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The PWM speed regulation of DC motor based on intelligent control

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Abstract

The PWM speed regulation of DC motor based on intelligent control is discussed. The simulation is carried out with the SIMULINK after that the mathematical model of controlled object is built. This article introduces the PWM bipolar drive of DC motor, designs a fuzzy controller and a neutral network controller and then discusses the application of artificial intelligence in the speed regulation of DC motor.

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Key Words: speed regulation of DC motor; PWM bipolar speed regulation; fuzzy PID control; neutral network control

1. Introduction

DC motor is widely used in metallurgy, machinery manufacturing and light industry because of its good performance in starting and breaking and its easily controlled speed regulation. In recent years, with the development of the power electronic technology, the thyristor rectifier is commonly used for the power supply of the DC motor, which replaces the AC motor—DC generator power supply system. But DC motor speed control system is a complex multivariable nonlinear control system, because the various parameters influence each other, it’s anti—interference ability is weak and it’s not suitable for high control performance occasion.

Therefore, in order to enhance DC motor speed control system of anti—jamming and robustness, and improve the response speed and stable precision of the speed regulation system, this paper discuss the PWM DC motor speed control system based on the fuzzy control and neural network control.
2. DC motor speed control system simulation model

In Fig. 1, it shows the simulation model built with MATLAB/SIMULINK, in which the ASR is the speed controller, the ACR is the armature current controller, the PWM module provides required PWM wave for the dual polarity H bridge[1]. A 5-HP DC motor of 240-V rating 1220 rpm is used in the simulation models. The equivalent circuit parameters of the DC motor used in the simulation are $R_f = 240 \Omega$, $L_f = 120 H$, $R_A = 0.6 \Omega$, $L_A = 12 mH$ [2].

![Fig.1. SIMULINK model of the DC motor speed control system](image)

In Fig.2, it shows the internal structure of the PWM model and the ACR model.[3]

![Fig.2. The internal structure of the PWM model and the ACR model](image)

3. Ordinary PID controller

As is known to all, the traditional PID control is a mature and widely used engineering control method. On condition that the structure and parameters of the linear time-invariant system are known, it has good control performance, and its algorithm is simple and it’s easy to realize. The adjustment object of the PID
controller is the system error, it’s a kind of scale, integral, differential adjustment rules, and its equation is:

\[ u(t) = K_p e(t) + K_i \int_0^t e(t) \, dt + K_d \frac{de(t)}{dt} \]

In the equation, \( K_p, K_i, K_d \) are the parameters of the PID controller, \( e(t) \) is the deviation input signal of the controller, \( u(t) \) is the control signal. In Fig. 3, it shows the simulation model of the ordinary PID controller.

**4. Fuzzy Controller**

Fuzzy control is a kind of computer intelligent control based on the fuzzy set theory, the fuzzy language variables and the fuzzy logic. The basic concept is proposed by the famous professor of the university L.A.Zadeh. After over 20 years’ development, it makes a great success in the fuzzy control theory.

Fuzzy controller is also called Fuzzy Logic Controller. Because the fuzzy control rules are described by the fuzzy conditional statement of the fuzzy theory, it’s a kind of language controller, so it’s also called Fuzzy Language Controller.[4]

The composition of the fuzzy controller is showed in Fig. 4:
4.1. Fuzzification Interface

The fuzzification of the input of the fuzzy controller is important so that it can be used for solving the control output, so it’s actually the input interface of the fuzzy controller. Its main effect is putting the true indeed quantitative into a fuzzy vector. In this case, it’s a single variable 2D fuzzy controller. The fuzzy set of error E, error rate EC and control quantity u is described as:

\[
e = \{\text{NB, NM, NS, Z, PS, PM, PB}\}
\]

The domain of discourse of E and EC is: \([-3, -2, -1, 0, 1, 2, 3]\)

The domain of discourse of u is: \([-4.5, -3, -1.5, 0, 1.5, 3, 4.5]\)

4.2. Knowledge Base

Knowledge base consists of Data base and Rule base. The data base consists of all membership vector value of all input and output variables’ fuzzy subsets. If the domain is a continuous domain, it’s a membership function. In solving the fuzzy relation equation of rule reasoning, it provides data to the reasoning machine.

The rule base consists of all the rules of the fuzzy control. In reasoning, it provides control rules to the reasoning machine. The number of the rules is concerned with the fuzzy subsets division of the fuzzy variables. The more fuzzy subsets, the more rules, but it does not represent that the accuracy of the rule base is higher. The accuracy of the rule base is also concerned with the accuracy of the expert knowledge.

4.3. Reasoning

In fuzzy control, reasoning is a part that uses input fuzzy quantity and the fuzzy control rules to complete fuzzy inference and solve fuzzy relations equation, and also get fuzzy control volume. In fuzzy control, considering the reasoning time, a simple method of reasoning is commonly used.

Foregoing fuzzy control rules can be described by the fuzzy rule table (Table. 1), there is 49 fuzzy rules, and the relationship between the various fuzzy statement is or.

The fuzzy rules that the table above shows can be expressed as follows:

\[
\begin{align*}
R1: & \quad \text{IF E is NB and EC is NB then U is PB} \\
R2: & \quad \text{IF E is NB and EC is NS then U is PM}
\end{align*}
\]

Table 1. The fuzzy rule table

<table>
<thead>
<tr>
<th>e</th>
<th>u</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>Z</th>
<th>PS</th>
<th>PM</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>PB</td>
<td>PB</td>
<td>PM</td>
<td>PM</td>
<td>PS</td>
<td>Z</td>
<td>Z</td>
<td></td>
</tr>
<tr>
<td>NM</td>
<td>PB</td>
<td>PB</td>
<td>PM</td>
<td>PM</td>
<td>PS</td>
<td>Z</td>
<td>ZS</td>
<td></td>
</tr>
</tbody>
</table>
The basic structure can be reduced to If A and B then C, among which A is a fuzzy subsets of domain U, and B is a fuzzy subsets of domain V. According to the control experience, the control decision table R can be organized offline. R is a fuzzy subsets of the cartesian product $U \times V$. In a moment, its control volume is given out by the following equation:

$$C = (A \times B) \circ R$$

(3)

In the equation, $\times$——fuzzy direct product operation
$\circ$——fuzzy synthetic operation

4.4. Defuzzification

After getting the results, the reasoning of the fuzzy control has been completed. However, at present, the results obtained is still a fuzzy vector, which can’t be directly used as a control volume. Therefore a conversion must be done on the results so that it can get a clear output. The process is the defuzzification. Usually the output part that has a conversion function is called defuzzification interface.

To obtain accurate control volume, it requires the fuzzy method to express the calculated output of the membership functions. In this paper, the weighted average method is used. For each element on the domain, $x_i (i = 1, 2, \cdots, n)$, it’s used as the weighting factor of the output fuzzy set membership degree $u(i)$, that is to take the product $x_i u(i)$, then calculate the sum of the product and the membership, and then calculate as follows:

$$x_0 = \frac{\sum_{i=1}^{n} x_i u(i)}{\sum_{i=1}^{n} u(i)}$$

(4)
The average $x_0$ is the required output of the fuzzy sets obtained by the weighted average method. Finally, the output $x_0$ is multiplied by the quantitative factor to meet the control requirement. Then the practical value of control volume is obtained.

In Fig. 5 and Fig. 6, it shows the SIMULINK model of the fuzzy PID controller and the fuzzy control rules, and also the fuzzy membership function graph of the error E, error change rate EC and the control volume u.

![Fig.5. The simulation model of the fuzzy PID controller](image)

![Fig.6. The fuzzy membership function graph of the error E, error change rate EC and the control volume u](image)
5. Neural network controller

The neural network control is one of the front subject in the automatic control field which is developed in the 1980’s. It is a new branch of the intelligent control and opens up new ways to solve the control problem of the complex nonlinear, uncertain and unknown system.

The single neuron adaptive intelligent PID controller which is consisted of the single neuron with self-learning and adaptive ability not only has a simple structure, but also can adapt to the changes of the environment. It also has strong robustness. PID control needs to adjust the three control effects include scale, integral and differential to form the coordinate and interdependent relationship in order to get good control effect. The relationship is not a simple linear combination, it can form the best relationship from the boundless change combination of nonlinear optimal relationship. Neural network has arbitrary nonlinear ability and can achieve the best combination of nonlinear optimal relationship. Neural network has arbitrary nonlinear ability and can achieve the best combination of nonlinear optimal relationship. Neural network has arbitrary nonlinear ability and can achieve the best combination of nonlinear optimal relationship.[5]

The learning rules of neurons: no supervision Hebb learning rules, supervision Delta learning rules and supervisory Hebb learning rules. The single neuron adaptive controller realizes its function of self-adaption and self-organization through the adjustment of the weighting coefficient. The realization of weight coefficient adjustment is according to the supervision Hebb learning rules. Control and learning algorithm are:

\[
\begin{align*}
    u(k) &= u(k-1) + K \sum_{i=1}^{3} w_i(k)x_i(k) \\
    w_i(k) &= w_j(k) / \sum_{j=1}^{3} |w_j(k)| \\
    w_1(k) &= w_1(k-1) + \eta_1 z(k)u(k)x_1(k) \\
    w_2(k) &= w_2(k-1) + \eta_2 z(k)u(k)x_2(k) \\
    w_3(k) &= w_3(k-1) + \eta_3 z(k)u(k)x_3(k)
\end{align*}
\]

In the equations, \( x_1(k) = e(k) \):

\[
\begin{align*}
    x_2(k) &= e(k) - e(k-1) \\
    x_3(k) &= \Delta^2 e(k) = e(k) - 2e(k-1) + e(k-2) \\
    z(k) &= e(k)
\end{align*}
\]
\( \eta_I, \ \eta_P, \ \eta_D \) are respectively the learning rate of integral, proportion and differential. \( K \) is the proportionality coefficient of neurons, \( K > 0 \).

The integral I, proportion D and differential P respectively used different learning rate \( \eta_I, \ \eta_P, \ \eta_D \). So as to separately adjust the different weight coefficient.

The choice of K value is very important. The greater the K value, the better the speed. But the big overshoot may even make the system out of stability. When the controlled object delay increases, the k value must be reduced to ensure that the system is stable. If K value selection is too small, it can also make the system efficiency becomes poor.

In Fig. 7, it shows the SIMULINK simulation model of the neural network PID controller.

6. Conclusion

In Fig. 8, it shows the square-wave response curve of the ordinary PID controller, the fuzzy PID controller and the neural network PID controller. We can see from the picture that the square-wave responses of the fuzzy PID controller and ordinary PID controller are similar, but the tracking curve of fuzzy PID controller is more smooth; Neural network PID controller has the most smooth tracking curve and the minimum error with the input signal. It is obviously that the application of neural networks PID control can be a very good way to improve the control performance, and fuzzy PID control can realize concise and effective control requirements in the face of a more complex nonlinear system for its simple application.

Fig.8. The square-wave response curve of the ordinary PID controller, the fuzzy controller and the neural network PID controller
References


