Comparative analysis and forecasting of isentropic efficiency of gas turbine compressor with ARIMA, VAR, NARNN and ANFIS approaches

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Abstract. It is extremely important to monitor the status of gas turbine to ensure its safe and reliable operation. In this work, the variation trend of isentropic efficiency of compressor is analysed based on the measured data of F-class heavy-duty gas turbine in practical industrial application. The actual measured data of F-class heavy-duty gas turbine includes the data under start-stop and unstable working conditions, which cannot be directly used for calculation and analysis. To solve this problem, the data selection rules are designed and determined according to the operating conditions of gas turbine to select the data under effective working state. The isentropic efficiency of compressor is calculated based on the selected data. Then the forecasting effects of four forecasting methods on the variation trend of isentropic efficiency of compressor are studied. Four indexes, namely, symmetric mean absolute percentage error (SMAPE), mean absolute percentage error (MAPE), root mean square error (RMSE), and similarity (SIM) values are utilized to evaluate the forecasting accuracy. The research results indicate that the Adaptive Neuro-Fuzzy Inference System (ANFIS) method has better forecasting effect than Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR) and Nonlinear Autoregression Neural Network (NARNN) for this F-class heavy-duty gas turbine. Through the ANFIS method, the SIM up to 96.77\%, the SMAPE and MAPE are less than 0.1, and the RMSE is only 0.1157. Therefore, the ANFIS method is suitable for forecasting the isentropic efficiency of this F-class heavy-duty gas turbine compressor.

Keywords: Gas turbine, compressor, isentropic efficiency, forecasting, ANFIS.
1. Introduction
Gas turbine is a high-end equipment of power generation equipment, which plays a very important role in national economy and energy and power industry. Gas turbines can generate lots of electricity with very little pollution. Thus power plants adopt gas turbines. The CO₂ emissions of natural gas-fired power plants are about half of that of supercritical coal-fired power plants. Gas turbines have become the most important mechanical equipment in carbon maximum and carbon neutral environment because of its very low pollution emission and excellent performance [1].

Nowadays, some gas turbines have been operating for many years, resulting in degradation of their performance. In order to ensure the safe and reliable operation of gas turbines, it is important to carry out condition monitoring and predictive maintenance of gas turbines [2-6]. The commonly used methods are model-based methods, data-driven methods and hybrid methods. The model-based methods need to establish the mathematical model of gas turbine. The structural parameters and actual data of gas turbine in actual industrial applications are difficult to obtain, and it is difficult to accurately verify the reliability of the established model to the gas turbine in actual industry. Thus it is difficult to accurately establish the gas turbine model. The data-driven methods mainly use the information and characteristics in the historical data of gas turbine to predict the future operation state, so as to evaluate the gas turbine performance. The hybrid methods combine the model and data-driven methods to evaluate the gas turbine performance [7-10].

In this study, the F-class heavy-duty gas turbine in actual industrial operation is taken as the research object. Due to commercial reasons, it is difficult to obtain the structural parameters of gas turbine to establish the gas turbine model, thus this work mainly studies the variation trend of gas turbine compressor performance based on data-driven method. For this F-class heavy-duty gas turbine, the measured data related to the compressor mainly include the ambient temperature, ambient pressure, total pressure difference of the filter, compressor outlet pressure and compressor outlet temperature. Based on these data, the isentropic efficiency of compressor can be calculated. The isentropic efficiency can reflect the operating status and performance of the gas turbine compressor. By predicting and analyzing the change trend of isentropic efficiency of gas turbine compressor, it can provide reference for early warning and predictive maintenance of gas turbine.

In order to predict and analyze the isentropic efficiency of gas turbine compressor, the classical methods include ARIMA and VAR are studied. In recent years, more and more forecasting methods based on neural networks have emerged with the rapid development of artificial intelligence, such as NARNN, CNN, RNN, LSTM, GRU, ANFIS, etc. The neural network-based method can effectively extract the nonlinear and non-stationary features. Moreover, some neural network-based methods can adaptively optimize the network structure, which can improve the forecasting performance [11-15]. Thus the neural network-based methods are adopted to forecast and analyze the isentropic efficiency of the gas turbine compressor in this work.

The main goal of this study is to establish a reliable and accurate forecasting method for predicting the variation trend of compressor isentropic efficiency, which can provide reference for predictive maintenance of gas turbine. The main work includes: (I) According to the operating conditions of this F-class heavy-duty gas turbine, the data selection rules for the effective working state are determined. Then the isentropic efficiency of compressor can be accurately and effectively calculated based on the selected data. (II) Four forecasting methods are studied to forecast the isentropic efficiency of compressor, and the forecasting effects are quantitatively evaluated based on quantitative evaluation index.

The paper is organized as follows. In section II, the fundamentals of four forecasting methods are introduced. In section III, the actual measured F-class heavy-duty gas turbine data are analysed and processed. In Section IV, the calculation results of four forecasting methods are compared and analysed. Finally, the conclusions are summarized in section V.

2. Methodology
2.1. Autoregressive Integrated Moving Average (ARIMA)
The ARIMA model is a widely used time series forecasting model. The calculation formula of ARIMA \((p, D, q)\) is as follows [16].

\[
(1 - \sum_{i=1}^{p} \varphi_i L^i)(1 - L)^D x_t = (1 - \sum_{i=1}^{q} \theta_i L^i) \varepsilon_t \tag{1}
\]

where \(L\) is represented the lag operator, \(\varphi_i\) are the parameters of the autoregressive part, \(\theta_i\) are the parameters of the moving average part, and \(\varepsilon_t\) is represented the error terms.

In this study, there are three steps to predict the isentropic efficiency of compressor based on the ARIMA model. The first step is to construct the stationary time series and select the model type according to the autocorrelation function and partial autocorrelation function. The second step is to determine the order \(q\) and \(p\) of the ARIMA model based on the Akaikes Information Criterion (AIC) and Bayesian Information Criterion (BIC). The last step is to use the established ARIMA model to predict the isentropic efficiency and analyze the prediction results.

2.2. Vector Autoregression (VAR)
VAR is a model based on the statistical properties of data, which can be used to predict time series. A VAR(p) model can be written as the following formula [17].

\[
Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{2}
\]

where \(c\) is an \(n\) by \(1\) constant vector, \(A\) is an \(n\) by \(n\) matrix, and \(\varepsilon_t\) is an \(n\) by \(1\) error vector.

In this study, The VAR (4) model is constructed for the prediction analysis of isentropic efficiency of F-class heavy-duty gas turbine compressor.

2.3. Nonlinear Autoregression Neural Network (NARNN)
The NARNN method is a widely used artificial neural network-based prediction method. The basic model calculation formula is as follows [18].

\[
Y_t = f(Y_{t-1}, Y_{t-2}, \cdots, Y_{t-d}) \tag{3}
\]

where \(Y_t\) is the value of \(Y\) in time \(t\), \(Y_t\) is the function of past \(d\) number.

In this study, the number of hidden neurons and the number of delays are respectively set 10 and 2, and the training algorithm is adopted the scaled conjugate gradient algorithm.

2.4. Adaptive Neuro-Fuzzy Inference System (ANFIS)
The ANFIS has the learning ability and self-adaptation. It mainly includes fuzzification layer, rule reasoning layer, normalization layer, defuzzification layer and output layer [19]. The fuzzification layer is responsible for fuzzing the input variable. The rule reasoning layer is responsible for multiplying the input signals to obtain the excitation intensity of the fuzzy rules. The normalization layer normalizes the above-mentioned excitation intensity. The defuzzification layer is responsible for defuzzifying the normalized result. The output layer is responsible for calculating the total output result of the entire network.

3. Analysis and processing of measurement data of F-class heavy-duty gas turbine
The isentropic efficiency of gas turbine compressor is calculated as follows [20].

\[
\eta = \frac{(T_i \times (P_i / P_2)^{k \cdot \ln k} - T_2) / (T_2 - T_i)}{T_2 - T_i} \tag{4}
\]

where \(\eta\) is the isentropic efficiency, \(T_1\) and \(T_2\) are the inlet and outlet temperature of compressor, \(P_1\) and \(P_2\) are the inlet and outlet pressure of compressor, the ideal gas adiabatic index \(k\) is 1.4.

According to the calculation formula of the isentropic efficiency of the gas turbine compressor, the isentropic efficiency is related to the inlet and outlet pressure and temperature of the compressor. For the F-class heavy-duty gas turbine in actual industrial applications, the compressor outlet pressure \((P_2)\) and compressor outlet temperature \((T_2)\) are measured by sensors. The compressor inlet temperature
can be regarded as the ambient temperature \( (T_A) \). The compressor inlet pressure \( (P_1) \) is the ambient pressure \( (P_a) \) minus the total pressure difference of the filter \( (P_F) \).

3.1. Analysis of gas turbine measurement data
The F-class heavy-duty gas turbine has been used for many years in practical industrial applications. Here, the measured data from January 2019 to December 2019 are selected for analysis. In the process of measuring data, the unit of compressor outlet temperature \( (T_2) \) and ambient temperature \( (T_A) \) is degree centigrade. The unit of ambient pressure \( (P_a) \), total pressure difference of the filter \( (P_F) \) and the compressor outlet pressure \( (P_2) \) are the mmHg(ABS), mmH₂O(ABS) and bar, respectively. In the following analysis and calculation, the units of temperature and pressure are uniformly converted into thermodynamic temperature \( (K) \) and Pa. The measured data of F-class heavy-duty gas turbine are shown in Fig. 1.

![Figure 1. The measured data of F-class heavy-duty gas turbine.](image)

For this F-class heavy-duty gas turbine, the data collection system collects data every 1 minute. This work focuses on analyzing the collected data from January 2019 to December 2019, which can be seen in Fig. 1. Since the data is collected continuously and uninterrupted, the collected data includes the data of gas turbine startup and unstable working state. It is obvious that the collected data cannot be directly used to calculate and analyze the isentropic efficiency of the compressor. Therefore, it is necessary to select the data of the gas turbine under effective working state for analysis and processing.

3.2. Determine and select the data of gas turbine under effective working state
In order to select the data of gas turbine under effective working state, this work adopts the following data selection rules:

1. Since the stable working speed of this F-class heavy-duty gas turbine is 3000 rpm, the data with speed fluctuations within 0.1% is selected first.

2. When the speed of the gas turbine reaches 3000±3 rpm for the first time from the start up, the gas turbines may not operate completely stably. In order to ensure the stable operation of gas turbine and consider the influence of acquisition system, the data of the gas turbine is selected after the speed reaches 3000±3 rpm for the first time and runs steadily for 10 minutes.

3. In order to select stable and effective data, the data that runs stably for less than 10 minutes in the 3000±3 rpm range is discarded.

4. In order to select stable and effective data, the data with the difference between two consecutive data points of compressor outlet pressure less than 0.5 MPa is selected.
(5) The data with natural gas flow greater than 10.5 kg/s is selected. Based on the data selection rules, the selected data of gas turbine are shown in Fig. 2.

**Figure 2.** The selected data of F-class heavy-duty gas turbine.

Compared the Fig. 2 with Fig. 1, it can be seen that the selected data of F-class heavy-duty gas turbine are stable, without wildly fluctuating data. Moreover, the fluctuation of ambient pressure and temperature is consistent with the actual situation within a year. Therefore, the selected data used to analyze the isentropic efficiency of the compressor is effective and reasonable.

3.3. Calculation results of isentropic efficiency of gas turbine compressor

When stable and effective data of gas turbine are selected, then the isentropic efficiency of compressor can be accurately calculated, and the calculation results are shown in Fig. 3.

**Figure 3.** The calculation results of isentropic efficiency of compressor.

**Figure 4.** The calculation results by ARIMA and VAR.
From Fig. 3, the isentropic efficiency of the compressor under normal and steady operation is about 93.5%. However, the isentropic efficiency of the compressor began to gradually decrease from October 2019. The decrease of isentropic efficiency may be due to the degradation of gas turbine performance, or it may be influenced by the environment. This requires further analysis.

4. Comparative analysis of forecasting effects of different forecasting methods
In order to forecast the changing trend of isentropic efficiency of gas turbine compressor, the classical ARIMA and VAR method are firstly adopted. The ARIMA(1,1,1) model which has the lowest AIC (-588582.49) and BIC (-588575.45) is adopted to forecast the isentropic efficiency. The VAR(4) model is established utilized to forecast the isentropic efficiency. The calculation results are shown in Fig. 4.

From Fig. 4, it can be seen that the forecasting effect is not good. The isentropic efficiency of gas turbine compressor is non-stationary and nonlinear, but the ARIMA and VAR are usually used to forecast the linear and stationary time series. Moreover, due to the large volatility and burr of gas turbine measurement data, the calculated isentropic efficiency fluctuates sharply, which increases the difficulty of accurate prediction. Thus the forecasting effect by ARIMA and VAR is not good.

In order to extract the nonlinear and non-stationary features of isentropic efficiency, the NARNN model is adopted. In NARNN model, the number of hidden neurons is 10 and the delay number is 2. The training algorithm is the scaled conjugate gradient algorithm. The forecasting results by NARNN are shown in Fig. 5.

From Fig. 5, it can be seen that the forecasting effect of NARNN method is better than that of VAR and ARIMA method. This is because the NARNN method adopts a nonlinear model, which is suitable for predicting nonlinear and non-stationary isentropic efficiency. However, the forecast result based on NARNN method is larger than the actual result. This may be because the NARNN model is not optimized enough, and each parameter cannot be adjusted adaptively. To overcome this problem, the ANFIS method is employed to forecast the isentropic efficiency. The ANFIS method can adaptively adjust the structure and parameters of the neural network. The forecasting results by ANFIS are shown in Fig. 6.

![Figure 5. The calculation results by NARNN.](image1)

![Figure 6. The calculation results by ANFIS.](image2)

From Fig. 6, the ANFIS method can accurately forecast the change trend of isentropic efficiency. This is because the ANFIS method can adaptively adjust the network structure and parameters
according to the nonlinear and non-stationary characteristics of isentropic efficiency, so as to improve the forecasting accuracy.

In order to quantitatively evaluate the forecasting effects, the four quantitative evaluation indexes, namely symmetric mean absolute percentage error (SMAPE), mean absolute percentage error (MAPE), root mean square error (RMSE), and similarity (SIM) are employed. For SMAPE, MAPE and RMSE, the smaller the value is, the better the forecasting effect is. For SIM, the larger the value is, the better the forecasting effect is. The calculated results are shown in Table 1.

Table 1. Comparison of calculation results of different forecasting methods.

| Forecasting methods | SMAPE   | MAPE   | RMSE   | SIM      |
|---------------------|---------|--------|--------|----------|
| ARIMA               | 0.5873  | 0.5900 | 0.6737 | 84.21%   |
| VAR                 | 0.3810  | 0.3815 | 0.4216 | 88.76%   |
| NARNN               | 0.2296  | 0.2296 | 0.2851 | 92.94%   |
| ANFIS               | 0.0975  | 0.0975 | 0.1157 | 96.77%   |

From Table 1, the SMAPE, MAPE and RMSE are respectively the 0.0975, 0.0975 and 0.1157 by ANFIS, which is the lowest value among these four forecasting methods. For SMAPE, MAPE and RMSE, the smaller the value is, the better the forecasting effect is. Thus the ANFIS has the best forecasting effect on the isentropic efficiency of compressor. In addition, the SIM value by ANFIS is 96.77%. The higher the similarity (SIM) between the forecast result and the actual result is, the better the forecasting effect is. Therefore, the ANFIS method is suitable for the forecasting of isentropic efficiency of gas turbine compressor.

5. Conclusions
The F-class heavy-duty gas turbines are widely used in power plants. At present, some F-class heavy-duty gas turbines have been running for many years and are approaching the maintenance deadline. In order to ensure the safe and stable operation of the F-class heavy-duty gas turbine, it is necessary to monitor and analyze the operating status of the gas turbine. This paper adopts the F-class heavy-duty gas turbine measurement data in actual industrial operation to analyze and research the change trend of isentropic efficiency of compressor, which can provide reference for the predictive maintenance of this F-class heavy-duty gas turbine.

For the measured gas turbine data for one year in 2019, the data collected by the data acquisition system includes the gas turbine start-stop and unstable working state data. In order to select the data of gas turbine under effective working conditions, the data selection rules are determined according to the actual operation of the gas turbine. By determining the data selection rules, it is beneficial to calculate and analyze the isentropic efficiency of gas turbine compressor.

In order to accurately forecast the isentropic efficiency, this paper studies four forecasting methods. Firstly, the ARIMA and VAR are respectively adopted to forecast the isentropic efficiency, but the forecasting effect is not good. This is because the nonlinear and non-stationary characteristics of the isentropic efficiency are not well extracted by ARIMA and VAR. In order to overcome this problem, the NARNN is employed to forecast the isentropic efficiency, and the forecasting effect is good. In order to further improve the forecasting accuracy, the ANFIS is utilized to forecast the isentropic efficiency. The ANFIS can adaptively adjust the structure and parameters of neural network. Based on the ANFIS, the similarity between the forecasting results and the actual results is 96.77%. Moreover, both the SMAPE and MAPE are less than 0.1, and the RMSE is only 0.1157. The research results indicate that the forecasting effect of ANFIS is the best in these four forecasting methods for the forecasting of isentropic efficiency of gas turbine compressor.

In this work, the actual F-class heavy-duty gas turbine data is utilized to calculate the isentropic efficiency of the compressor, and the ANFIS method is suitable to forecast the change trend of isentropic efficiency. In the future, the transferability and applicability of ANFIS method to different gas turbines can be studied.
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