Optimization of Coordinated Control System on Radial Basis Function Neural Network

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Abstract. Coordination control system is an indispensable part of the thermal power unit, which is a multi-input and multi-output, complex structure of the system. The coordinating way of boiler-follower has the ability of high respond to load, but this method will cause excessive fluctuation of steam pressure in the boiler, what worse is that will produce excessive pressure cause explosion if you operate in a wrong way. Above all, this paper show a new method which combines the advantages of neural network and conventional PID control to improve the load response rate of the coordinated control system. According to the characteristics of non-linearity, large inertia and large delay of the system, a 300MW unit model is adopted in this paper. After analyzing its dynamic characteristics, we decide to use PID decoupling controller to eliminate the coupling phenomenon of the system itself. A control approach based on RBF neural network is proposed. The experimental results show that the dynamic response of the system is obviously improved, the system is more stable, the response speed is faster and the satisfactory control effect is achieved.

1. Introduction
As the basic unit of power grid, thermal power plant unit carries the load of power grid, the task of peak-shaving and frequency modulation, which directly affects the stability and economic operation of power grid. Conventional boiler-engine system has simple structure and poor ability to adapt different operation modes and working conditions. Coordination control system regards boiler and steam as a whole system to control. It has a variety of control functions and can satisfy the control requirements in different conditions. In this paper, we establish the mathematical model, and design the coupling controller based on the widely used PID control method [1]. Eventually, using the self-learning approach of neural network and compile the S-function module to build blocks, in order to meet the design requirements of the system.

2. The composition of coordinated control system
The control objects of the unit are boiler and steam. They are an inseparable entirety. In this system, the steam, boiler, dynamo and auxiliary equipment are closely linked and form the second transmission system. The top level of that system is called as the main control system of the unit, which is the core part of the whole system, and the sub-control systems are at the basic control level. The load control system of the unit generates boiler and turbine instructions; the basic control level executes the instructions delivered by the load control system and complete the control tasks. The system is shown in figure 1, and the schematic diagram of the system is shown in figure 2.
3. Model of coordinated control system

The unit is a complex and multivariable system, we usually simplify it as a double input and double output control object [2]. Above this, we treat fuel and opening of steam regulating valve as input and steam pressure, power as output. The working mode of a thermal power plant is a process of energy conversion, fuel combustion converts chemical energy into thermal energy, thermal energy is converted into mechanical energy in the steam turbine. Turbine rotation drives the generator to revolve together, and mechanical energy is converted into electrical energy. Therefore, we first linearize the nonlinear model at a certain working point, and the resulting linearized model can reflect the dynamic and static characteristics of the system more accurately near the working point. Then, according to the needs of the coordinated controller design, we need to simplify the linear model and get a set of linear equations describing the dynamic characteristics of the unit energy transfer process. We can express it with the transfer function in a matrix way, which is shown in formula 1 and simulated in the MATLAB environment [3-4]. The simulation model is shown in figure 3. The data of the system is shown in table 1.

$$
\begin{pmatrix}
 Pt \\
 N
\end{pmatrix} = 
\begin{pmatrix}
 0.124(205s + 1) \\
 (128s + 1)^2(11.7s + 1) \\
 2.069(311s + 1) \\
 (149s + 1)^2(22.4s + 1)
\end{pmatrix}^{-1}
\begin{pmatrix}
 0.139(0.04 + 0.96) \\
 -70s + 1 \\
 4.665s(99s + 1) \\
 (582s^2 + 50s + 1)(4.1s + 1)
\end{pmatrix}
\begin{pmatrix}
 B \\
 \mu
\end{pmatrix}
$$  

(1)
Table 1. Several sampling data

| Data | Amount of fuel (t/h) | Power (MW) | Air pressure (MPa) | Steam turbine valve (%) |
|------|----------------------|------------|-------------------|------------------------|
| 1    | 255.652              | 659.013    | 24.071            | 92.3891                |
| 2    | 258.351              | 660.361    | 24.213            | 94.9030                |
| 3    | 246.013              | 649.771    | 24.192            | 94.7861                |
| 4    | 238.798              | 641.856    | 24.168            | 93.6237                |
| 5    | 249.667              | 653.214    | 24.199            | 94.7637                |
| 6    | 234.992              | 637.809    | 24.149            | 93.9731                |
| 7    | 247.131              | 651.637    | 24.195            | 93.9572                |
| 8    | 253.478              | 659.749    | 24.197            | 94.3621                |
| 9    | 257.573              | 659.749    | 24.197            | 94.9891                |

Figure 3. The simulink model of system

4. APPLICATION AND SIMULATION OF RBF NEURAL NETWORK

Neural network has been developed for more than 30 years and has become a research topic that cannot be ignored. With the development of intelligence, it also dabbled in the field of Auto-Control. This is mainly because that is suitable for linear and nonlinear systems, continuous and discontinuous systems, certain and uncertain systems. Neural network has the performance of high parallel structure, strong learning ability, approximation ability to nonlinear function, low fault-tolerant rate and so on. These features can promote and expand the application of neural network technology in the identification and control of nonlinear systems [5]. The RBF neural network we use includes 3 levels: input layer, hidden layer and output layer. The activation function of the hidden layer is made up of radial basis functions. The array operation unit formed by hidden layer is called hidden layer node. Each hidden layer node contains a central vector \( c \), \( c \) and input parameter vector \( x \) with the same dimension, and the Euclidean distance between them is defined as \( \| x(t) - c_j(t) \| \).

The output of the hidden layer is composed of nonlinear activation function \( h \), as shown in formula 2:

\[
h_j(t) = \exp \left( - \frac{\| x(t) - c_j(t) \|^2}{2b_j^2} \right), \quad j = 1, 2, \ldots, m
\]  

According to the form above, \( b_j \) is a positive scalar, indicating the width of the Gauss basis function; \( m \) is the number of nodes in the hidden layer. The output of the network is implemented by weighting the function, as shown in formula 3:
\[ y_i(t) = \sum_{j=1}^{w} \omega_{ji} h_j(t), \quad i = 1,2, \ldots, n \]  

(3)

From the formula 7, \( w \) is the weight of the output layer, \( n \) is the number of output nodes; \( y \) is the output of the neural network. The connection weights of neurons between the hidden layer and the output layer can be calculated directly by the least square method, as shown in formula 4:

\[ \omega = \exp \left( \frac{h}{c_{\text{max}}} \sqrt{x(t) - c_j(t)} \right)^2, \quad j = 1,2, \ldots, m \]  

(4)

Through the self-learning ability of the neural network, we can get the best parameters of the PID controller\[6\]. It has a strong input-output mapping function and the learning process converges quickly\[7\]. We use 400 sets of data to error analysis, which can be seen that the network is very close to the original nonlinear system\[8\]. The first graph in figure 4 is the model of the original system, the second is the graph used RBF network, and the third is the error comparison between the two.

Figure 4. Error analysis of RBF neural network

5. Simulation and conclusion

The Simulation model of the control system is established by S function, and then input the parameter name in the code. Run the written code to generate the module and enter the function variable, then create the subsystem as shown in figure 5 below. Finally shield the subsystem. The connection diagram of the subsystem is shown in figure 6.

Figure 5. Neural network control system
After we obtain the simulation system, adding step disturbance signal to the input. Meanwhile, compared with the traditional PID network, the yellow curve is the optimized system and the purple curve is the PID control system. The first picture in figure 7 is the experimental result of the main steam pressure under the step disturbance of the fuel quantity. The second picture in figure 7 is the experimental result of the system power under the disturbance of fuel step disturbance. The third picture in figure 10 is the experimental result of system power under step disturbance of steam turbine valve. The last in figure 7 is the experimental result of system pressure under the step disturbance of steam turbine valve.

The results show that the RBF controller can be applied to the nonlinear system and has good control response to the large inertia system. Compared with the PID controller, the RBF controller is a great improvement in response speed and also has the characteristics of neural network itself. The overshoot of the system is reduced to a certain extent. For the main steam pressure wave under fuel disturbance, there is a small overshoot and some fluctuations in the system itself. After improvement, the overshoot of the system is reduced to 0, and in the output of the power, the system itself has a large overshoot. After improvement, the system has no obvious fluctuation, and the overshoot is changed to 0. More than this, the adjustment time and peak time of the system have been significantly reduced.

Under the work of steam turbine valve step. The fluctuation range of power output is smaller than PID controller, and this method can improve the economic benefit of the unit when the unit runs under constant pressure and sliding pressure.

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