Research on a hybrid controller combining RBF neural network supervisory control and expert PID in motor load system control

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Abstract
Considering the contradiction among the response speed, overshoot and stability of system when the motor load system adopts PID control, a control strategy combining RBF (Radial Basis Function) neural network supervisory control and expert PID control is designed to effectively improve this problem in this paper. First of all, the related algorithms of RBF neural network supervisory control composed of RBF neural network and PID control (RSC-PID) is introduced. This method can make the motor load system reach a steady state faster than simple PID control. But RSC-PID is also unsatisfactory in terms of overshoot. Based on the RSC-PID control method, a hybrid controller combining RBF neural network supervisory control and expert PID control (RSC-EPID) is proposed. This method combines RSC-PID control theory with expert PID control ideas, further improves the stability and rapidity of the system, reduces the overshoot. Moreover, when the input signal is a time-varying signal with interference, the motor load system shows better anti-interference performance after using RSC-EPID. The simulation results show that RSC-EPID control improves the tracking effect of the output signal of the motor load system, ensures the stability of the system, and improves the performance of the system.

Keywords
RBF neural network, supervisory control, expert PID, RSC-EPID

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Introduction
With the continuous development of science and technology, the research on related motor load systems has become more and more in-depth. For example, Lv et al. studied the optimal tracking problem of unknown multi-motor drive load systems. Zhang et al., discussed the explosion shock and bifurcation mechanism of related motor load systems, while Bai et al. combined the two dynamic model, the dynamic model of the motor gear system is established, and its dynamic characteristics under sudden load changes and voltage transients are analyzed. In Maresch et al., a scheme for low-frequency load shedding of asynchronous motors is studied. This method of load shedding is usually the last method used when the power system collapses, but in some power systems, load shedding may cause some low-frequency relays to operate abnormally, so Maresch et al. proposed a high safety and reliability...
Sexual methods to avoid this problem, and so on. However, there are not many researches on the intelligent control of motor load systems. It is common to use PID controllers to control them. Since PID control appeared earlier, the research in this area has been more in-depth, but there are various motor load control systems. Due to its complexity, simple PID control has been difficult to meet the current needs. Neural network makes up for the deficiencies of PID control to a certain extent, and has good processing ability when facing nonlinear systems, which drives the development of neural network related research in motor load systems.

In Refs., the related research of PID control in motor load system is mainly introduced. Vanchinathan and Selvaganesan proposed a Fractional Order PID controller optimized by artificial ant colony algorithm in the self-adjusting regulator structure to solve the poor controllability of Brushless DC motor caused by long stability time, fluctuation of steady-state error, power fluctuation and other factors in practical application. In Deviaene et al., a PID algorithm is proposed to control and estimate the load angle technology. This technology can realize sinusoidal current supply without position feedback or user input, so as to improve the energy efficiency of Brushless DC motor. In Abdulelah Alawan and Mohammed Al-Furaiji, the genetic system is used to adjust the parameters of the PID controller, and it is applied to the wide speed load range control of the DC parallel motor, and the tests are carried out under different sudden load values and different working speeds. In addition, there are other studies on PID control in motor load system, which can be referred to Ekinci et al., Jakovljević et al., Li and Zhu, and Sharma et al. Although PID controller has simple structure, good robustness, and it does not depend on the system model, its parameter setting is relatively complex, which is not suitable for complex systems and high-performance applications. Moreover, it is not widely used in nonlinear systems. If the parameter adjustment is not good, it will lead to poor control performance with poor adaptability.

Because the conventional PID control has the above problems, through people's efforts to explore the research, it can be found that the expert control can solve the conventional PID control problems. The reason is that expert controls are good at handling controls with time-varying, nonlinear, and large disturbances. In addition, expert control can also accumulate knowledge by adding and modifying rules, aiming to improve the control performance of the system. In Joa et al., a drift control algorithm is proposed, which makes use of the driving characteristics of expert drivers in order to realize automatic drift. This controller can realize steady drift without knowing the balance of the vehicle. In Nourian et al. and Hadizadeh et al. the application of the combination of expert control and fuzzy control in gas decompression station and plantscale validated in factory is introduced respectively. The simulation results illustrate the benefits of expert control. In addition, some other applications of expert control are introduced in Arof et al. and Liu and Sui. However, expert control aims to use expert experience to make reasoning decisions and solve problems. However, it does not imitate human beings in a real sense. Moreover, it still has limitations in the problem of knowledge acquisition, dealing with large complex problems and other difficulties.

Due to some limitations of PID control and expert PID control, and with the rapid development of science and technology, these control methods can no longer meet the needs, making neural network control in artificial intelligence, medical research, industrial, commercial, and other fields have gradually emerged. Although the development time of neural network is very short, its good dynamic characteristics show that it has great development potential a variety of fields. Neural network control is extensively used and its types are complex and changeable. Among them, RBF neural network has attracted the attention of scholars because of its good generalization ability, simple network structure and avoiding unnecessary and lengthy calculation. In Zhang, the RBF neural network is used in the PID parameter tuning of diesel generators. The results show that this control method reduces the overshoot, accelerates the response speed, and improves the dynamic performance of the system. In the study of Gao et al., an improved method combining RBF neural network with PID control was proposed and applied to an inverted pendulum system. Compared with other methods, the results show that the overshoot of the tracking signal is further reduced and the response speed is further improved. In the research on variable pitch wind turbines by Asgharnia et al. RBF neural network is used to select the parameters of the proposed gain scheduling Fractional Order PID method. The trained RBF neural network database is established by using chaotic differential evolution algorithm to optimize the gain scheduling Fractional Order PID under multiple wind speeds. In addition, there are some researches on the control of relevant motor load system by using the characteristics of RBF neural network, which can be referred to Lei et al., Wu et al., Mejia-Barron et al., Cherif et al., and Çetin et al.

RBF neural network can approximate any continuous function, and it adopts local approximation method, which can achieve good results in non-linear system, and is suitable for real-time control with a fast-learning speed. The PID controller has simple structure and strong adaptability, but its nonlinear ability is weak. Expert PID control can work in nonlinear and large deviation environment, which can flexibly choose
the adaptive rate, but can not completely simulate the reasoning process of human experts. There remain limitations in large complex problems. Inspired by the above discussion, in order to meet the requirements of the motor load system during operation, intelligent control can be realized. And it has a satisfactory effect on the response speed of the expected value and the stability of the system, and in the case of external interference, the system has a certain anti-interference ability. This study proposes a control method for RSC-EPID. In general, there are three aspects of contribution in this paper:

- This paper innovatively combines PID control, RBF neural network and expert PID control, designs the RSC-EPID control strategy, gives the RSC-EPID related algorithm design, and applies the algorithm to the motor load system.
- The existing monitoring based on PID controller and RBF neural network cannot choose the control law flexibly. But based on the expert PID control rule base, combined with the self-learning ability of RSC-PID, the designed RSC-EPID can design control rules flexibly, so that the system can achieve the desired effect.
- PID control often has a large overshoot. When RSC-PID controls the system, the amount of calculation is often large, which makes the output of the system track the input for a long time. RSC-EPID combines the characteristics of expert PID control rule base, which can achieve the tracking effect of the system in a shorter time without overshoot, so as to improve the control performance of the system.
- Combined with the expert PID control idea, the advantages of PID control and the self-learning ability of RBF neural network, the RSC-EPID control method has good anti-interference ability in the face of time-varying signal interference, and can recover the control of the system in a fast time.

The research content of this paper includes the following parts. The second part is the introduction of RSC-PID related algorithms. The third part is the introduction and design of RSC-EPID. The fourth part is the simulation study of the actual system model, which verifies the validity of the simulation results. Finally, the fifth part is a summary of the full text.

**Design of RSC-PID related algorithms**

The RBF method is a three-layer static forward network, which is an input layer, a hidden layer and an output layer. The first layer is the input layer, which consists of signal source nodes, the second layer is the hidden layer, the number of units depends on the problem to be described, and the third layer is the output layer, which responds to the effect of the input mode. It is a neural network learning method that extends the input vector into a high-dimensional space. The basic idea of forming an RBF network is to use RBF as the "base" of the hidden layer neurons to form the hidden layer space, so that the input vector can be directly (that is, not connected by weights) mapped to the hidden space. When the center of the RBF is determined, the mapping relationship is also determined. The mapping from the hidden layer space to the output layer space is linear, that is, the output of the network is a linear weighted sum of the outputs of the neurons in the hidden layer, and the weight here is an adjustable parameter of the network. In general, the mapping of the network from input to output is nonlinear, while the network is linear to adjustable parameters. In this way, the weights of the network can be solved by linear equations or recursively calculated by the RLS (recursive least squares) method, thereby greatly accelerating the learning speed and avoiding the local minimum problem.

With the research of supervisory control, the choice of controller plays an important role in supervisory control. RBF neural network can approximate any continuous function with any precision, which has good generalization ability, fast learning speed and strong nonlinear fitting ability. Because of the above advantages of RBF neural network, it is widely used in medical data processing, automobile fault diagnosis, ship heading control, manipulator control and other fields. Figure 1 shows the typical supervisory control structure of RBF neural network.

According to the analysis presented in Figure 1, the input of RBF neural network is \( r(k) \), the input of the controller is the difference between the input of neural network and the output of the controlled object, and the performance index of neural network regulation is the output of the controller. The sum of the output of the controller and the output of RBF neural network is the input of the controlled object. Finally, the control
input signal is sent to the controlled object to obtain the output result, and the output result is fed back to the input to realize the cycle. The main control idea is: use the controller to control at the beginning stage, and then transition to use the RBF neural network to control the system. When a large error occurs, the controller plays a major role, while the RBF neural network plays a role in regulation.

In the RBF neural network structure, the input of the network is \( x(k) = (x_1, x_2, \ldots, x_n)^T \), the radial basis vector of the network is \( H = (h_1, h_2, \ldots, h_m)^T \) and \( h_j \) is gaussian basis function. Following:

\[
    h(j) = \exp \left( -\frac{||x(k) - C_j||^2}{2b_j^2} \right) \tag{1}
\]

where \( j = 1, \ldots, m \), \( m \) is the number of hidden layer neurons, \( b_j \) is the basis width parameter of node \( j \), \( C_j \) is the center vector of the \( j \) node of the network, \( C_j = [c_{1j}, c_{12}, \ldots, c_{1m}]^T \) and \( B = [b_1, b_2, \ldots, b_m]^T \). The weight vector of the network is \( W = [w_1, w_2, \ldots, w_m]^T \).

The output of the RBF neural network is the sum of the product of the hidden layer output and the network weight, which can be expressed as:

\[
    u_n(k) = \sum_{j=1}^{m} h_j w_j = h_1 w_1 + h_2 w_2 + \ldots + h_m w_m \tag{2}
\]

The systematic error is:

\[
    e(k) = r(k) - y(k) \tag{3}
\]

Where \( r(k) \), \( y(k) \) and \( e(k) \) respectively represent the input signal, output signal, and the error between the input signal and the output signal of the system. The control law of the system is:

\[
    u(k) = u_p(k) + u_n(k) \tag{4}
\]

Among them, \( u(k) \), \( u_p(k) \), and \( u_n(k) \) respectively represent the input signal of the controlled object, the output of the controller, and the output of the RBF neural network.

The error index of the RBF neural network selects the difference between the output of the RBF neural network and the total control input, which can be expressed as:

\[
    E(k) = \frac{1}{2} (u_n(k) - u(k))^2 \tag{5}
\]

Take \( \frac{\partial u_n(k)}{\partial u(k)} = \frac{u_n(k)}{u(k)} \) here, and the resulting inaccuracy needs to be compensated by weight adjustment.

In this paper, the gradient descent method is used to adjust the weights of the RBF neural network. The learning algorithm of the connection weight \( \Delta w_j(k) \) between the output layer and the hidden layer is as follows:

\[
    \Delta w_j(k) = -\eta \times \frac{\partial E(k)}{\partial w_j(k)}
    = -\eta \times \frac{\partial E(k)}{\partial u(k)} \times \frac{\partial u(k)}{\partial w_p(k)} \times \frac{\partial w_p(k)}{\partial w_j(k)}
    = -\eta \times \frac{\partial E(k)}{\partial u(k)} \times \frac{\partial u(k)}{\partial w_p(k)} \times \frac{\partial w_p(k)}{\partial w_j(k)} \tag{6}
\]

In order to reduce the shock and slow convergence in the weight adjustment process, the influence of the last weight on the current weight needs to be considered, and the momentum factor \( \alpha \) needs to be added. Using \( w_j(k) \) to represent the current weight, \( w_j(k-1) \) to represent the weight of the previous moment, and \( w_j(k-2) \) to represent the weight of the previous two moments. The adjustment process is:

\[
    w_j(k) = w_j(k-1) + \Delta w_j(k) + \alpha(w_j(k-1) - w_j(k-2)) \tag{7}
\]

where \( \eta \) is learning efficiency, \( \alpha \in [0, 1] \).

It can be further expressed as:

\[
    w_j(k) = w_j(k-1) + \eta(u_n(k) - u(k))h_j(k) + \alpha(w_j(k-1) - w_j(k-2)) \tag{8}
\]

The RSC-PID controller designed in this paper uses PID controller. PID control algorithm can be written as:

\[
    u_p(k) = k_p e(k) + k_i \sum_{i=0}^{k} e(i) + k_d [e(k) - e(k-1)] \tag{9}
\]

where \( k_p, k_i, k_d \) are parameter of P, I, D, \( \sum_{i=0}^{k} e(i) \) represents the accumulated error, \( e(k-1) \) represents the error of the previous time, and \( e(k) - e(k-1) \) represents the difference between the current error and the error of the previous time.

The total control of the system can be written as:

\[
    u(k) = u_p(k) + u_n(k)
    = k_p e(k) + k_i \sum_{i=0}^{k} e(i) + k_d [e(k) - e(k-1)]
    + \sum_{j=1}^{m} h_j w_j \tag{10}
\]
RSC-EPID algorithm design and stability analysis

Design of RSC-EPID algorithm

Expert PID control is a kind of expert control. Expert control combines the theory and technology of expert system with the theory and method of control, and imitates the experience of experts to control the system under unknown circumstances. It can meet the needs of dynamic process control, and is suitable for strong disturbance, nonlinear and time-varying control. Expert control can also qualitatively describe the performance of the system, and can improve the system performance by modifying and adding control rules and accumulating experience. There are two types of expert controller: direct type and indirect type. The expert PID controller used in this paper is a kind of direct type expert controller. Figure 2 shows the structure of direct expert controller.

In Figure 2, after obtaining the information, it first passes through the knowledge base and reasoning mechanism, and then through the judgment of the control rule base, acts on the controlled object to produce an output signal. The output signal is sent back to the sensor again through the sensor, so that the output signal and the input signal are consistent.

Based on PID control, RBF neural network control theory and expert PID control ideas, the RSC-EPID control strategy is proposed. Then, the related algorithm of RSC-EPID is designed. Figure 3 shows the structure of RSC-EPID.

In Figure 3, the sum of the output signal of the controller and the output signal of the RBF neural network is sent to the rule base for judgment, and the judged signal of the rule base is sent to the controlled object to obtain the output signal. Then the output signal is fed back to the input terminal through the sensor, and the error between the input signal and the output signal is compared, and then sent to the controller and RBF neural network, so as to achieve the effect that the output signal is consistent with the input signal.

The changing trend of the error can often reflect the quality of a system controller. In this article, the design method of the rule base is designed according to the changing trend of the error. The detailed design is as follows:

1) When $|e(k)|>M_1$, it means that the absolute value of the error is relatively large. At this time, no matter how the error trend changes, the output of the controller should be output at a fixed value in order to quickly adjust the error, reduce the maximum speed of the error, and avoid overshoot as much as possible. At this point, it is equivalent to an open loop control.

\[
\begin{align*}
\Delta e(k) &= e(k) - e(k-1) \\
\Delta e(k-1) &= e(k-1) - e(k-2)
\end{align*}
\]
When \( |e(k)| \geq M_2 \), it shows that the error is relatively large at this time, and the controller can adopt a stronger control method. The powerful control function can make the absolute value of the error change in a decreasing direction. The control rules can be designed as follows:

\[
u(k) = u(k - 1) + k_1 [e(k) - e(k - 1)] + k_i e(k) + k_d [e(k) - 2e(k - 1) + e(k - 2)]\tag{12}
\]

When \( |e(k - 1)| < M_2 \), it means that although the variation of the error changes in the direction where the absolute value increases, the absolute value of the variation of the error itself is not very large. The general control effect can be used to change the trend of the change of the error, so that it changes in the direction of decreasing the absolute value of the change of the error. The control rules can be designed as follows:

\[
u(k) = u(k - 1) + kp [e(k) - e(k - 1)] + k_i e(k) + k_d [e(k) - 2e(k - 1) + e(k - 2)]\tag{13}
\]

3) When \( e(k) \Delta e(k) < 0 \), \( \Delta e(k) \Delta e(k - 1) > 0 \) or \( e(k) = 0 \), it means that the absolute value of the error is changing in the direction of decreasing, or has remained unchanged. At this time, the controller output can be kept unchanged.

4) When \( e(k) \Delta e(k) < 0 \) and \( \Delta e(k) \Delta e(k - 1) < 0 \), it indicates that the error is at an extreme value. If the absolute value of the error is relatively large, that is, \( |e(k)| \geq M_2 \), a stronger control effect can be considered, that is,

\[
u(k) = u(k - 1) + k_1 k_p e_m(k)\tag{14}
\]

If the absolute value of the error is relatively small, that is, \( |e(k - 1)| < M_2 \), then the weaker control effect can be considered,

\[
u(k) = u(k - 1) + k_2 k_p e_m(k)\tag{15}
\]

5) When \( |e(k)| \leq \epsilon \) (precision), it means that the absolute value of the error is very small, and then the integral part is added to reduce the steady-state error.

In the above varieties, \( e_m(k) \) is the \( k \) extreme value of the error \( \epsilon \); \( k_1 \) is the gain amplification factor, \( k_1 > 1 \); \( k_2 \) is the inhibition coefficient, \( 0 < k_2 < 1 \); \( M_1 \), \( M_2 \) is the error limit set, \( M_1 > M_2 \geq 0 \); \( k \) is the serial number (natural number) of the control period; \( \epsilon \) is an arbitrarily small positive real number.

By analyzing the above-mentioned error trend and designing corresponding control rules, the system can achieve the tracking effect faster.

**Stability analysis of control algorithm**

Now consider the state equation of the Lyapunov discrete-time system as:

\[
x(k + 1) = Lx(k)\tag{16}
\]

Then the condition for the system to be gradually stable in the equilibrium state \( x_e = 0 \) is: the eigenvalues of \( L \) are all in a unit open disk.

For a given arbitrary positive definite real symmetric matrix \( F \), if there is a positive definite real symmetric matrix \( P \), it satisfies:

\[
L^T P L - P = -F\tag{17}
\]
Then the Lyapunov of the system can be taken as:

\[ V(x(k)) = x^T(k)Px(k) \]  \hspace{1cm} (18)

To make the system progressively stable, \( V(x(k)) < 0 \) should be satisfied. Now replace \( V(x) \) in the linear system with the difference between \( V[x(k + 1)] \) and \( V[x(k)] \), which can be expressed as:

\[ \Delta V[x(k)] = V[x(k + 1)] - V[x(k)] \]  \hspace{1cm} (19)

Make

\[ \bar{V}[x(k)] = \frac{1}{2} \sum_{i=0}^{k} \bar{e}^2(i) \]  \hspace{1cm} (20)

From equation (19), \( \Delta \bar{V}[x(k)] \) can be expressed as \(41\):

\[ \Delta \bar{V}[x(k)] = \bar{V}[x(k + 1)] - \bar{V}[x(k)] \]
\[ = \frac{1}{2} \sum_{i=0}^{k+1} \bar{e}^2(i) - \frac{1}{2} \sum_{i=0}^{k} \bar{e}^2(i) \]
\[ = \frac{1}{2} \sum_{i=0}^{k} \bar{e}^2(i) + 1) - \bar{e}^2(i) \]  \hspace{1cm} (21)
\[ = \frac{1}{2} \sum_{i=0}^{k} \{ \bar{e}(i) + \Delta \bar{e}(i) \}^2 - \bar{e}^2(i) \]
\[ = \frac{1}{2} \sum_{i=0}^{k} [2\bar{e}(i) \cdot \Delta \bar{e}(i) + \Delta \bar{e}^2(i)] \]

According to the adjustment process of the error and the weight, \( \bar{e}(k + 1) \) can be written as:

\[ \bar{e}(k + 1) = \bar{e}(k) + \left( \frac{\bar{e}(k)}{\bar{e}(k)} \right)^T \times \Delta \bar{w}_j(k) \]
\[ = \bar{e}(k) + \Delta \bar{e}(k) \]  \hspace{1cm} (22)

Combining equation (6), equation (7) and equation (19), we can get:

\[ \Delta \bar{e}(k) = \left( \frac{\bar{e}(k)}{\bar{e}(k)} \right)^T \times \Delta \bar{w}_j(k) \]
\[ = \left( \frac{\partial \bar{e}(k)}{\partial w_j(k)} \right)^T \times \left( -\eta \frac{\partial \bar{e}(k)}{\partial \bar{e}(k)} \bar{e}(k) \right) \]  \hspace{1cm} (23)
\[ = - \eta h_j \bar{e}(k) B^T \cdot \bar{e}(k) \]

Where \( B = \frac{\bar{e}(k)}{\bar{e}(k)} \). Let \( A = \eta h_j \), equation (23) can be expressed as:

\[ \Delta \bar{e}(k) = - ABB^T \cdot \bar{e}(k) \]  \hspace{1cm} (24)

Substituting equation (21) into equation (24), it can be obtained

\[ \Delta \bar{V}[x(k)] = \frac{1}{2} \sum_{i=1}^{k} [2\bar{e}(i) \cdot \Delta \bar{e}(i) + \Delta \bar{e}^2(i)] \]
\[ = - \frac{1}{2} \sum_{i=1}^{k} [B^T \cdot \bar{e}(i)]^T \times (2A - A^2 B B^T) (B^T \bar{e}(i)) \]  \hspace{1cm} (25)

According to the Lyapunov stability theory, when \( \Delta \bar{V}[x(k)] < 0 \), the system is in a stable state, and the combined equation (25) should have \( 2A - A^2 B B^T > 0 \), therefore the value range of \( A \) is \( 0 < A < 2(AB^T)^{-1} \). Further we can get \( \frac{1}{2} \bar{e}^2(k + 1) < \frac{1}{2} \bar{e}^2(k) \), and when \( k \to \infty \), \( \lim \bar{e}(k) = 0 \).

In other words, as time goes by, the error gradually approaches zero, and the control algorithm converges.

### Simulation results

In order to verify the effectiveness of RSC-EPID control method, we compare and analyze PID, RSC-PID and RSC-EPID control methods. The above method is verified and analyzed by using the actual motor load system model.

At present, a practical model of a simple motor load system is considered, \(42\) which can be expressed as:

\[ J\ddot{\theta} = -b\dot{\theta} + u(t) \]  \hspace{1cm} (26)

where \( \theta \) is angle, \( J \) is rotational inertia, \( b \) is coefficient of viscosity, and \( u \) is control input.

The meanings of variables in equation (26) and specific data can be expressed as: the rotational inertia \( J = \frac{1}{133} Kg \cdot m^2 \) and the coefficient of viscosity is \( b = \frac{25}{133} \).

We take the input signal of the network \( r(k) = 1 \), and the number of hidden neurons \( m = 4 \). The parameter of the Gaussian-base function is \( C_j = [-2, -1, 1, 2]^T \), \( B = [0.5, 0.5, 0.5, 0.5]^T \). The initial weight of the neural network is a random value between 0 and 1.

When \( |e(k)| < M_1 \) mentioned in the third section, it means that the absolute value of the error has changed greatly. It should be considered that the output of the controller is output according to the fixed value. At this time, the corresponding parameters are shown in Table 1.

| \( M_1 \) | 0.8 | 0.6 | 0.4 | 0.2 | 0.1 | 0.01 |
| \( u(k) \) | 0.7 | 0.6 | 0.5 | 0.4 | 0.3 | 0.15 |
In the control rule library, the gain method coefficient $k_1 = 4.3$, the suppression coefficient $k_2 = 0.2$, the accuracy $e = 0.00001$, and the error limit $M_2 = 0.02$.

In the control algorithm, the learning rate $\eta = 0.30$, the momentum factor $\alpha = 0.05$, and the gains of each coefficient in the PID controller are $k_p = 38$, $k_i = 22.26$, and $k_d = 18$ respectively.

The simulation is mainly divided into four parts: the input signal adopts a step signal, the input signal is a time-varying signal, the input signal is a time-varying signal with interference and compare with other literature. The results are as follows:

(a). The input signal adopts a step signal

In Figure 4, the simulation results show that when the system uses PID control, the tracking error of the output signal to the input signal can be reduced to less than 0.005 in about 8.5 s, and there is an overshoot with a peak value of 1.138. When using RSC-PID control, the tracking error of the output signal to the input signal can be reduced to less than 0.005 in about 7.4 s, and there is an overshoot with a peak value of 1.153. When using RSC-EPID control mode, the tracking error can be controlled within 0.005 in about 0.5 s, and there is no overshoot. Therefore, in the tracking effect of the output signal on the input signal, it can be seen that the system can achieve the tracking effect faster after using the RSC-EPID control method, and the response speed is faster than the other two control methods, and it can keep the system in a stable state.

(b). The input signal is a time-varying signal

Figure 5 is the error comparison of output tracking input after using PID, RSC-PID and RSC-EPID three control schemes. It can be seen from the figure that using the RSC-PID control method can reduce the error faster and approach zero faster than when using the PID control method. However, when using RSC-EPID control, the error reduction speed is significantly faster than the other two control schemes, and can approach zero faster, which illustrates the superiority of the RSC-EPID control method.

Figure 6 means that when the input signal adopts time-varying signal (sine signal) $r(t) = \sin(6\pi t)$, the output signals of PID, RSC-PID and RSC-EPID three control methods track the comparison of the input signal. At 0.07 s, it can be seen that the partial magnification of the image. At this time, the value of the
The ordinate of the RSC-EPID tracking curve is greater than 0.88 and less than 0.90, and the abscissa of the expected value calculated by Matlab is sin(6π × 0.07) = 0.9686, so the error value at this time is less than 0.1. At 0.4 s, it can be seen from the partial enlarged view that the ordinate of the tracking curves of the two control methods RSC-PID and PID is 0.86, and the abscissa of the expected value calculated by Matlab is sin(6π × 0.4) = 0.9511, and the error value at this time is less than 0.1. So within the same error range, the RSC-EPID control method designed in this paper is better than the other two control schemes in performance.

Figure 7 shows the error comparison of output signal tracking input signal when using PID, RSC-PID and RSC-EPID control these three control schemes after using time-varying signal as input signal. The simulation results show that when using PID control and RSC-PID control, the error range is obviously larger than when using RSC-EPID. RSC-EPID control can reduce the tracking error to less than 0.1 in about 0.07 s, and PID Control and RSC-PID control can only control the tracking error within 0.1 in about 0.4 s, and the error reduction speed when using RSC-EPID control is significantly faster than the other two methods. Through the above analysis, the control effect of RSC-EPID control method is better.

(c). The input signal is a time-varying signal with interference

Figure 8 shows the comparison of the effect of output signal tracking input signal when the input signal is time-varying signal (sine signal) r(t) = sin(6πt) + d(t) with interference and three control schemes of PID, RSC-PID and RSC-EPID control are used. Interference signal d(t) = 6.0 starts at 0.5 s and ends at 0.7 s. It can be seen from the partial enlarged diagram that when there is external interference, the maximum error between the RSC-EPID tracking curve and the expected value is the smallest among the three control methods. This shows that the anti-interference ability of the RSC-EPID control method designed in this paper is better than the other two control methods. By observing the local magnification images at 0.7 and 1.26 s, it can be found that the error between the tracking curve using the RSC-EPID method and the expected value is less than 0.1 at the end of the 0.7 s perturbation. When using RSC-PID and PID control methods, after 0.7 s of interference, until 1.26 s, the error is less than 0.1 by calculation. This shows that the RSC-EPID control method designed in this paper can still achieve a better tracking effect after the interference is over.

Figure 9 shows the error comparison of the output signal tracking the input signal when using PID, RSC-PID, and RSC-EPID to control these three control schemes after using a time-varying signal with interference as the input signal. It can be seen from the simulation results that after adding interference, when using RSC-EPID control, the maximum error with the expected value is the smallest among the three control methods, which also shows that its anti-interference ability is stronger when dealing with interference. And at the end of the 0.7 s interference, the error using the
RSC-EPID control method was within 0.1, while with the other two methods, their errors could not be reduced to within 0.1 until 1.26 s.

d). Compare with other literature

In order to further demonstrate the superiority of the method designed in this paper, the method designed in this paper is compared with an improved PID controller based on RBF neural network supervision control strategy (IPID-RBF) method designed in Gao et al. The specific results are shown in the tables below:

Table 2. The time required for the system to stabilize under various desired signals.

| Control methods       | RSC-EPID (s) | IPID-RBF (s) |
|-----------------------|--------------|--------------|
| Step signal           | 0.5          | 9            |
| Time-varying signal   | 0.07         | 0.39         |
| Time-varying signal   | 0.7          | 0.96         |

RSC-EPID control method was within 0.1, while with the other two methods, their errors could not be reduced to within 0.1 until 1.26 s.

Table 3. Response speed and peak value under step signal.

| Control methods | RSC-EPID | IPID-RBF |
|-----------------|----------|----------|
| Response speed  | 0.4 s    | 0.8 s    |
| Peak value      | 1        | 1.082    |

and the IPID-RBF method under the step signal. It can be found from the table that the response speed of the method designed in this paper is doubled compared to the method using IPID-RBF. In terms of peak value, RBF-EPID is smaller than IPID-RBF, so in terms of overshoot, RSC-EPID is smaller than IPID-RBF. To sum up, the method designed in this paper is better than the method using IPID-RBF in improving the dynamic performance of the system.

Conclusion

To sum up, this paper studies two control methods RSC-EPID and RSC-PID, and compares these two methods with traditional PID control methods. Compared with RSC-PID and PID control methods, RSC-EPID has the advantages of fast response, good stability and strong anti-interference ability. In the simulation part, three control methods of PID, RSC-PID and RSC-EPID are simulated and verified in combination with the specific motor load system model. The results show that the dynamic performance of the system is better than that of PID and RSC-PID control methods when the RSC-EPID method is used. Therefore, the RSC-EPID control method designed in this paper is effective and has certain reference significance in motor load control. For example, when there is a sudden disturbance from the outside world, the system needs to be dealt with quickly to avoid accidents. The method designed in this paper can quickly restore the system to a stable state without human operation, and the system can act according to the set expected value, thereby reducing unnecessary losses. In the era of rapid development of intelligent control, the control strategy of combining neural network and expert control proposed in this paper has positive significance and broad application prospects in various fields.

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