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Application Of PID Control Based On BP Neural Network In The Expansion Machine Of Organic Rankine Cycle System

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BP neural network, PID control, energy, Organic Rankine cycle system, expander

ABSTRACT

With the rapid development of China's economy, the relative shortage of energy has become one of the important factors restricting economic and social development. At present, the research and development of energy-saving technology in industrial process have important practical significance. The Organic Rankine Cycle (ORC) system is considered to be a technology for the efficient use of low-temperature heat energy, and many researchers have made efforts on the efficiency of ORC system. In this paper, the dynamic performance of the system is adjusted by using the neural network-based PID control method for the expander in the system. Firstly, the control model of the expander in the system is established, and then the control algorithm is applied to the controlled object to make the system run efficiently. The simulation results show that the algorithm has a good control effect compared with the traditional PID control. This control method can effectively improve the efficiency of ORC system.

1. Introduction

The development of human society can not be separated from the energy problem. With the increasing consumption of fossil energy, such as coal, oil, natural gas, and the environmental burden of energy consumption, environment and energy issues have become a major concern in the world. The form of energy utilization should not only be environmentally friendly, but also be efficient in terms of energy efficiency. In this context, ORC system recovering the low-grade energy has been paid more and more attention. ORC also called bottom cycle, is widely used in industrial waste heat and new energy field (Hu et al., 2013). The basic principle of ORC is similar to that of conventional Rankine cycle. The biggest difference between the two is that the working medium of the ORC is low boiling point and high vapor pressure, not water. With the emergence of the system, energy has been effectively utilized and energy utilization rate has been improved.

2. System Description

The ORC system is consisted of an evaporator, an expander, a condenser and a working fluid pump, as shown in Figure 1. In the evaporator, heat is absorbed by working fluids from low temperature heat sources and organic steam is produced, which in turn pushes the expander to rotate and drives the generator to generate electricity (Tian et al., 2016). After the work of the expander, the spent air is entered the condenser and cooled into a liquid, which is driven into the evaporator by the working medium pump to complete a cycle. The ORC system can be used in the following forms: industrial waste heat, geothermal energy, solar energy, biomass energy (Qiu et al., 2014).

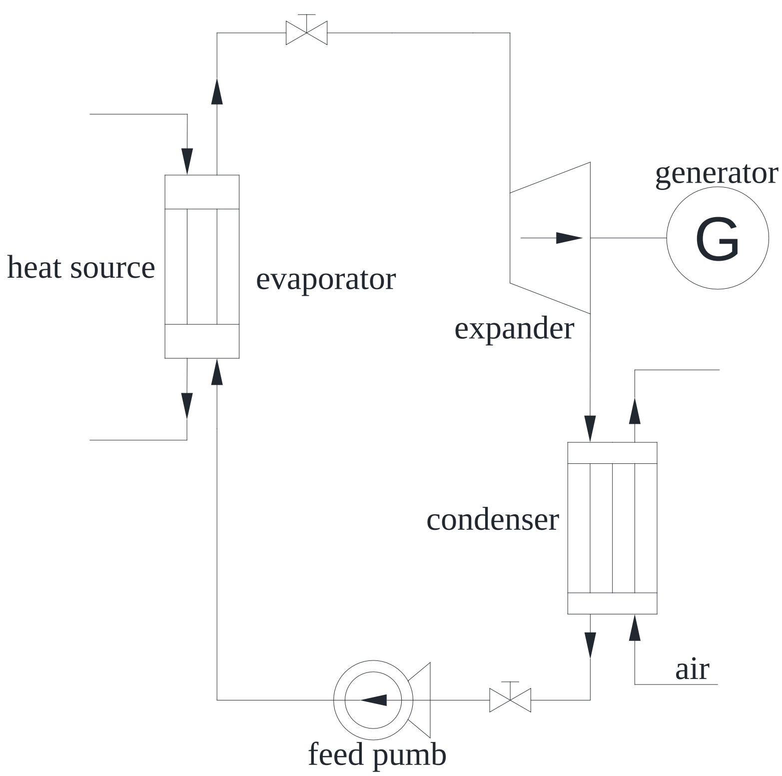

Figure 1: Schematic diagram of ORC

3. Mathematical Model of The Expander

When the gas has a certain pressure and temperature, the corresponding gas has a certain potential energy and kinetic energy, the sum of these two kinds of energy is internal energy. In the expander, gas is inflated by adiabatic heat, exerting work on the outside and consumed its internal energy. The function of the expander is realized by this principle, and makes the pressure and temperature of the gas drop greatly to be realized the purpose of refrigeration and cooling (Hui et al., 2010).

According to the characteristics of large lag and large inertia of the expander and referring to the relevant data, the control system of the expander can be approximately simplified. After linearization, the transfer function can be expressed as follows:

$$G(\mathrm{s}) = K_0 \frac{e^{-\tau s}}{Ts+1} \tag{1}$$

The simulated temperature control system is represented by a first-order link with pure delay. When K_0=1,T=60, τ=80s, its transfer function is:

$$G(s) = \frac{e^{-80s}}{60s+1} \tag{2}$$

4. Control Algorithm

4.1 PID Control Algorithm

PID control is one of the earliest developed control strategies. The regulator controlled by proportion, integration and differentiation of errors is called the PID controller and it is the most widely used regulator with mature technology in continuous system. Because of its mature technology, simple algorithm, simple realization, good robust performance and high reliability, a large class of industrial objects can be effectively controlled by traditional PID regulators and so on. It is especially suitable for deterministic control system which can be established with precise mathematical model. The control diagram is shown in Figure 2:

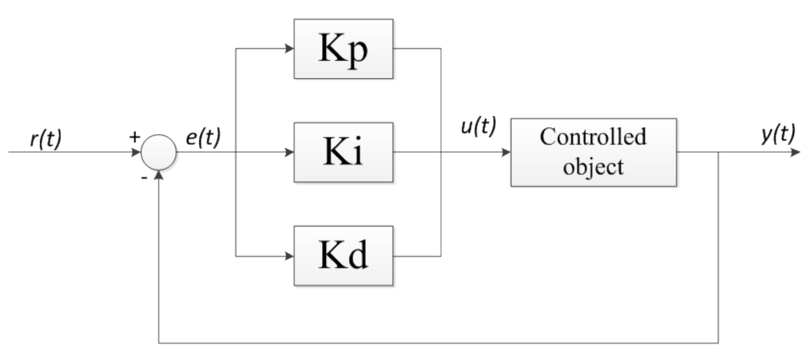

Figure 2: PID control schematic diagram

PID regulator is a linear regulator, the control object is controlled by the regulator, and by a linear combination of the proportion, integration and differentiation of errors between the given value and the actual output value to form the control quantity. The transfer function of the PID regulator is listed as follows:

$$D(S) = \frac{U(S)}{E(S)} = K_P(1 + \frac{1}{T_I S} + T_D S) \tag{3}$$

The function of each correction link of PID regulator (Gui et al., 2009):

1.Proportion link: Respond in proportion to the error signal $e(t)$ of the control system in real time. Once the error is generated, the regulator immediately controls to reduce the error.

2. Integral link: It is mainly used to eliminate static error and improve the system's error free degree. The strength of the integral is determined by the integral time constant T_I. When T_I gets bigger, the integral becomes weaker; T_I becomes smaller, and the integral becomes stronger.

3. Differential link: The change trend of error signal can be reflected by it, and before the value of error signal becomes too large, an effective early correction signal is introduced into the system, the system action speed is accelerated, and the adjustment time is reduced.

4.2 PID Control Algorithm

The so-called neural network system is a kind of technical system which is simulated the structure and function of human brain neural network by means of engineering technology. It is a large-scale parallel nonlinear dynamic system. Because neural network has the advantages of distributed storage, parallel processing and self-learning, it has a broad application prospect in the fields of information processing, pattern recognition, intelligent control and so on.

As shown in Figure 3, the BP neural network is a neural network with three or more layers of neurons, including the input layer, the middle layer and the output layer. There is a full connection between the upper and lower layers, but no connection between the neurons in each layer. When a pair of learning samples are provided to the network, the activation values of the neurons propagate from the input layer through the middle layer to the output layer, and the input response of the network is obtained from each neuron in the output layer (Wang et al., 2013). Then, according to the direction of reducing the error between the target output and the actual output, the output layer goes back to the input layer through each middle layer, and the connection weights are revised layer by layer. This algorithm is called "error back-propagation algorithm", that is, BP algorithm.

4.3 PID Controller Based on BP Neural Network

The PID control system based on BP neural network is mainly composed of PID controller and neural network. The structure diagram is shown in Figure 4.

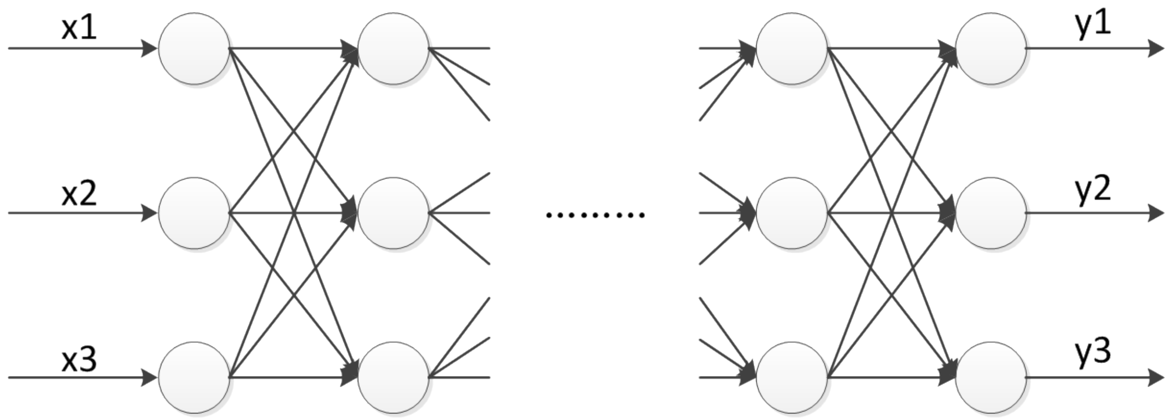

Figure. 3: BP neural network structure diagram

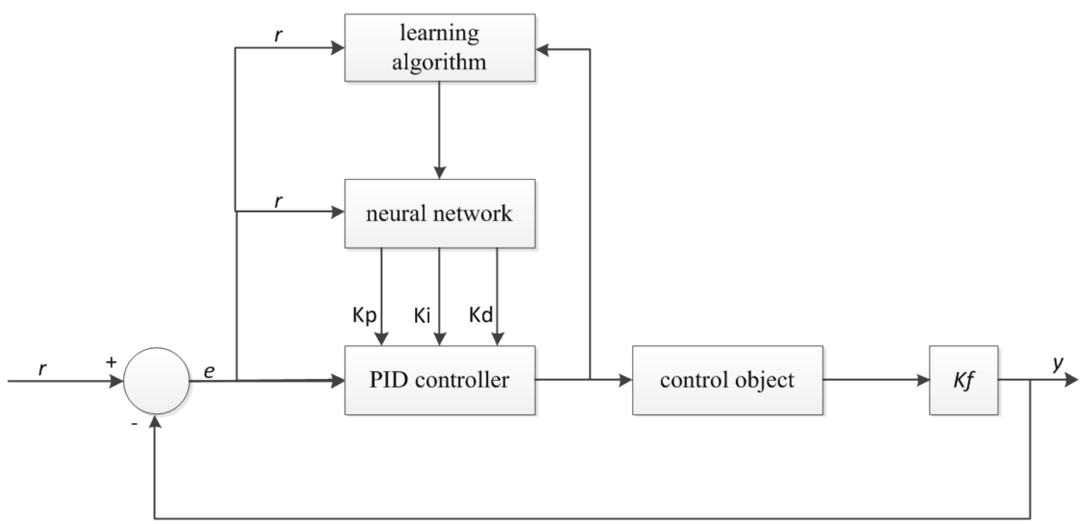

Fig.4 Structure diagram of PID control system based on BP neural network

The controlled object is controlled directly by the classical PID controller, and the three parameters K_p, K_i, K_d are online setting. The parameters of PID control are adjusted by the neural network according to the operating state of the system in order to achieve the optimization of some performance index. Output layer neuron output state corresponding to the three parameters of PID controller K_p, K_i, K_d, by learning the neural network and adjusting its weight, the stable state of the neural network is corresponding to the PID control parameters under some optimal control law. The incremental PID control algorithm is described as follows:

$$u(k) = u(k-1) + K_p[e(k) - e(k-1)] + K_i e(k) + K_d[e(k) - 2e(k-1) + e(k-2)] \tag{4}$$

In the above formula, $e(k)$ is the error between the actual output and the expected value of the system; $u(k)$ is the output of the controller. The learning algorithm of the weighted coefficients in the output layer of the neural network is shown as follows:

$$\Delta w_{li}^{(3)}(k) = \alpha \Delta w_{li}^{(3)}(k-1) + \eta \delta_i^{(3)} O_i^2(k) \tag{5}$$

$$\delta_i^{(3)} = e(k) sgn\left(\frac{\partial y(k)}{\partial u(k)}\right) \frac{\partial u(k)}{\partial O_l^{(3)}(k)} g'(net_l^{(3)}(k)) \tag{6}$$

The learning algorithm of weighting coefficient of neural network hidden layer is shown as follows:

$$\Delta w_{li}^{(2)}(k) = \alpha \Delta w_{ij}^{(3)}(k-1) + \eta \delta_i^{(2)} O_j^{(1)}(k) \tag{7}$$

$$\delta_i^{(2)} = f'(net_i^{(2)}(k)) \sum_{l-1}^{3} \delta_l^3 w_{li}^{(3)}(k) \tag{8}$$

In formula, $g'(\cdot) = g(x)(1-g(x))$, $f'(\cdot) = (1-f^2(x))/2$, η is learning rate, α is coefficient of inertia (Ding et al., 2010).

The controller control algorithm is summarized as follows (Xue et al., 2009):

(1)The structure of the BP network is determined, the input layer node number M and the hidden layer node number Q are determined, the initial values $w_{ij}^{(2)}(0)$ and $w_{li}^{(3)}(0)$ of the weighting coefficients of each layer are given, and the learning rate η and inertia coefficient α are selected, at this time K=1.

(2)$rink(k)$ and $yout(k)$ are sampled to get, the time error $\mathrm{e(k) = rink(k) - yout(k)}$ is calculated.

(3)The input and output of each layer of neurons are calculated by the neural network, the output of the output layer is three adjustable parameters K_p, K_i, K_d of the PID controller .

(4)The output $u(k)$ of the PID controller is calculated according to equation (4) .

(5)Neural network learning, online adjustment of the weighted coefficient $w_{ij}^{(2)}(k)$ and $w_{li}^{(3)}(k)$, PID control parameters to be achieved adaptive adjustment.

(6)Make k=k+1, go back to (2).

5. Research on System Simulation

Compiling m functions in MATLAB, the controller is applied to the temperature control system of the expander, and its control effect is verified by simulation (Liu et al., 2002). In this simulation, M=4， Q=5, η=0.0001,α=0.5, the system is controlled according to the previous algorithm, the results are compared with the traditional PID control algorithm and analyzed. The results of the simulation are shown in Figure 5, Figure 6 and Figure 7.

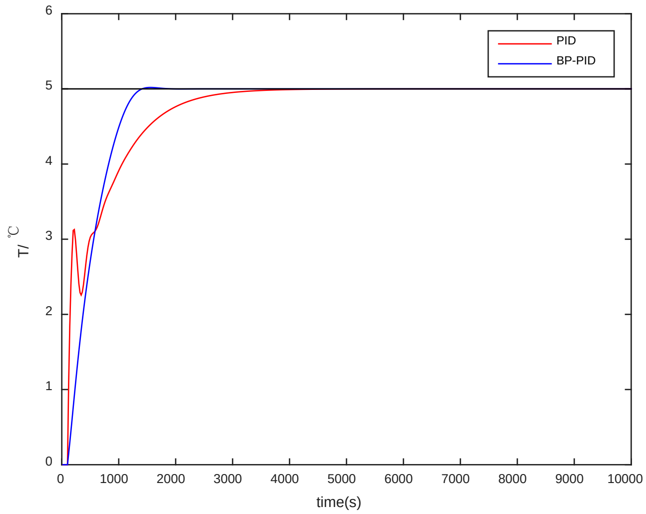

Figure 5: Tracking capability curves

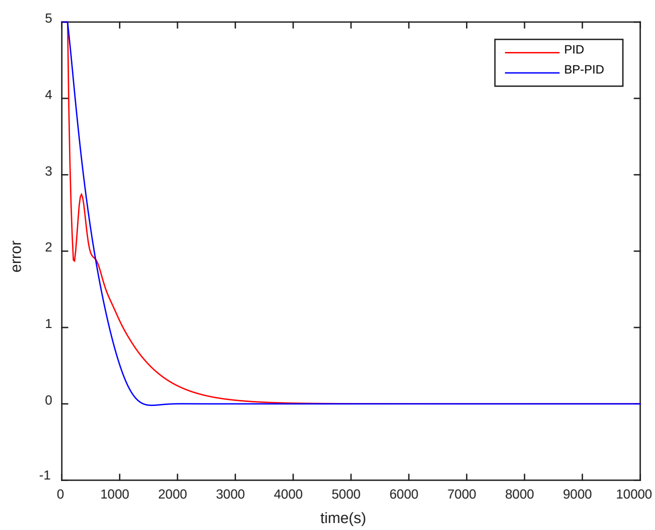

Figure 6: Erroe

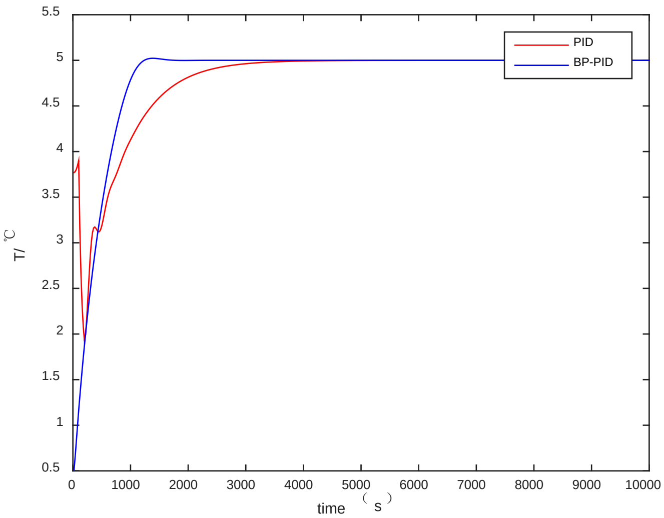

Figure 7: Control quantity curves

From the above figure, when the time is 1360 seconds, the system under the control of BP-PID algorithm is reached the set value, and the error is zero from now on. The curve is smooth before reached the stable value, and the overshoot is almost zero. When the time is 3600 seconds, the system under the control of the traditional PID algorithm is reached the set value. The error is zero from now on, and the overshoot is almost zero. However, before the system is reached the stable state, a certain amplitude of oscillation is generated by the control curve. The stability of the system is affected. The former saves 62.2% more time than the latter to achieve steady state.

From the above figures, it can be seen that the control performance of the PID control algorithm based on BP neural network is better than the traditional PID control algorithm. Compared with the traditional PID algorithm, the advantage of this algorithm is that the three parameters of PID control need not be set artificially, and the adaptive adjustment of parameters can be realized through the learning of neural network and on-line adjustment of weighting coefficient. Then the control effect can be optimized.

6. Conclusion

In this paper, the expander in ORC system is taken as the research object, the inlet temperature is controlled, thus the refrigerating capacity is controlled, and the expander can run efficiently in order to save energy. PID control method is generally selected by the traditional temperature control system. However, in the process of temperature control using this algorithm, the delay is often encountered, which has a serious impact on the stability of the system, resulting in the overshoot of the system and the longer the adjustment time. Even oscillations and divergences occur, so that the dynamic characteristics of the system are greatly reduced. To solve this problem, the BP neural network and PID control algorithm are combined to improve the problem. It can be seen that the BP neural network has better stability, higher control precision and faster stable state than the traditional PID, which is of great significance to the control system.

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