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Dynamic Performance Analysis of Gas Turbine with Intermediate Cooling and Regenerative Based on Neural Network Algorithm

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Abstract: Gas turbine is one of the most important large-scale equipment power plants at present, which has been widely used in the industrial field. Mechanical performance test is a very important parameter for gas turbine. Neural network algorithm can play a great role in system data processing and monitoring. Therefore, in order to observe the dynamic performance of gas turbine, neural network is used to study the data changes related to intermediate cooling and regeneration of gas turbine. This paper mainly uses the experimental method to compare, control the variable of pressure ratio, and analyze its dynamic performance through computer group efficiency, fuel consumption rate and the quality of carbon dioxide and oxygen. The experimental results show that, under rated load, the unit operates with variable pressure ratio. When the pressure ratio is less than 11, if efficiency is required, the unit power can be kept basically constant by changing the fuel quality.

1. Introduction

To measure the dynamic performance of gas turbine, the most important thing is to determine its working state. This is also a way to ensure the normal operation of the unit, improve efficiency and reduce energy consumption. With the development of modern industry, various heat load problems have become increasingly prominent, especially in gas turbines. In order to better control its operation and ensure normal use, this paper intends to study the neural network algorithm and its role in the dynamic performance analysis of gas turbine with intermediate cooling and regeneration.

There are many theoretical studies on the dynamic performance analysis of gas turbine with intercooling and regenerative relying on neural network algorithm. For example, some people put forward that the rapid development of computer and intelligent technology has provided new means and methods for research in many fields, and injected new vitality into the research of gas turbine simulation and optimal control [1-2]. Some people provide some technical references for the design, development, optimization and use strategies of actual intercooled cycle gas turbines [3-4]. In addition, some scholars said that dynamic characteristic simulation is the key research direction in the field of gas turbine [5-6]. Therefore, this paper believes that the key to the dynamic performance analysis of gas turbine with intermediate cooling and heat regeneration is to accurately monitor and judge the fault using the existing digital technology and neural network algorithm.

In this paper, the intercooling (regenerative) cycle gas turbine is first studied, and its working principle is described and its characteristics are analyzed. Then the application of neural network in gas turbine performance monitoring is studied. Then, the off design performance of some regenerative gas turbine combined cycles is described. Finally, a conclusion is drawn through the design experiment and performance analysis of the gas turbine cycle system.

2. Intercooled regenerative cycle gas turbine based on neural network algorithm

2.1. Intercooled (Regenerative) cycle Gas Turbine

The working principle of gas turbine is to change the friction between the combustion chamber wall and gas molecules to generate high temperature in the air gap, thus forming pressure difference and thermal damping. Therefore, the gas turbine rotor needs to bear a huge load when rotating. In the working process of gas turbine, combustion chamber is an important part for generating electricity, transporting chemical fuel and water. The gas preheating system is composed of heating pipe, steam drum and expansion valve. It can transfer the heat when the material temperature in the boiler is lower than a certain set value to the evaporation position or other positions; Adjust the steam pressure to make the compressed hot water burn under high load [7-8].

Intercooled cycle gas turbine is a kind of heating technology. During operation, fuel vapor (gaseous or liquid) at high temperature and pressure is compressed. The intercooling circulator is mainly used to provide coolant for the mechanical tempering combustion system to ensure that it can be thermally prepared at low temperature, and at the same time absorb and utilize combustible gas (or gaseous fuel). When high temperature and high pressure gas is sucked into the cylinder of gas turbine, a pressure difference will be formed. Due to the high temperature, the expansion valve is closed and the air inlet is opened to enter the exhaust pipe. Then, the throttling device provides heat to the reheating furnace to drive the turbine generator unit to rotate, so as to cool down and cool the combustion system. In the simple cycle system of gas turbine, the gas directly enters the combustion chamber after passing through the low-pressure and high-pressure compressors to mix with fuel for combustion. The intercooling cycle gas turbine is to install an intercooler between the low-pressure compressor and the high-pressure compressor to reduce the compression power consumption of the high-pressure compressor by reducing the gas temperature. The HP coal-fired generator set of indirect cooling cycle machine is two-stage cooling, with simple structure and high unit efficiency [9-10].

2.2. Performance Monitoring and Fault Diagnosis Method of Gas Turbine Based on Neural Network

Many neurons are organized together in a certain way to form a neural network. The neural network can be divided into feedforward type and feedback type. When using neural networks to identify nonlinear systems, the characteristics of the system are stored in the hidden layer neurons.

Therefore, the number of hidden layers and neurons is the key parameter to determine the neural network model.

Due to the complex internal structure of gas turbine and the working condition of many components, it is easy to cause various faults. The occurrence of fault will affect relevant performance parameters of gas turbine, among which the health parameters of relevant components (compressor and turbine) are the most directly affected, including flow coefficient and efficiency coefficient [11-12].

This paper proposes a method to carry out gas turbine performance monitoring based on gas turbine NARX model. The system takes the real-time input status of gas turbine as input, and outputs the deviation between the real-time operation parameters of the monitored gas turbine unit and the reference value generated by the model. Parameter deviation is the basis for fault detection and identification. When the deviation exceeds the preset threshold, the occurrence of fault can be inferred. On the other hand, since each measurement parameter is measured by each sensor installed in the unit, even if the sensor works under normal conditions, it will inevitably bring large or small measurement errors, which may make the value of some operation parameter exceed the reference range [13-14].

The fuzzy logic method can be used for reasoning based on prior knowledge, with fast response performance, easy implementation, high accuracy and strong global response capability. Based on T-S fuzzy model, a fuzzy neural network for gas turbine fault detection is established. The neural network has good compatibility with different inputs, and can also realize the adaptive adjustment of fuzzy rules. In order to realize these two points, two processing methods are mainly adopted: one is to use fuzzy method to describe the input of neural network fuzzily. The second is to use the learning algorithm of neural network to realize the adaptive adjustment of fuzzy rules. The network can be used for fault diagnosis of gas turbine based on the deviation of each operating parameter from the reference value. The fuzzing layer fuzzies the input [15-16]. The membership degree is used to describe the membership relationship between the input and the fuzzy subset. The formula is as follows:

$$\mathrm{v_a}(\mathrm{m_k}) = \exp\left(-\left(\mathrm{m_k} - X_k^{\mathrm{i}}\right)^2 / Y_k^{\mathrm{i}}\right) \tag{1}$$

In the formula, X_k^{i} and Y_k^{i} are respectively the center and variance values of the selected Gaussian distribution function. $\mathrm{v_a}(\mathrm{m_k})$ is the membership degree of the deviation component $\mathrm{m_k}$ in the fuzzy subset a.

The hidden layer calculates the fuzzy rules, and the number of nodes is equal to the number of fuzzy rules. Because the relationship between the input conditions in the fuzzy rule is "and", the multiplication operator is used in the calculation process to multiply the membership of each component as a whole input mode.

$$\mathrm{q}^i = \prod_{k=1}^{l} v_{a_k^i}(m_k) \tag{2}$$

In the fuzzy neural network, the process of realizing the automatic adjustment of fuzzy rules in the model is essentially to find the most suitable group of values by learning different samples.

2.3. Off Design Performance of Partial Regenerative Gas Turbine Combined Cycle

The combined cycle power plant can improve the cycle efficiency by using traditional heat regeneration, but the bottom cycle performance will be reduced to a certain extent due to the influence of the inlet gas temperature of the waste heat boiler and the inlet temperature of the steam turbine. The total power output of the system will be greatly reduced, and the bottom cycle parameters will be greatly reduced, leading to the complexity of the bottom cycle transformation. Therefore, a new type of partially regenerative gas turbine combined cycle power generation system is proposed in this study. The system is based on S109FA gas turbine combined cycle unit, and is optimized through partial heat regeneration transformation [17-18].

The new partial regenerative combined cycle system is composed of regenerator, gas turbine generator, waste heat boiler, steam turbine generator unit and other auxiliary systems. The proposal of some regenerative units and corresponding operation strategies provides a feasible scheme for the improvement of the performance of gas steam combined cycle units under all working conditions, the unit transformation mode and the optimized operation scheme. The main ways to improve the efficiency of combined cycle under variable working conditions are to change the amount of working medium (regulate IGV to reduce the air mass flow) and to reduce the specific work through system integration (such as proper heat regeneration).

For the general off design model of gas turbine, it is still necessary to improve its accuracy at low load. It is mainly to correct the compressor pressure ratio and turbine inlet temperature at low load, combined with the combustion efficiency decline and incomplete combustion caused by different combustion methods and other factors in the combustion chamber at low load. It is necessary to adopt more appropriate modeling methods and revise the off design model of combustion chamber.

For some regenerative gas turbine combined cycle units, the double pressure reheat waste heat boiler used in the bottom cycle of this study can be changed to a three pressure primary reheat waste heat boiler with better waste heat utilization effect, further improving the full working condition performance of some regenerative units, and fully reflecting the improvement of the combined cycle performance by some regenerative units. At the same time, the influence of different ambient temperature, compressor pressure ratio and turbine initial temperature on some regenerative units can also be analyzed.

For some regenerative units, some regenerative units can be combined with common retrofit schemes such as intercooling and reheating to further improve the full working condition performance of combined cycle units.

3. Gas turbine cycle system design and performance analysis

3.1. Gas Turbine System Design

The design and thermal calculation of gas turbine adopt the EBSILON calculation simulation software to build the thermal calculation model, and conduct debugging and modification on this calculation model until it meets the design requirements. In this paper, the EBSILON software is used for the thermodynamic design and off design calculation of gas turbines. The main modeling elements required for gas turbine modeling include compressor, combustion chamber, gas turbine, mixing header, generator, controller, boundary input elements, etc. The modeling process of BSILON is shown in Figure 1:

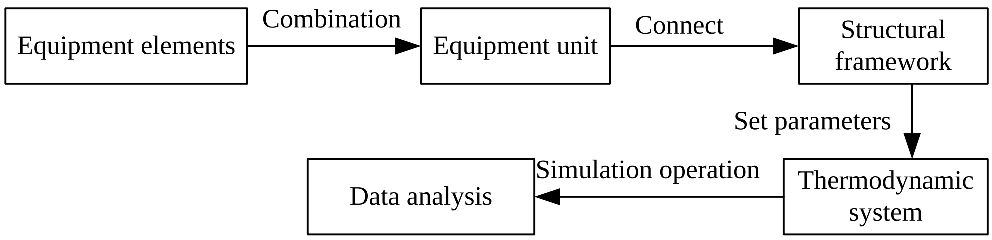

Figure 1. EBSILON modeling process

3.2. Layout Scheme of Gas Turbine Cycle System

One scheme is that the compressor directly compresses CO2, and O2 and CO2 are mixed behind the compressor and sent to the combustion chamber as combustion promoter. Since the inlet pressure of the gas turbine is above 2MPa, the inlet pressure of the gas turbine is provided by the compressor, so the oxygen also needs to be pressurized to the corresponding pressure, which requires a compressor for oxygen pressurization, thus limiting the gas turbine to be a double shaft arrangement. The design principle of gas turbine is that in view of the heavy workload, long time and high cost of developing a new gas turbine, it is a safe and economical way to adopt the existing parent gas turbine with better performance.

3.3. Thermal Performance Scheme of Gas Turbine

Under rated load, change the unit pressure ratio and discuss the thermal performance change of the unit. There are two control methods to discuss the influence of pressure ratio on the thermal performance of equipment. Scheme A: By adjusting the mass flow of combustion promoter and fuel, its temperature is basically unchanged. Scheme B: For variable working conditions, only one parameter is required. By adjusting the fuel, the performance of the device remains basically unchanged.

4. Off design performance analysis of gas turbine

4.1. Analysis of Influence of Pressure Ratio Change on Thermal Performance of Unit

Table 1 shows the corresponding relationship between circulating carbon dioxide mass flow rate and oxygen mass flow rate and pressure ratio change. When scheme A control is adopted, the circulating carbon dioxide mass flow rate and oxygen mass flow rate are both at the design value, that is, the pressure ratio is 11 and reach the minimum value. When Scheme A is adopted, the mass flow of carbon dioxide and oxygen decreases first and then increases with the increase of pressure ratio.

As shown in Figure 2, we can find that when Scheme B is adopted for control, the circulating carbon dioxide mass flow and oxygen mass flow both decrease with the increase of pressure ratio. When Scheme A is adopted, the mass flows of carbon dioxide and oxygen both decrease first and then slowly rise.

According to Table 2, when the pressure ratio reaches 20, the unit efficiency of Scheme A can reach the maximum value of 0.395, and that of Scheme B can reach the maximum value of 0.384.

The highest fuel consumption rate of Scheme A is 0.16, and that of Scheme B is 0.155.

Table 1. Effect of pressure ratio changes on carbon dioxide and oxygen flow rates

	Carbon Dioxide		Oxygen	
	Plan A	Plan B	Plan A	Plan B
5	1775	1845	290	303
8	1760	1810	288	293
11	1745	1750	286	287
14	1745	1730	285	283
17	1748	1710	286	279
20	1755	1680	287	277

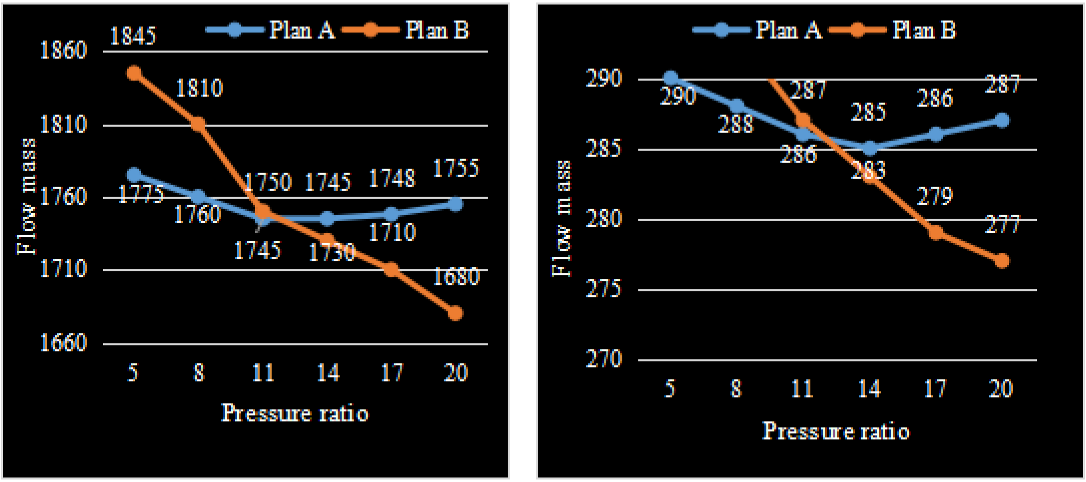

Figure 2. Effect of pressure ratio changes on carbon dioxide and oxygen flow rates

Table 2. Effect of pressure ratio change on fuel consumption rate and efficiency

	Efficiency		Fuel consumption	
	Plan A	Plan B	Plan A	Plan B
5	0.341	0.351	0.160	0.155
8	0.356	0.361	0.153	0.151
11	0.369	0.37	0.148	0.147
14	0.378	0.375	0.144	0.146
17	0.386	0.382	0.142	0.145
20	0.395	0.384	0.140	0.144

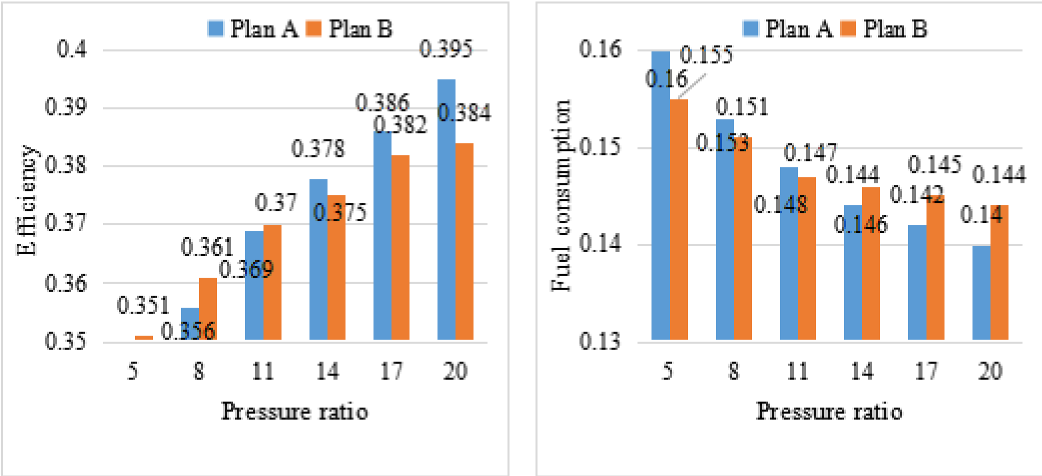

Figure 3. Effect of pressure ratio change on fuel consumption rate and efficiency

The left and right figures in Figure 3 respectively show the corresponding relationship between unit efficiency and fuel consumption rate and unit pressure ratio change. It can be seen from the left figure of Figure 3 that the efficiency of Scheme A or Scheme B increases with the change of pressure ratio. It can be seen from the right figure of Figure 3 that the fuel consumption rate of Scheme A or Scheme B decreases with the change of pressure ratio.

5. Conclusion

In order to improve the thermal efficiency of the unit, the process needs to be calculated and analyzed to determine its dynamic performance. In the actual operation process, the dynamic performance of the cooling and regenerative system will be affected by various external factors. These external conditions have a great impact on the internal structure and working characteristics of gas turbine. After establishing the dynamic characteristic equation of gas turbine, the system can be meshed by computer software, and then the corresponding mathematical model can be constructed according to the boundary conditions and constraints. This paper analyzes the off design performance of gas turbine through the change of pressure ratio.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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