2022 Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus) | 978-1-6654-0993-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/ElConRus54750.2022.9755484

Research on Parameter Self-tuning PID Control Algorithm Based on BP Neural Network

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***Abstract*—PID is a control algorithm of proportional, integral and differential control laws. Now it has been widely used in many aspects. However, there are many complex control objects in industry, which can't establish accurate mathematical models, and it is more complex for nonlinear control objects. If the traditional PID control is adopted, it is difficult to obtain a more reasonable control effect. At present, due to the lack of operation experience in the industrial field, the regulation effect of many control circuits is not ideal. Therefore, PID automatic adjustment is very important for the operation of field researchers and engineers. Aiming at the above problems, this paper studies the theory and application of PID self-tuning technology, and simulates a process object with MATLAB combined with BP neural network.**

Keywords—parameter self-tuning, BP neural network, PID control

I. INTRODUCTION

PID controller has the advantages of easy algorithm implementation and strong anti-interference. It is first applied in process control, especially favored by industrial control. It has unique advantages for deterministic control system which can establish accurate mathematical model. In engineering, the methods of PID controller parameter tuning include dynamic characteristic parameter method, stable boundary method and attenuation curve method [1].

The control object of industrial production process is often nonlinear and time-varying. It is difficult to establish an accurate mathematical model. The conventional PID controller can't achieve the preset control effect, and the parameter adjustment methods are diverse. The parameters of conventional PID controller can't be adjusted accurately in theory, and the abnormalities in the operation process can't be effectively overcome. In the process of application, people also optimize the structure of PID itself. For example, add differential PID with inertia link, PID with dead zone and PID with anti-integral saturation. With the development of intelligent algorithm, people combine the traditional PID controller with fuzzy control, neural network control and expert control, and form the current intelligent PID control by giving full play to the advantages of various algorithms. The tuning of intelligent PID parameters is divided into model-based automatic adjustment method and rule-based automatic adjustment method [2]. Using the model-based self-optimization method, the process object can be modeled by step response output image and frequency response method. The rule-based optimization method does not need to model the process object, but is similar to the manual optimization of experienced operators [3]. The rule-based tuning method is more suitable for continuous adaptive control, and the model-based method is more suitable for setting value change [4]. The research objects of intelligent control often have bad operating conditions, uncertainty and high nonlinearity [5]. Common intelligent control methods include expert control, fuzzy control, neural network control and so on [6].

The development of the new generation controller has two directions: one is the modern control theory, which was created and gradually improved before the 1950s and the beginning of this century [7]. Because the mathematical model of this method needs to solve differential equations, the control algorithm is complex and less realizable [8]. The other is the modern PID controller. Due to the use of PID parameter management strategy, it not only retains the advantages of simple structure, strong adaptability and convenient adjustment of PID controller, but also uses intelligent technology to adjust the parameters of PID controller online to adapt to the changes of the characteristics of the controlled object [9]. Intelligent control is gradually becoming the main direction of automatic control research [10].

II. PID CONTROL

A. PID control principle

Proportional integral differential control (PID control for short) is one of the earliest developed control strategies. Because of its simple algorithm and high reliability, it is widely used in the management of production process. So far, about 90% of industrial controllers adopt PID structure [11]. From a simple point of view, the controller performs proportional differential integral operation on the difference between the expected value and the actual output, and takes the result as the input of the actuator to control a process parameter [12]. The control effect of PID on process parameters depends on its parameter setting, and the setting effect depends on the selection of setting method [13]. The early adjustment of parameters is manual adjustment. In particular, the engineer draws the dynamic characteristic curve or frequency response curve of the process through a series of adjustment tests, and then uses these curves to obtain the manual adjustment of PID parameters from the adjustment formula [14]. However, distributed control systems often contain hundreds of PID circuits in industrial processes, so it is unrealistic to use manual adjustment method [15].

Most of the continuous controllers use PID method to adjust the industrial process, which can adapt to most industrial links and meet most control requirements [16].

PID control expression is:

$$u(t) = k_p(e(t) + \frac{1}{T_i}\int_0^t e(t)dt + \frac{T_d de(t)}{dt}) \tag{1}$$

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Where, $u(t)$ is the output of PID controller, $e(t)$ is the difference between setting and output as the input of PID controller, k_P is the proportional coefficient, T_i is the integral time constant, T_d is the differential time constant, , and the transfer function of PID regulator is [17]:

$$G(s)=\frac{U(s)}{E(s)}=k_p(1+\frac{1}{T_i s}+T_d s) \quad (2)$$

B. Performance index of control system

The three performance indexes of automatic control system are stability, rapidity and accuracy. The specific analysis is as follows: stability: it is to keep the system in a stable state [18]. Even due to changes in the external environment, it can return to the original state through its own adjustment. Rapidity: that is, when the set value of the system changes or when a disturbance is received, the system can respond quickly to meet new expectations [19]. For example, in the missile tracking system, if the missile can't respond quickly to the displacement of the target after locking the target, it is meaningless to hit the target even when the time tends to infinity. Accuracy: expressed by steady-state error, it is a measure of whether the system can accurately meet the expectations. When the system is adjusted, if the deviation from the expectations is small, it indicates that it is accurate.

Generally speaking, the performance indicators of the control system are divided into two categories [20]. One is the steady-state error of the control system, that is, the difference between the system output and the set value. The premise of having the steady-state error is that the system is stable. If the system is divergent oscillation or equal amplitude oscillation, it is meaningless to calculate its steady-state parameters [21].

The dynamic process of the system, that is, the stability, response speed and damping of the system, is expressed in the form of attenuation, divergence, constant amplitude oscillation and described by dynamic performance indicators. The static characteristics of the system are described by static errors. The performance indicators of a control system mainly include rise time TR, peak time TP and overshoot δ%、 Adjustment time Ts, and steady-state error es [22].

III. BP NEURAL NETWORK

Multilayer perceptron (MLP) is the most widely used artificial neural network (ANN) [23]. Neural network is a computational model excited by human neural network, which is used to approximate commonly unknown features. The structure of an ANN is forward, as shown in Fig. 1.

Each circle represents a unit or neuron, and the connection between each unit has a weight. Generally speaking, ANN can use three types of layers: input layer, hidden layer and output layer [24].

Back propagation neural network (BPN) is an MLP network, which consists of two stages: feed-forward and back propagation. It has an input, at least one hidden layer and an output layer. In the feed-forward stage, the influence of input variables is diffused layer by layer through the artificial neural network system until the output is generated. Then, the actual output value of the ANN network is compared with the target value (expected output), and the error signal is measured for each node of the output layer.

The error measured at the output layer will propagate back to the input layer. As shown in Fig. 3. The structure of BPN has three interrelated layers, with weight (uik) between input layer and hidden layer and weight (WKl) between hidden layer and output layer. Hidden layer and output layer also have deviation, and they have uniform weight. BPN algorithm approximates the nonlinear relationship between the input and output nodes of the layer through internal optimization weights. All nodes of the hidden layer contribute to the error performance of the output layer nodes. The error signal is transmitted reversely from the output layer node to each node of the hidden layer and immediately contributes to the output layer node. This process is periodic; It is carried out layer by layer until the output node of BPN system receives an error signal, indicating its relative impact on the overall error [25].

By studying the physiological structure of human brain, a neural network (NN) for machine simulation of human brain is proposed. That is, neural network is used to simulate the processing unit in human brain to solve the problems that are difficult to deal with by traditional mathematical methods. Neural network is an important part of intelligent control theory. With the deepening of research, there are more and more systematic research methods and problems that can be solved. So far, the use of neural networks has penetrated into pattern recognition, nonlinear optimization, speech processing, image processing and natural language understanding [26]. Some progress has also been made in the fields of robot vision system and industrial process expert system. Neural network theory is integrating many traditional disciplines, including neurophysiology, cognitive science, mathematics, psychology, optics, computer science, microelectronics, bioelectronics and so on [27].

Theoretically, the combination of intelligent algorithm and traditional technology will greatly improve the work efficiency and production efficiency. Because neural network has the advantage of dealing with nonlinear systems, it has become an effective solution to compensate traditional methods [28]. At present, the utilization rate of neural network is not very high in practical operation. Firstly, it is because of its slow learning speed and long learning time, and the lack of high-quality sample set for its learning. Secondly, the method is easy to fall into local minimum and ignore the global minimum deviation [29]. There is also the difficulty of structural optimization, because the number of neurons in each layer and the selection of input are lack of theoretical support, with a certain randomness. Finally, the neural network and its algorithm have no good solution in theory, and its controllability and stability need to be demonstrated [30.

Therefore, compared with other more mature management theories, the ongoing research on the use of neural networks in control systems should focus on solving the following problems: looking for a fast neural network learning algorithm that can be fused in a wide range to match real-time control; In the problem of approximating nonlinear function, the existing theory can only solve the problem of whether it exists or not. At present, there is no clear theoretical basis for what kind of neural network structure is suitable for various control conditions and technological processes [31]. For the forward propagation neural network,

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the selection of the number of neurons in the hidden layer and the input layer is blind; At present, the main application method of neural network is to use it to identify the model of the controlled object, and then the engineers give the control scheme [32]. Or the neural network can be directly used as the controller to control the target parameters. The basis of this control is that there is a high-quality data base to train the network, so its real-time performance is not good and can only be used in relatively stable working conditions. In addition, the stability and controllability of the two schemes need to be further studied. Due to the diversity and complexity of nonlinear systems and the nonlinearity of neural network itself, this problem is more difficult to solve. At present, when using neural network model, it is difficult to obtain ideal training samples by using the method of "off-line learning and on-line correction" [33]. If the process object identification and controller parameter tuning are combined, the above problems can be solved [34. However, if this assumption is to be realized, the identification network must have good identification accuracy, and the identification method also needs to be studied and improved. Generally, in complex process control systems, there are many external or uncertain factors of the system itself. In order to successfully apply neural network to the management of complex systems, we must try to improve the adaptability of neural network controller and the reliability of control system [35].

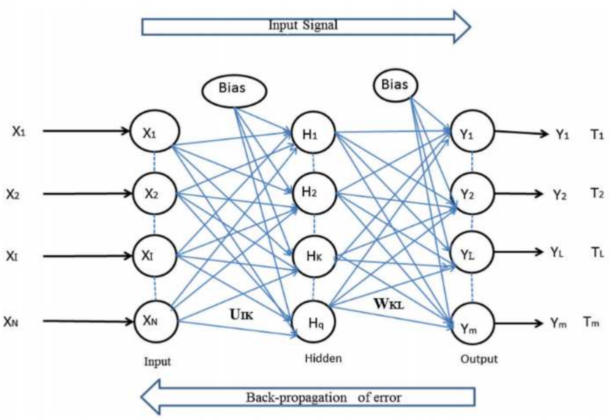

Fig. 1. ANN structure

A. Single Neuron Mathematical Model

Neural network is a parallel distributed system, which is composed of a large number of simple processors that can be connected with variable weight. The mathematical model of neuron simulates the synapse of human brain nerve. When there is an input signal and certain conditions are met, the neuron will become excited and transmit its output to the next neuron. People use this characteristic to simulate the human brain by using numerical value as the transmission medium and activation function as the excitation condition of neurons. The structure of artificial neuron is shown in the Fig.:

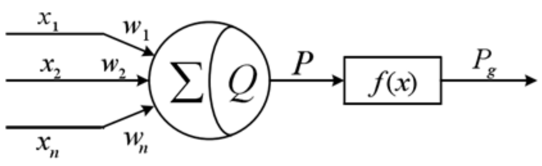

Fig. 2. Structure of artificial neuron

Xi (I = 1,2... N) simulates the signals transmitted by other neurons, and wi (I = 1,2... N) represents the sensitivity of the current neuron to the signals transmitted by other neurons. The greater its value, the more sensitive it is, and the greater its impact on the current neuron [12]. Σ Represents the spatial accumulation of postsynaptic signals, Q represents the threshold of neurons, f (x) is the activation function, and PG is the output of neurons [13].

B. Activation Functions Are Divided Into The Following Types

- Piecewise linear function.

$$f(x)=\begin{cases}1 & x\geq 1\\ 0 & -1<x<1\\ -1 & x\leq -1\end{cases}$$

- Sigmoid (S).

$$f(x)=\frac{1-\exp(-x)}{1+\exp(-x)}$$

- Gaussian function.

$$f(x)=e^{-(x^2/\sigma^2)}$$

C. The Working Process Of Neurons

The most important thing for people to study neurons is to use them to imitate the learning ability of the human brain. Among them, the learning method of neurons is to change their sensitivity to a certain signal through certain rules, which is manifested as the adjustment of weight. There are usually three adjustment rules:

- Unsupervised Hebb learning rule.

Hebb learning is a kind of correlation learning. It is the earliest training algorithm. Its basic idea is that if two neurons are excited at the same time, the enhancement of the connection strength between them is directly proportional to the product of their excitation [14]. Oi represents the activation value (output) of neuron I, OJ represents the activation value of neuron J, and Wij represents the connection weighting coefficient from neuron I to j, then Hebb learning rule can be expressed by the following formula:

$$\Delta w_{ij}=\eta o_i(k)o_j(k) \tag{3}$$

Where η Is the learning rate.

- Supervised delta learning rule.

In the Hebb learning rule, the teacher signal is introduced, that is, OJ is replaced by the difference between the desired output DJ and the actual output OJ, which constitutes the delta learning rule of supervised learning [15]:

$$\Delta w_{ij}=\eta(d_j(k)-o_j(k))o_i(k) \tag{4}$$

- Supervised Hebb learning rules.

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Combining unsupervised Hebb learning rules and supervised delta learning rules constitutes [16] supervised Hebb learning rules:

$$\Delta w_{ij} = \eta(d_j(k) - o_j(k))o_j(k)o_i(k) \quad (5)$$

Supervised learning methods are often used in practical applications.

IV. PID Tuning By Neural Network

After research and demonstration, PID parameters can be adjusted by BP neural network. Through this combination, it has become an intelligent parameter adjustment method. In this method, the coefficients of the three links of PID are determined by training neural network, and then applied to the controller for actual control.

BP network (back propagation of error) introduces the least square training algorithm, that is, in the process of network training, the error between network output and expected output propagates in the opposite direction, and the connection strength (weight coefficient) is adjusted to make the error equal. The training process can be divided into two parts: the direct calculation of the network and the correction of the connection weight coefficient with error back propagation. Repeat the two parts in turn. Before the end of the training process, if there is an error between the output calculated by the direct network and the expected output value, it will be transmitted in the opposite direction, and the error will be sent back to the original connection path as the basis for changing the weight coefficient. The purpose is to reduce errors to meet control requirements.

Only when the three parameters of PID cooperate with each other and meet certain requirements can the control requirements be realized. With the change of parameters, the control effect also changes. When the control requirements are met to the greatest extent, it can be regarded as the best parameter. Because of its discrete and arbitrary transformation characteristics, BP neural network can fit any nonlinear function. Through the learning of the network itself, the P, I and D parameters under an optimal control law can be found [17].

A. System Structure

The system architecture of the combination of BP neural network and PID controller is shown in Fig. 4-1. The controller consists of two parts. One is the classical PID controller: the incremental PID control algorithm is used to directly control the controlled object in the closed loop, and the three parameters KP, Ki and KD are the method of on-line adjustment. The second is BP neural network (part of system model identification): adjust the parameters of PID controller according to the running state of the system to realize the optimization of specific performance indexes [18].

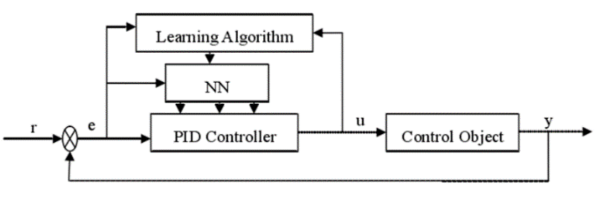

Fig. 3. Structure of PID control system based on BP neural network

Among them, the control algorithm of PID controller is incremental 6.

$$\Delta u(k) = k_p(e(k) - e(k-1)) + k_i e(k)T + k_d \frac{e(k) - 2e(k-1) + e(k-2)}{T}$$

(6)

B. BP network structure

According to the existing experience, the number of neural network layers is selected as three layers, and its structure is shown in Fig. 4-2. Its input nodes, hidden layer nodes and output layer nodes are 4, 5 and 3 respectively. The input factor selection is the system set value, system output value, error (i.e. the difference between input and output) and unit influence quantity.

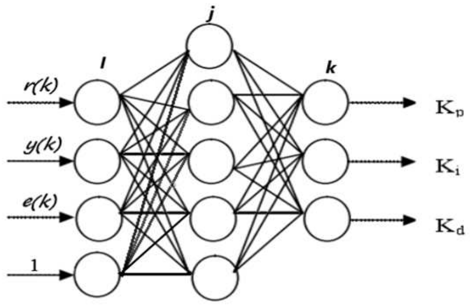

Fig. 4. Network structure

The choice of input layer signal depends on the complexity of the system. The more complex the system is, the more the number of input signals will be. In real-time control, the directly connected neural network can use the hidden layer because it is proved that the directly connected multilayer neural network with hidden layer and sigmoid function can approximate the nonlinear function with arbitrary accuracy. The more neurons in the hidden layer, the more computation is required, and the system is more easily disturbed by small components. Therefore, the number needs to be selected. At present, there is no definite theoretical calculation of the number of neurons, and trial and error is generally carried out through experiments. Generally speaking, its quantity can be determined by the following empirical formula: $q = \sqrt{(n + m)} + f$. [19] In the formula, N, Q and m are the number of neurons in the input layer, hidden layer and output layer respectively. In the formula, f can be taken as 1 ~ 10. Too many nodes will increase the amount of calculation, and too few nodes can't approach the given function well. Comprehensively, q is taken as 5.

V. Matlab Simulation Verification

Take a process object as the simulation object, and the transfer function of the simulation object is:

Y=1.2(1-0.8*(exp(-0.1*k)))^3* (6)

Set the sampling time as 0.001 seconds, the BP network structure as 4, 5 and 3 layers, and the input vectors as [R (k), y (k), e (k), 1], and take the parameters ρ = 0.25， γ = 0.05。 The change of input and output with time is shown in Fig. 5.

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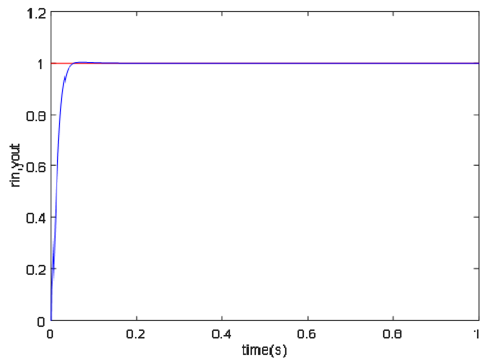

Fig. 5. Input and response

The horizontal axis represents time and the vertical axis represents input and output values. It can be seen from the Fig. that the output can follow the input quickly. The variation of error with time is shown in the Fig.6:

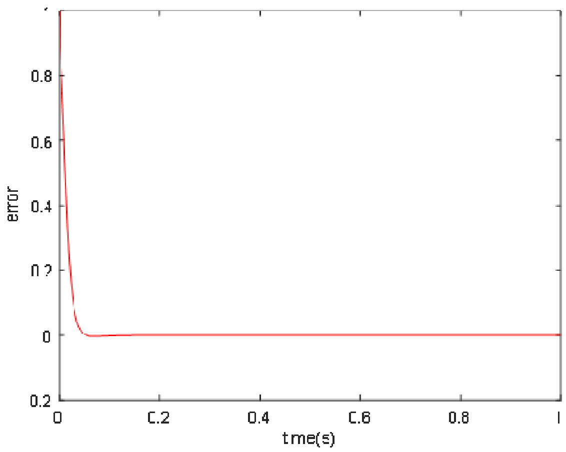

Fig. 6. Error variation

It can be seen from the Fig. that the output of the system is always changing in the direction of error reduction.

The output of the controller is shown in the Fig.7:

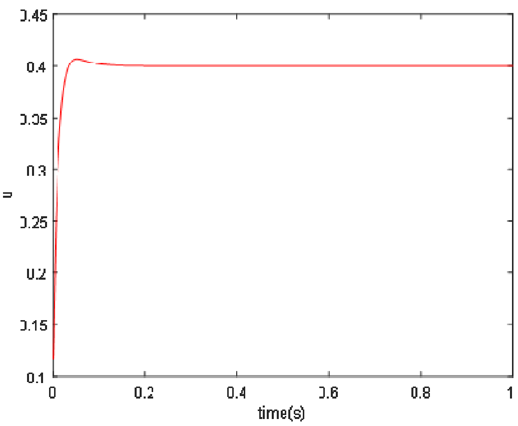

Fig. 7. Controller output change

It can be seen from the Fig. that the controller output of the system can change rapidly with the input, and then reach the steady-state value. The variation of PID parameters adjusted by neural network with time is shown in the Fig.8:

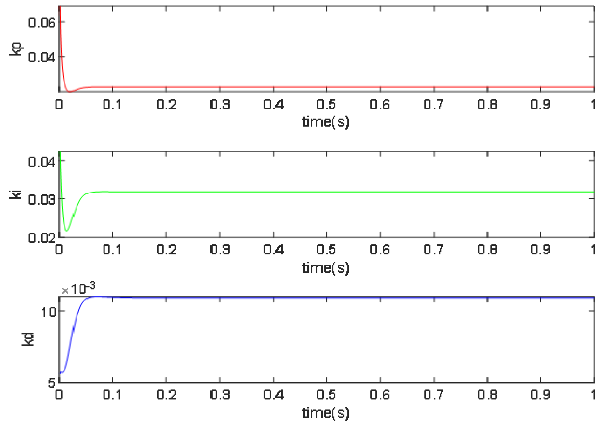

Fig. 8. PID parameter change

It can be seen from the Fig. that the controller parameters of the system can be adjusted by the neural network according to the steepest descent method, and then reach the steady-state value.

ACKNOWLEDGMENT

Thank my teachers and classmates for their valuable comments in the writing process and the Russian teachers for their help in the format of the paper.

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