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Study on the determination method of the normal value of relative internal efficiency of the last stage group of steam turbine

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A R T I C L E I N F O

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A B S T R A C T

The characteristics of the last stage group of condensing steam turbine are analyzed, and a method based on the synthetic BP (back-propagation) neural network is proposed for determining the normal value of relative internal efficiency of the last stage group. In order to consider the influence of the regenerative system, the influential factors of the relative internal efficiency of the last stage group firstly are determined, and the corresponding mathematical model is set up, and finally using the BP neural network to fit the equation. In this paper, the relative internal efficiency could be calculated by the method of BP instead of finding the exhaust enthalpy in the wet region first. The results show that the average relative errors between the network output values and the calculated values of off-design condition are less than 1%, which verify the accuracy, feasibility and validity of this method.

1. Introduction

The faults of flow passage such as deposition, erosion of flow passage and internal steam leakages are the most common faults found in steam turbine [1]. Fault diagnosis indicates the fault-root discrimination which was basically done by using an analytical system model, representing the normal system behavior in the absence of any fault [2]. These faults directly influence the safety and the economic operation of steam turbine. The turbine's operators attempt to diagnose these faults as early as possible by monitoring and analyzing their thermal parameters, enabling them to take timely measures to prevent the fault from escalating into an accident. Accordingly, more attentions have been paid on monitoring the condition of steam turbine and its auxiliaries, while diagnosing any faults as they appear [3–6].

Therefore, more attention was given to the fault diagnosis of the steam turbine's flow passages [1,7–10]. From experiences, using a fault diagnosis system of machinery will reduce production and maintenance costs by approximately 5–20% and 30%, respectively, while equipment accidents will reduce by 75% [11]. The relative internal efficiency of the steam turbine is an important indicator when evaluating the operating condition of its flow passage. Under a condition of blockage or wear, variations in temperature, pressure, mass flow and other thermal parameters could cause a reduction in the relative internal efficiency of the steam turbine.

In addition, during normal flow passage conditions, variations of the regenerative system's parameters have a certain impact on the steam turbine's relative internal efficiency. The possible reasons for low relative internal efficiency include the following, corrosion or deposit in the flow passage, an increase in the terminal difference of regenerative heaters, and loss of steam extraction pressure. Each of these factors makes determining the normal value of the relative internal efficiency of the steam turbine difficult. Therefore, the relative internal efficiency of stage groups is applied when evaluating the operating condition of steam turbine's flow passage [12].

However, the last stage group is located in the wet region and the exhaust enthalpy cannot be obtained accurately. Thus, much of the existing scientific literature does not consider the diagnosis of faults located in the last stage group [12]. In practical operation, faults could appear in the flow passage of the last stage group.

In this paper, through analyzing the main factors that influence the relative internal efficiency of a condensing steam turbine's last stage group, a method of determining the normal value is proposed based on the synthetic BP (back-propagation) neural network.

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2. Mathematical model

In definition, the relative internal efficiency of the last stage group is calculated by solving the following equation:

$$\eta_{\mathrm{rim}} = (h_{\mathrm{i}} - h_{\mathrm{o}})/(h_{\mathrm{i}} - h_{\mathrm{t}}) \tag{1}$$

where η_{rim} is the relative internal efficiency of the last stage group, h_{i} is the input steam enthalpy of the last stage group, h_{o} as well as h_{t} are the output steam enthalpy of the last stage group during the practical and isentropic processes, respectively.

According to Eq. (1), because the exhaust enthalpy in the wet region cannot be determined accurately, its normal value of η_{rim} could be correspondingly hard to determine. We found that the relative internal efficiency of the last stage group is strongly influenced by various factors. One factor is that variations in the exhaust pressure and mass flow could result in a change of leaving-velocity loss. Another factor could be attributed to the number of regenerative heaters in the front. This is because variations in the terminal difference of heaters can result in a change of mass flow rate. In addition, the reheat steam temperature is a crucial factor, because the humidity of the entrance and the amount of moisture loss found in the last stage group are functions of the reheat steam temperature.

Taking a 200 MW reheat condensing steam turbine as an example, there are eight steam extracting points, and one of them leads up to the deaerator. Its principle thermodynamic system is illustrated in Fig. 1. The relative internal efficiency of the last stage group is a function of ten unknown variables that can be expressed as:

$$\eta_{\mathrm{rim}} = f(g, p_{\mathrm{c}}, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, t_{\mathrm{r}}) \tag{2}$$

where g is the ratio of actual mass flow to rated mass flow, p_{c} is the exhaust pressure, θ is the terminal difference of heater, subscript 1, 2, 3, 4, 5, 6, 7, is the serial number of the high pressure heater and low pressure heater, t_{r} is the reheat steam temperature.

The variables outlined in Eq. (2) have a strong non-linear relationship with the relative internal efficiency of the last stage group. The non-linear relationship cannot be accurately fit by the traditional multivariate linear regression methods. However, the synthetic BP neural network with direct connection weight has an advantage on fitting into a non-linear relationship.

3. Synthetic BP neural network

3.1. Conventional BP neural network

Artificial neural networks made up of a lot of interconnected nodes are a computing model. Every node represents a certain output function which is called activation function. The connection of two nodes between layers is a weight which is equivalent to the memory of neural networks. As a result, some operation parameters which are unable to monitor online or hard to indirect calculation can be fit to some non-linear function of direct monitor parameters or indirect calculation parameters for the fault diagnosis and performance analysis through the non-linear mapping of artificial neural networks [13–18].

In recent years, the flexibility and simplicity of neural networks have made them a popular modeling and forecasting tool across a number of dissimilar research areas [19–23]. Thus, various neural network models have been developed, among which the BP neural network is the most widely embraced by contemporary studies [24–26].

The BP neural network is made up of input, hidden and output layers. The hidden layer can have one or more. When a single hidden layer has enough nodes, the BP neural network can approximate any continuous function. To facilitate calculation, single hidden layer BP neural network is commonly used. The topology of typical conventional BP neural network is shown in Fig. 2. The weights are limit to the connections of the adjacent layer nodes.

The BP neural network can learn and store a lot of mapping relations of input–output modes, without the mathematical equation in the mapping relations. As we know, the fault diagnosis and thermo-economy diagnosis present strong nonlinearity because of the complex structure and system of steam turbine. So, the BP neural network is appropriate for the fault diagnosis and performance analysis which have multiple fault modes, such as steam turbine.

However, the BP neural network has the following chief drawbacks that the velocity of learning and convergence are slow. Furthermore, its learning process converges easily to local minimum.

In order to solve these problems, the synthetic BP neural network with direct connection weight is given to improve the conventional BP neural network algorithm.

3.2. Synthetic BP neural network

The topology of synthetic BP neural network with direct connection weight is shown in Fig. 3. The connection of nodes between the input layer and the output layer is defined as direct connection weight which is different from the conventional BP neural network algorithm.

The synthetic BP neural network with direct connection weight, based on the conventional BP algorithm, can be seen as a synthesis of both linear and non-linear networks. Given an appropriate number of hidden layer nodes, this neural network is able to approximate any non-linear function to an arbitrary degree of

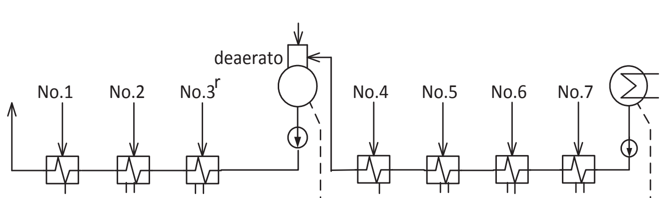

Fig. 1. Principle thermodynamic system of a 200 MW steam turbine.

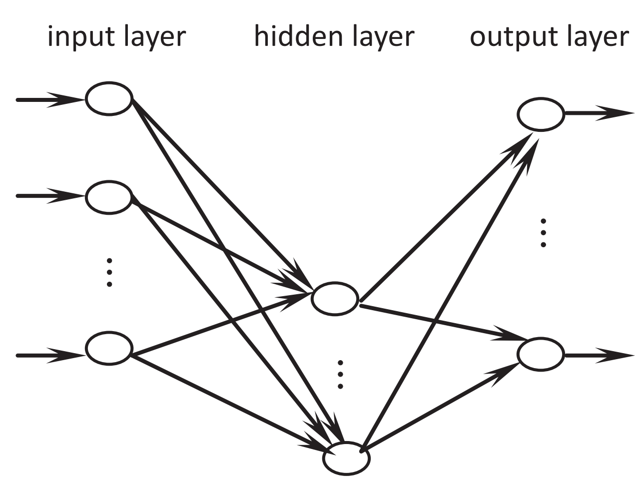

Fig. 2. Topology of conventional BP neural network.