTOR EQUIPMENT

Permanent magnet brushless motor is the experimental platform of this paper, the related hardware devices are shown in Fig. 3 and Fig. 4.



(a) (b)

FIGURE 3. Experimental platform (hardware and driver).(a). PMSM motor, (b). Motor drive plate.

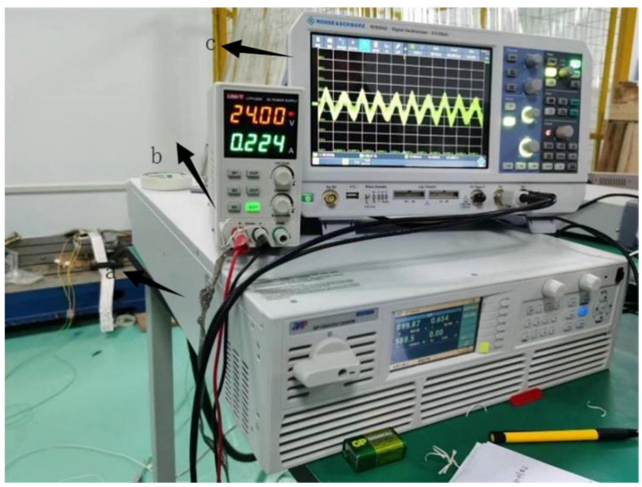


FIGURE 4. Experimental platform (Power supply and test). (a). main power,(b). auxiliary power, c. digital oscilloscope.

B. FEEDBACK CONTROL MOTOR SYSTEM

In this paper, BP neural network is used to dynamically adjust PID control gain, i.e., K_i, K_p, K_d. Based on previous experience accumulation, the real-time current I of our motor and the speed position error e(t) have great influence on the motor speed control. According to the real-time current I of the system and the rotational speed position error e(t), in order to pursue PID optimal control, usually PID control gain especially K_i, K_p need timely adjustment. Hence, according to the real-time current I of the motor and the speed position error e(t), this paper uses neural network to estimate the optimal control gain in the PID controller K_i, K_p. Neural network can dynamically estimate the optimal PID control gain and adjust the relevant parameters of electromechanical system in time. This can not only enhance the anti-interference of the motor control system and attenuate the jitter phenomenon of the motor, but also effectively reduce the speed overshoot, and reduce the speed and motor tracking error, which has good practical application capability.

Controller output status:

$$u(t) = K_p(I, e(t))e(t) + K_i(I, e(t)) \int_0^t e(t)\,dt + K_d \frac{de(t)}{dt}, \quad (2)$$

where $K_p(I, e(t))$, $K_i(I, e(t))$ are functions that depends on $I, e(t)$.

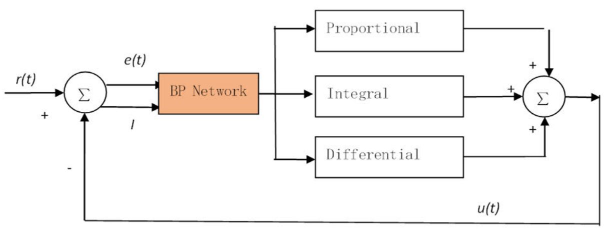


FIGURE 5. PID feedback control scheme based on neural network.

The PID feedback control scheme based on neural network is shown in Figure 5. In Figure 5, the red part is the control gain $K_p(I, e(t))$ and $K_i(I, e(t))$ of BP neural network dynamic estimation formula(2), where K_d is a fixed value. BP neural network is used to estimate the control gain of PID controller $K_p(I, e(t))$ and $K_i(I, e(t))$. The algorithm is described as follows:

Step1 Training neural network: In the early stage of motor operatin,We get samples of optimal combinations of $I, e(t)$ and K_p, K_i. Take $P_i = (I, e(t))$ as the input vector of the neural network, Take $T_i = (K_p, K_i)$ as the target vector, $i = 1,2, \ldots, n$. The training process is as follows:

a) Set the initial values of each weight and threshold, the maximum number of iterations is M_d;
b) Input learning sample: Input vector P_i, ($i = 1, 2, \ldots, n$) and target vector T_i ($p = 1, 2, \ldots, P$) $i = 1,2,\ldots, n$;
c) Determine whether the number of iterations is less than M_d. If it is less than M_d, calculate the actual output of the network and the state of the hidden cell; calculated training error; modify weights and thresholds; If not, go to (4);
d) Determine whether the indicator meets the accuracy requirements, end if the requirements are met, If not, go to (3);
e) End, save the trained neural network as BP_PID.net.

Step2 Neural network estimation of PID control gain: according to the actual current I and speed error $e(t)$ in the motor system, use it as an input to train the neural network BP_PID.net to estimated control gain K_p, K_i. According to the estimates of the neural network, controller(2) updates the control gain in real time.

Remark 1: Note that after training the neural network to estimate the control gain Kp, Ki, it is necessary to increase the upper and lower limits when updating the control gain to prevent unpredictable unexpected situations that may occur in the system.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

In the early stage, based on our electromechanical system, through experience adjustment, we obtain the sample data table1 of the PI control gain of the outer loop of the system1.

TABLE 1. Control gain and motor speed sampling data.

	Motor parameter		Control gain		
	revolving speed n(rpm)	compensation angle	Difference coefficient K_P	Integral coefficient K_i	wave form distortion
1	700	0.12	1.1	0.02	none
2	800	0.13	1.2	0.025	none
3	900	0.09	1.4	0.03	none
4	1000	0.1	1.6	0.033	none
5	1100	0.12	1.9	0.037	none
6	1200	0.12	2.1	0.039	none
7	1300	0.07	2.15	0.036	none
8	1400	0.19	2.3	0.041	none
9	1500	0.2	2.5	0.045	none
10	1600	0.17	2.65	0.048	none
11	1700	0.18	2.68	0.048	none
12	1800	0.11	2.7	0.049	alittle
13	1900	0.12	2.75	0.05	alittle
14	2000	0.13	2.8	0.052	alittle
15	2100	0.12	2.83	0.055	alittle

The waveform distortion rates shown in Table 1 are all less than 1%, This means that the overall control gain value is better under different motor output conditions.

BP neural network was constructed by Matab2021b, The network structure consists of four layers: input layer, hidden layer 1, hidden layer 2 and output layer. The number of neural clouds in each layer was 2,88,77,2 respectively(Figure 6). Set the relevant parameters of neural network training: the maximum number of iterations is 5000, the accuracy is 0.0001, the excitation function of hidden layer 1 is 'purelin', the excitation function of hidden layer 2 is 'tansig', the transfer function of the output layer is 'purelin', the optimization iteration function is 'traingdm'. Table 1 shows that the current I and

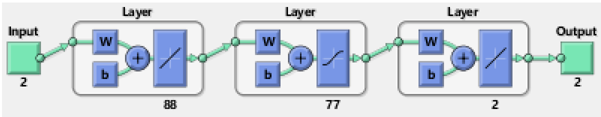
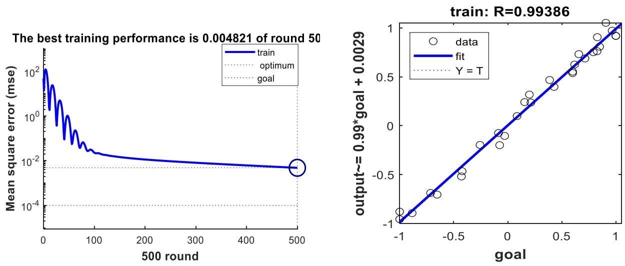
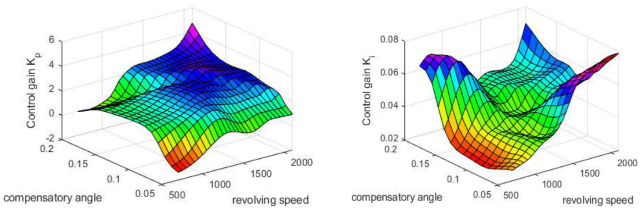


FIGURE 6. Neural network structure diagram (Matlab 2021b).



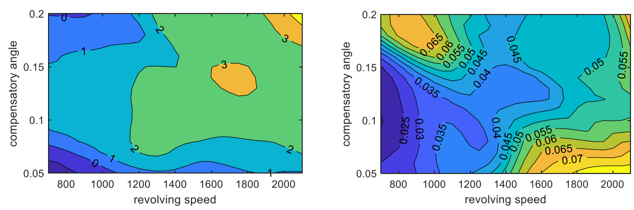
(a) (b)

FIGURE 7. Neural network training performance diagram. (a) error; (b)fitting effect.



(a) (b)

FIGURE 8. (a) The influence of speed and compensation Angle on the difference coefficient K_p of external loop control gain; (b)The influence of speed and compensation Angle on the difference coefficient K_i of external loop control gain.



(a) (b)

FIGURE 9. (a) Effect of speed and compensation Angle on K_p contour plot; (b) Effect of speed and compensation Angle on K_i contour plot.

the position error e(t) are input vectors of the neural network, the gain difference coefficient K_P and integral coefficient K_i of external loop are output vectors of the neural network.

Fig. 7 is a graph of neural network performance. Fig. 7(a) is the error analysis chart of training effect, Fig. 7(b) is the regression analysis diagram of fitting effect. Fig. 7 shows that, The training error and fitting effect of the model are quite ideal. Further, Fig. 8 shows that the influence of rotational speed and compensation Angle on difference coefficient K_P and integration coefficient K_i of external loop control gain respectively. Its three-dimensional contour diagram is shown in Fig. 9.

From the above simulation results, it can be concluded that PID adaptive feedback motor method based on neural network has the following three advantages compared to other control systems:

1) This design verifies the effectiveness and stability of neural network-based PID for PMSM drive control through simulation and experiments;

2) It can dynamically estimate the optimal PID control gain and adjust the relevant parameters of electromechanical system in time;

3) It can enhance the anti-interference of the motor control system and attenuate the jitter phenomenon of the motor.

At different rotational speeds, we compare the PID algorithm combined with BP neural network with the traditional PID algorithm. It is obvious that this method has better signal waveform. Observing the motor phase current curve through an oscilloscope, the lower noise and the closer to a sine wave in the phase current curve, the better the stability. Figure 10-13 shows experimental results. This indicated that in the motor speed, this method has better stability and control precision performance. In addition, table 2 shows that the proposed method has a lower distortion rate, This implication that the motor speed is stable and smooth, producing lower noise to the environment, the control system has good followability.

In summary, the proposed neural network-based PID adaptive feedback motor method was discussed, from theoretical analysis and software simulation to prototype design and experimental verification (with speeds ranging from 700rpm to 2100rpm). This method dynamically estimates the optimal PID control gain and adjusts the relevant parameters of the mechanical and electrical system in time, which can effectively enhance the anti-interference performance of the motor control system and reduce the vibration phenomenon of the motor.

(a) (b)

FIGURE 10. Current curve versus time when n = 750rpm. (a) Classical PID control strategy; (b) Frequency feedforward parameter compensation PID control strategy.

(a) (b)

FIGURE 11. Current curve versus time when n = 950rpm. (a) Classical PID control strategy; (b) Frequency feedforward parameter compensation PID control strategy.

(a) (b)

FIGURE 12. **Current curve versus time when n = 1150rpm. (a) Classical PID control strategy; (b) Frequency feedforward parameter compensation PID control strategy.**

(a) (b)

FIGURE 13. **Current curve versus time when n = 1350rpm. (a) Classical PID control strategy; (b) Frequency feedforward parameter compensation PID control strategy.**

TABLE 2. **Two control strategy parameters and test results.**

number	revolving speed n(rpm)	Classical PID Control strategy	PID control strategy based on BP neural network	Control improvement
		current waveform	current waveform	
1	750	loud noise, wave form distortion	no noise, sine wave	Obvious improvement
2	950	loud noise, wave form distortion	no noise, sine wave	Obvious improvement
3	1050	loud noise, wave form distortion	no noise, sine wave	Obvious improvement
4	1150	loud noise, wave form distortion	no noise, sine wave	Obvious improvement
5	1350	loud noise, wave form distortion	no noise, sine wave	Obvious improvement

V. CONCLUSION

In this paper, we proposed a permanent magnet brushless motor system and developed a PID feedback control method utilizing a BP neural network. Through rigorous testing and verification on the experimental platform, we reached the following conclusion: the PID feedback control method based on the BP neural network optimizes and adjusts the parameters of the transfer function. This can not only enhance the anti-interference of the motor control system and attenuate the jitter phenomenon of the motor, but also effectively reduce the speed overshoot, and reduce the speed and motor tracking error, which has good practical application capability.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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