A gas turbine thermal performance prediction method based on dynamic neural network

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Abstract. In order to ensure safety and reliability of energy transportation, it is necessary to understand and predict the performance of the gas turbine components. A prediction frame of the gas turbine compressor isentropic efficiency is established using the neural time series theory based on the Dynamic Neural Network. In order to obtain appropriate parameters for the network, a validation set is introduced to generalize the model. The compressor isentropic efficiency can be predicted based on the suggested model which provides an effective technical mean for the early warning of gas turbine performance. The experiment verified that the performance calculation model and the isentropic entropy efficiency prediction model based on the neural time series are effective.

Keywords: Gas turbine, State prediction, Dynamic Neural Network, Neural time series.

1. Introduction
The core components of gas turbine work continuously in complex conditions like extreme temperature, high pressure and high speed, and are easy to fail in such working condition [1, 2]. On the one hand, the main systems will deteriorate in long-term operation, and the untimely maintenance will lead to the increase of inlet pressure loss or partial seal leakage. On the other hand, the frequent shutdown caused by excessive maintenance will also reduce unit operation benefit. Therefore, it is of great significance for the safe and economic performance of gas turbine unit to study condition evaluation methods for inlet filtration system performance of the gas turbine [3, 4].

Prediction is becoming an indispensable part of the field of modern industrial condition monitoring in recent years. As an important construction machinery in the industry, gas turbines has been studied for years based on predictions. For example, Wang [5] et al. applied Markov nonlinear estimation to the tracking of aero-engine performance degradation, taking into account the progressive degradation and sudden failure of the engine. The results show that the performance tracking and degradation prediction errors are within 1%. Since there are many parameters that affect the operation of gas turbines, the use of a single time parameter to predict the performance trend of gas turbines in the
process of gas turbine performance prediction will have large errors. In contrast, the use of multi-parameter prediction methods will obtain more good result. Rahman [6] et al. took micro gas turbines as the research object and selected 7 types of degradation parameters (compressor isentropic efficiency, compressor flow, turbo-entropy efficiency, turbine flow, heat exchanger efficiency, compressor exhaust leakage, Shaft efficiency) to discuss the effect of one or more degradation parameters on performance. However, an overly complex model will bring computational pressure, and too many parameters will cause the algorithm adjustment process to be more time-consuming.

In recent years, many neural networks have been used for mechanical state degradation and prediction [7, 8]. However, most popular deep networks have the same static reasoning paradigm. After the training is completed, the network structure and parameters remain unchanged during the testing phase, which limits the representation ability of model, reasoning efficiency and interpretability to a certain extent. Dynamic neural networks, which include tapped delay lines are used for nonlinear filtering and prediction [9]. The dynamic network can adaptively adjust its own structure or parameters according to the input in the inference stage, so that it has good characteristics that the static network cannot have in many aspects. In this paper, a prediction model of the gas turbine compressor isentropic efficiency is established using the neural time series theory based on the Dynamic Neural Network.

2. Basic theory

The prediction model of the compressor and the basic theory of the dynamic neural network is described in this section.

2.1. Prediction model of the compressor

In the thermal system, the main performance parameters of the compressor include pressure ratio, speed, flow, efficiency and so on. It is worth noting that the performance parameters in the compressor are not completely independent. Under the condition that the internal structure and working fluid of the compressor remain unchanged, when the compressor inlet pressure, inlet temperature, flow rate, and speed are constant, the corresponding outlet pressure and outlet temperature are also determined.

The pressure ratio of the compressor $PR_c$ and the isentropic efficiency $\eta_c$ can be expressed function as follows

$PR_c = f_{11}(G_{i',n'}, n_{i'}) \cdot G_{i'} = \frac{G \sqrt{T}}{P}$

$\eta_c = f_{12}(G_{i',n'}, n_{i'}) \cdot n_{i'} = \frac{n'}{\sqrt{T}}$

The functional relationship $f_{11}$ and $f_{12}$ is determined by the design structure of the compressor. In theory, $f_{11}$ and $f_{12}$ remain unchanged in the same types. Where, $G$ is the real mass flow rate of the compressor inlet, $T$ and $P$ are the inlet temperature and inlet pressure.

Therefore, a prediction model for the isentropic efficiency of the compressor is established (the training sample of the model is $(\text{In}_{i'}, \text{Out}_{i',n'})$. $\text{In}_{i'}$ is the input vector, include the model sample compressor isentropic efficiency $\eta_c$, compressor inlet temperature $t$, compressor inlet pressure $p$ and rotating speed $r$. Where n is the time step, that is, the current data is used to predict the future $n$ time.

$\begin{align*}
\text{In}_{i'} & = [\eta_c, t, p, r] \\
\text{Out}_{i',n'} & = \eta_{i',n'}
\end{align*}$

2.2. Time series model based on dynamic neural network

The structure and parameters of the network remain unchanged after the training is completed, which is the same static similarity that most popular deep networks have. This static property limits the representation ability, reasoning efficiency and interpretability of a model to a certain extent.
Considering the different importance of inputs at different moments, the dynamic network is designed to adaptively decide whether to allocate calculations to the inputs at each moment. The dynamic network can also skip a certain amount of input at each moment and decide to read the input from the certain area of data.

The dynamic network can adaptively adjust its own structure or parameters according to the input in the inference stage. Therefore, it has good characteristics in terms of computing efficiency, adaptability and expressive ability by comparing with static networks.

The defining equation of the DNN model is shown as equation (4) and the basic construct is shown as Figure 1.

\[ y(t) = F(y(t-1), y(t-2), \ldots, y(t-my), u(t-1), u(t-2), \ldots, u(t-\mu)) \] (4)

![Figure 1. Basic construct of time series model, where the output \( y(t) \) is estimated based on a previous independent input and the corresponding output signal.](image)

3. Experimental verification

The actual operating gas turbine data is collected for experiment to verify the effectiveness of the method. The actual degradation data was collected from M701F4 gas turbines operating in a certain area of East China. The collection time starts in January 2019 and ends in June 2020.

In order to improve the practicability of the model, the time step \( n \) is selected as 1 day. The gas turbine thermal parameters of the day are used to predict the isentropic efficiency of the compressor at 1d in the future. Since the historical data of gas turbine thermal parameters are tested once every 1 minute, a large number of historical data samples will affect the calculation time of the model. It is necessary to process the sample data before establishing the prediction model due to the large temperature change within a day. Take average of daily sample data of the M701F4 gas turbine to obtain the average compressor inlet temperature, compressor inlet pressure, speed and other parameters within a day. 98 data samples (each sample has a time interval of 1d) are obtained.

The results of time series response and relative errors of the isentropic efficiency prediction model of the compressor are shown in Figure 2. In addition, regression prediction results are shown in Figure 3. The results show that the whole state prediction can be achieved based on the suggested method. An obvious sample point deviation appeared because the gas turbine has been shut down at the corresponding time.
4. Conclusions
A prediction model of the gas turbine compressor isentropic efficiency is established using the neural time series theory based on the Dynamic Neural Network. The model for the isentropic efficiency of the compressor is established based on isentropic efficiency, compressor inlet temperature, compressor inlet pressure and rotating speed. Data samples (each sample has a time interval of 1d) are obtained by taking average of daily sample data, which are utilized to predict the gas turbine during a long time.

The compressor isentropic efficiency can be predicted based on the suggested model which provides an effective technical mean for the early warning of gas turbine performance. The experiment
verified that the performance calculation model and the isentropic entropy efficiency prediction model based on the neural time series are effective.

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