Comparative study on control effect of permanent magnet synchronous motor based on Fuzzy PID control and BP neural network PID control

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Abstract. Aiming at the problems of low control precision, poor anti-interference ability and poor stability of traditional PID controller, the improvement effect of fuzzy control and BP neural network in closed-loop control of PMSM is compared. In the case of variable speed and variable load, the stability, real-time, anti disturbance and robustness of PMSM system with traditional PID controller, fuzzy self-tuning PID controller and BP neural network PID controller as speed regulator are simulated and analyzed. The simulation results show that the fuzzy self-tuning PID controller has more advantages in the response speed of the system, and can make the system quickly recover to the initial state in case of sudden change. The BP neural network PID controller can ensure the relative stability of the system is better, and can restrain the sudden fluctuation.

Key words: Permanent magnet synchronous motor control Fuzzy self tuning PID control BP neural network PID control variable speed Variable load.

1. Introduction
Permanent magnet synchronous motor (PMSM) is widely used in modern AC speed control system due to its advantages of small size, high efficiency, easy heat dissipation and maintenance. In recent years, the application fields characterized by high control accuracy and high reliability have higher requirements for the speed regulation, stability and torque smoothness of the motor [1] - [3]. Therefore, how to design a higher precision control strategy and a better quality control system for PMSM has attracted many scholars' research [4].

PID controller with its simple structure, easy to use and other advantages, has been widely used in various control occasions [5]. But for the complex nonlinear system such as PMSM, the simple linear PID control can not meet the high-precision requirements of motor operation in the harsh environment. In order to improve the dynamic response performance and anti disturbance ability of the motor, some scholars proposed to combine intelligent control technology with PID control to realize real-time self-tuning of PID control parameters [6]. At present, many excellent control algorithms, such as fuzzy control and neural network control, have good application in nonlinear control system. The fuzzy control PID can adjust PID parameters in real time according to the system changes, and the control performance is good [7] - [8]. Neural network is an intelligent algorithm to realize information processing by imitating the synaptic connection structure of brain. It has good self-learning and adaptive ability [9]. BP neural
network PID uses BP neural network to adjust the connection weights of each layer in the continuous learning and training process, so as to output the optimal parameters of PID controller [10] - [11]. All the above intelligent control algorithms are designed to improve the overall performance of PMSM speed control system on the basis of traditional PID control, but there is no comparative analysis on their improvement effects in PMSM system stability, response speed, robustness, anti disturbance and so on.

Therefore, according to the PMSM vector control principle, this paper builds the simulation model of PMSM double closed-loop control system, applies the fuzzy self-tuning algorithm and BP neural network algorithm to the traditional PID controller of speed loop, compares and analyzes the improvement effect of the two intelligent algorithms in the PMSM closed-loop control, and provides certain reference value for users to choose the PMSM control algorithm.

2. Vector control system of PMSM

2.1. Coordinate transformation

The commonly used coordinate systems are ABC three-phase stationary coordinate system, \( \alpha - \beta \) two-phase stationary coordinate system and \( d - q \) two-phase rotating coordinate system. Fig. 1 shows the relationship among the coordinate systems.

![Fig. 1 Relationship of coordinate systems](image)

In ABC three-phase static coordinate system, it is very difficult for PMSM to realize AC speed regulation by using traditional control strategy, so the motor stator variable coordinates are often transformed into \( d - q \) two-phase rotating coordinate system, and PMSM control method is approximately transformed into separately excited DC motor control method to control.

According to the principle of power invariant constraint, permanent magnet synchronous motor (PMSM) can realize static coordinate transformation (Clark transformation), synchronous rotation coordinate transformation (Park transformation) and their inverse transformation.

The coordinate transformation from ABC three-phase coordinate system to \( \alpha - \beta \) coordinate system is Clark transformation. The coordinate transformation matrix \( T_{ABC\rightarrow\alpha\beta} \) can be expressed as follows:

\[
T_{ABC\rightarrow\alpha\beta} = \frac{1}{\sqrt{2}} \begin{bmatrix}
1 & -\frac{1}{2} & -\frac{1}{2} \\
0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\
\sqrt{2} & \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2}
\end{bmatrix}
\]  

(1)

The coordinate transformation from \( \alpha - \beta \) coordinate system to \( d - q \) coordinate system is park transformation, and its coordinate transformation matrix \( T_{\alpha\beta\rightarrow dq} \) can be expressed as follows:
\[ T_{\text{2-2}} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \] (2)

2.2. Vector control system
Based on the mathematical model of PMSM in \(d-q\) two-phase rotating coordinate system, SVPWM modulation mode and \(i_t = 0\) control mode are adopted in this paper. The block diagram of field oriented vector control system of three-phase permanent magnet synchronous motor is shown in Fig. 2.

![Fig. 2 block diagram of vector control system](image)

The vector control system includes coordinate transformation, SVPWM modulation, speed loop and current loop. The speed loop is an outer loop. The difference between the feedback speed and the given speed is adjusted by the speed controller to output the reference current \(i_q^*\) of q axis. The current loop is an inner loop. The difference between the feedback current and the corresponding reference current is input into the current controller to obtain the voltage values \(u_d\) and \(u_q\) in d-q coordinate system, where the reference current of d-axis is \(i_d^* = 0\). Finally, the voltage is converted into pulse signal by park inverter and SVPWM module, and then added to PMSM by inverter to drive motor rotation.

In this paper, the current controller uses the traditional PI controller, the speed controller uses the traditional PID controller, the fuzzy control PID controller and the BP neural network controller.

3. Design of Controller

3.1. Fuzzy self tuning PID controller
Fuzzy control does not need accurate mathematical model. It gives fuzzy solution according to the current state of the system by simulating various laws and human thinking characteristics. The fuzzy self-tuning PID control combined with fuzzy control and traditional PID control can use the fuzzy controller to adjust the parameters of PID regulator on-line and improve the shortcomings of traditional PID. Its structure diagram is shown in Fig. 4.
PID controller technology adjusts the behavior of the controlled object according to the proportion, integral and differential links by continuously calculating the difference between the set value and the measured output. The calculation formula is as follows:

$$u(t) = kp \left( e(t) + \frac{1}{T_i} \int_0^t e(t) \, dt + T_d \frac{de(t)}{dt} \right)$$

(3)

Where \( kp \) is the proportional time constant, \( T_i \) is the integral time constant, \( T_d \) is the differential time constant, and \( e(t) \) is the difference value.

Fuzzy controller has four important processes: fuzzification, establishing fuzzy rules, fuzzy reasoning and resolving fuzziness. The error \( E \) and error change rate \( EC \) are input into the fuzzy controller, and the PID correction parameters \( k_p \), \( k_i' \) and \( k_d' \) are output after four important processes. The quantization level of input and output variables of fuzzy controller is 7 levels, the fuzzy subset is \{NB,NM,NS,ZO,PS,PM,PB\}, and the universe after quantization is \{-4, -3, -2, -1, 0, 1, 2, 3, 4\}. Trigonometric distribution function is selected as membership function. The fuzzy rule table of \( k_p' \), \( k_i' \) and \( k_d' \) is obtained by summarizing the speed regulation experience of permanent magnet synchronous motor. See table 1-2. The min-max method is used for fuzzy reasoning, and the barycenter method is used for fuzzing.

**Table 1. KP fuzzy rule table**

| Kp   | NB  | NM  | NS  | ZO  | PS  | PM  | PB  |
|------|-----|-----|-----|-----|-----|-----|-----|
| NB   | PB  | PB  | PM  | PM  | PS  | ZO  | ZO  |
| NM   | PB  | PB  | PM  | PM  | PS  | PS  | ZO  |
| NS   | PM  | PM  | PM  | PS  | ZO  | NS  | NS  |
| ZO   | PM  | PM  | PS  | ZO  | NS  | NM  | NM  |
| PS   | PS  | PS  | ZP  | NS  | NS  | NM  | NM  |
| PM   | PS  | ZO  | NS  | NM  | NM  | NM  | NB  |
| PB   | ZO  | ZO  | NM  | NM  | NM  | NB  | NB  |
Table 2. Ki fuzzy rule table

| Ki | 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 | NS | NS | ZO | PS | PS |
| ZO | NM | NM | NS | ZO | PS | PM | PM |
| PS | NM | NS | ZO | PS | PS | PM | PB |
| PM | ZO | ZO | PS | PS | PM | PB | PB |
| PB | ZO | ZO | PS | PM | PM | PB | PB |

3.2. BP neural network PID controller

BP neural network is a kind of multilayer feedforward neural network trained according to the error back propagation algorithm. It can map any complex nonlinear relationship, so it can make up for the defects of traditional PID controller in nonlinear field. The structure block diagram of BP neural network PID controller is shown in Figure 5. The incremental PID algorithm is used in PID controller. The increment of control is only related to the system deviation signal at $t$, $t-1$, $t-2$ time, and the control system has a fast processing speed. The formula is as follows:

$$u(kT - T) = kp \cdot e(kT - T) + ki \cdot \sum_{j=0}^{k-1} e(jT) + kd \cdot [e(kT - T) - e(kT - 2T)]$$  (4)

Fig. 4 Structure block diagram of BP neural network PID controller

The BP neural network designed in this paper has three layers, including one input layer, one hidden layer and one output layer. There are 3 neurons in the input layer and output layer, and 5 neurons in the hidden layer. The input is the given value, error and actual value of the system, and the output is three parameters of PID. Its structure is shown in Figure 6.
Figure 5. Neural network structure

The input and output of network input layer \( j \) are as follows:
\[
O_j^{(1)} = x(j) \quad j = 1, 2, 3
\]  
(5)

The input and output of hidden layer \( l \) are as follows:
\[
\text{net}_i^{(2)}(k) = \sum_{j=1}^{3} w_{ij}^{(2)} O_j^{(1)}
\]
\[
O_i^{(2)} = f(\text{net}_i^{(2)}) \quad i = 1, 2, 3, 4, 5
\]  
(6)

The input and output of the output layer \( l \) are as follows:
\[
\text{net}_i^{(3)}(k) = \sum_{i=0}^{5} w_{li}^{(3)} O_i^{(2)}
\]
\[
O_i^{(3)} = g(\text{net}_i^{(3)}) \quad i = 1, 2, 3
\]
\[
k_p = O_3^{(3)} \quad k_r = O_2^{(3)} \quad k_d = O_1^{(3)}
\]  
(7)

The activation function of network hidden layer is positive and negative symmetric sigmoid function, and the activation function of output layer is non-negative sigmoid function
\[
f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}
\]
\[
g(x) = \frac{e^x}{e^x + e^{-x}}
\]  
(8)

In the above formula, \( w_{ij}^{(2)} \) is the network weight between the input layer and the hidden layer, and \( w_{li}^{(3)} \) is the network weight between the hidden layer and the output layer. Superscripts (1), (2), (3) denote the input layer, the hidden layer, and the output layer, respectively.

The second power of output error is used as the performance index
\[
E(k) = \frac{(\text{rin}(k) - \text{yout}(k))^2}{2}
\]  
(9)

According to the gradient descent method, the weight coefficient of the network is adjusted according to the negative gradient direction of \( E(k) \), and an inertia term is added to make the search quickly converge to the global minimum
\[
\Delta w_{li}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{li}^{(3)}} + \alpha \Delta w_{li}^{(3)}(k - 1)
\]  
(10)

Among them,
\[
\frac{\partial E(k)}{\partial w_{li}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial \Delta u(k)} \cdot \frac{\partial \Delta u(k)}{\partial O_i^{(3)}(k)} \cdot \frac{\partial O_i^{(3)}(k)}{\partial \text{net}_i^{(3)}(k)} \cdot \frac{\partial \text{net}_i^{(3)}(k)}{\partial w_{li}^{(3)}(k)}
\]  
(11)

\[
\frac{\partial \text{net}_i^{(3)}(k)}{\partial w_{li}^{(3)}(k)} = O_i^{(2)}(k)
\]  
(12)

\[
\frac{\partial \Delta u(k)}{\partial O_i^{(3)}(k)} = \text{error}(k) - \text{error}(k - 1)
\]  
(13)
Because \( \frac{\partial y(k)}{\partial \Delta u(k)} \) is unknown, so the approximation is:

\[
\frac{\partial y(k)}{\partial \Delta u(k)} = \text{sgn}\left(\frac{\partial y(k)}{\partial \Delta u(k)}\right)
\]

(16)

Based on the above analysis, we can see that the learning algorithm of network output layer \( l \) is as follows:

\[
\Delta w^{(l)}(k) = \alpha \Delta w^{(l)}(k-1) + \eta \delta^{(l)} O^{(l)}(k)
\]

(17)

Similarly, the learning algorithm of hidden layer \( i \) is as follows:

\[
\Delta w^{(i)}(k) = \alpha \Delta w^{(i)}(k-1) + \eta \delta^{(i)} O^{(i)}(k)
\]

(18)

Of which

\[
\delta^{(i)} = \text{error}(k) \cdot \text{sgn}\left(\frac{\partial y(k)}{\partial \Delta u(k)}\right) \cdot \frac{\partial \Delta u(k)}{\partial O^{(i)}(k)} \cdot g'(\text{net}^{(i)}(k))
\]

(19)

\[
\delta^{(3)} = f'(\text{net}^{(3)}(k)) \sum_{i=0}^{2} \delta^{(i)} w^{(i)}(k)
\]

Where \( \eta \) is the learning rate, \( \alpha \) is the inertia coefficient, \( g'(\cdot) = g(x)(1-g(x)) \), \( f'(\cdot) = (1-f^2(x))/2 \)

4. Matlab / Simulink simulation design and result analysis

4.1. Simulation design

Figure 7 is the model of PMSM double closed-loop speed control system established by Simulink. The speed regulator PI speed is designed as traditional PID controller, fuzzy self-tuning PID controller and BP neural network PID controller respectively.

![Simulation model of PMSM double closed loop speed control system](image)
4.2. Result analysis

In this paper, the simulation of variable speed and variable load is carried out. The simulation time is set to 0.4s, and the simulation parameters of the motor are shown in Table 3.

| Parameters                        | Values       |
|-----------------------------------|--------------|
| Direct current voltage            | 311V         |
| Stator resistance                 | 2.75Ω        |
| Inductance on d/q frame           | 8mH          |
| Flux                              | 0.273Wb      |
| pn                                | 4            |
| Moment of inertia                 | 8.15 × 10⁻⁴ kg·m² |
| Target speed                      | 800r/min     |
| Target torque                     | 2N·m         |

1) At 0.2S, the target torque of the motor changes from 800r/min to 600r/min. It can be seen from Fig. 10 that the traditional PID controller can cause the overshoot of PMSM system to reach 11.5%, and the adjustment time is 0.054s. The overshoot of motor system with fuzzy self-tuning PID controller is 4.8%, and the regulating time is 0.007s; the overshoot of motor system using BP neural network PID controller is 0.1%, and the regulating time is 0.01s. Compared with BP neural network PID controller, the motor system with fuzzy self-tuning PID controller has faster response speed and shorter time to reach the given speed. However, when the motor adopts BP neural network controller in the case of variable speed, the changes of motor speed, current and torque are relatively stable, the motor speed almost has no overshoot, the overshoot of motor torque and starting current is well restrained, and the fluctuation of current in the mutation stage is small.

2) At 0.2S, the target torque of the motor changes from 2N·m to 4N·m. It can be seen from Fig. 11 that the traditional PID controller will cause the speed drop of PMSM system to reach 6.5%, and the time to return to the initial state is 0.043s. After the sudden load disturbance, the motor system with fuzzy self-tuning PID controller as speed regulator can reduce the speed by 10.8%, but it only takes 0.006s to recover the initial speed; compared with the fuzzy self-tuning PID controller, the motor system using BP neural network PID control has only 1.4% speed drop, and the process of restoring the initial speed, torque and current changes is more stable. Therefore, the BP neural network PID controller can make the PMSM system fluctuate little and relatively stable under the disturbance, while the fuzzy self-tuning PID controller can make the system recover the target state quickly.
Figure 7. Simulation diagram of speed and torque of permanent magnet synchronous motor

Figure 8. Simulation diagram of speed and torque of permanent magnet synchronous motor

5. Conclusion
In this paper, the simulation model of double closed-loop control system of permanent magnet synchronous motor is built. The traditional PID controller, fuzzy self-tuning PID controller and BP neural network PID controller are used as the speed loop of the system. The improvement effect of fuzzy control and neural network control on the traditional PID controller under the condition of variable speed
and variable load is simulated. The simulation results of the three controllers show that the traditional PID controller can make the permanent magnet synchronous motor system have the defects of large overshoot, long adjustment time, poor stability and robustness. The fuzzy self-tuning PID controller has more advantages in the system response speed, and the use of BP neural network PID controller can ensure the relative stability of the system is better. In the case of sudden change, the anti disturbance ability of the two methods is reflected in the recovery speed and system fluctuation respectively, that is, the fuzzy self-tuning PID controller can make the system quickly recover to the initial state, and the BP neural network PID controller can suppress the sudden change fluctuation of the system.

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