ISSN 2616-5767 Vol.7, Issue 6: 23-28, DOI: 10.25236/AJETS.2024.070604

Gas turbine generator unit intelligent alarm system

Chen Yonggang[1,a], Kong Jing[2,b], Jiang Haiming[2,c]

[1]Hudian Co. LTD Shanghai Branch, Shanghai, China
[2]Huadian Electric Power Research Institute Co. LTD, Hangzhou, China
[a]yongg-chen@chd.com.cn, [b]392665572@qq.com, [c]haiming-jiang@chder.com

Abstract: *Gas turbine generator units operate in high-risk environments with a high incidence of failures, necessitating an effective and timely alarm system to ensure their safe operation. However, existing alarm systems commonly use fixed-threshold alarms and lack correlation analysis between variables, leading to false negatives or false positives at certain normal operating points. This paper proposes applying the Dynamic Multivariate State Estimation Technique (DMSET) for real-time assessment of thermal power equipment operational states. The intelligent warning algorithm based on DMSET is designed to evaluate the health status of systems and equipment. Testing results indicate that, under normal operation, the Euclidean distance between the estimated vector and the real-time observation vector is short, resulting in high prediction accuracy; whereas, in abnormal conditions, the Euclidean distance is significantly larger than that in normal states. The study demonstrates that the proposed DMSET intelligent warning algorithm can sensitively detect abnormal information in equipment.*

Keywords: *Gas Turbine; Intelligent Alarm; Dynamic Multivariate State Estimation Technique; Euclidean Distance*

1. Introduction

Under the 3060 target, China's power system is continuously increasing the proportion of renewable energy and accelerating the deep transformation towards a new type of power system. To achieve this, the grid requires stable, low-carbon baseload power sources as well as a high proportion of flexible power sources, with gas turbine power generation unit to play a crucial role[1]. However, the strong coupling between gas turbine power generation equipment and process systems, the complexity of these systems, and the specialized working environments (high temperature, high pressure, high-speed rotation) make gas turbine power plants high-risk areas with significant potential for failures. Any shutdown accident caused by a fault can result in substantial economic losses and severe social consequences. Therefore, ensuring the safe production and efficient operation of gas turbine power plants is of great importance, with the alarm system playing a critical role.

When the production process deviates from the normal range, alarms can timely alert operators to take corresponding actions to bring the production process back to normal[2]. However, existing alarm systems typically use fixed-threshold alarms, where alarm thresholds are set independently without considering the relationships between relevant process variables. This can lead to false alarms at certain normal operating points and missed alarms at some abnormal points, failing to effectively ensure the safe operation of the unit over the entire load range[3]. Additionally, in actual production, due to the interrelationship and coupling between variables, once an abnormal condition arises, a large number of process variables may trigger alarms in a short period, resulting in alarm flooding[4]. This severely impacts the efficiency of fault handling by operators, making it difficult and unreliable to manually identify the root cause of alarms based on experience[5], highlighting the urgent need for scientific methods to assist in this process.

The intelligent alarm system for gas turbine generator units relies on the industrial internet platform, using historical operational data of gas turbine generator units as the source of data analysis. It categorizes and classifies equipment across the entire plant, performing comprehensive analysis on multiple related variable measurement points within the model. The system dynamically monitors the operational status of critical equipment and process systems. It can issue alarms before abnormalities deteriorate into serious faults and helps operators quickly identify the fault location through root cause and degradation point analysis, historical data storage, and visualization functions. This enables timely intervention measures to prevent faults or minimize their impact, significantly enhancing the safety,

ISSN 2616-5767 Vol.7, Issue 6: 23-28, DOI: 10.25236/AJETS.2024.070604

reliability, and economic efficiency of gas turbine power generation.

2. Modeling Principles of DMSET Intelligent Early Warning Algorithm

2.1 Establishment of Static Historical Matrix

Select M mutually correlated measurement parameters of a certain device as monitoring variables. The vector composed of these M variables under a certain normal operating condition of the device is denoted as the observation vector $X(j)$, that is

$$X(j) = [x_1(j), x_2(j), x_3(j), \dots, x_i(j), \dots, x_M(j)]^T \tag{1}$$

where $x_i(j)$ is the measurement value of measurement point i in normal state j.

Select N historical normal states of the device. These N states cover the entire range of normal operation of the device. The observation vectors under these N states form the static historical memory matrix D, that is,

$$D_{M\times N} = \begin{bmatrix} x_1(1) & x_1(2) & \dots & x_1(k) & \dots & x_1(N) \\ x_2(1) & amp; x_2(2) & \dots & x_2(k) & \dots & x_2(N) \\ & \vdots & & & \vdots & \\ x_M(1) & x_M(2) & \dots & x_M(k) & \dots & x_M(N) \end{bmatrix} \tag{2}$$

The static historical memory matrix is the foundation for modeling the MSET intelligent early warning algorithm. Each column observation vector in the historical memory matrix represents a normal operating state of the device. The N historical observation vectors selected after preprocessing the historical data cover the entire dynamic process of full-load operation of the device.

2.2 Normalization of Static Historical Matrix Data

The data of each measurement point of the equipment are normalized based on their respective extreme values, transforming the measurement values to the [0,1] interval. The normalized static historical matrix is $D'_{M\times N}$. The normalization algorithm is:

$$x_i'(j) = \frac{x_i(j) - x_{i,min}}{x_{i,max} - x_{i,min}} \tag{3}$$

$$x_{i,max} = \max[x_i(1), x_i(2), \dots, x_i(k), \dots, x_i(N)] \tag{4}$$

$$x_{i,min} = \min[x_i(1), x_i(2), \dots, x_i(k), \dots, x_i(N)] \tag{5}$$

Where $x_i'(j)$ is the normalized value of $x_i(j)$; $x_{i,max}$ and $x_{i,min}$ are the maximum and minimum values of $x_i(j)$ respectively.

2.3 Dynamic Modeling

If the real-time observation vector of the device at a certain moment is X_{obs}, and after normalization it becomes X'_{obs}. First, calculate the Euclidean distance between this observation vector X'_{obs} and each column vector in the static historical memory matrix $D'_{M\times N}$. Select Z historical observation vectors with smaller Euclidean distances to the real-time observation vector to form the dynamic matrix D_d. Therefore, the memory matrix is dynamically changing with each calculation.

$$D_d = \begin{bmatrix} x_1''(1) & x_1''(2) & \dots & x_1''(k) & \dots & x_1''(Z) \\ x_2''(1) & x_2''(2) & \dots & x_2''(k) & \dots & x_2''(Z) \\ \vdots & & & & \vdots & \\ x_M''(1) & x_M''(2) & \dots & x_M''(k) & \dots & x_M''(Z) \end{bmatrix} \tag{6}$$

Let the weight vector be $W = [w_1, w_2, \cdots w_Z]^T$. The estimated vector X'_{est} of the current state of the device is a linear combination of the Z historical observation vectors in the dynamic matrix, that is,

$$X'_{est} = D_d \cdot W \tag{7}$$

The weight vector W can be obtained when the Euclidean distance between the estimated vector X'_{est} and the real-time observation vector X'_{obs} is minimized. Let the residual vector between the estimated vector X'_{est} and the observation vector X'_{obs} be ε, which exists as in equations (8) to (9).

ISSN 2616-5767 Vol.7, Issue 6: 23-28, DOI: 10.25236/AJETS.2024.070604

$$\varepsilon = X'_{est} - X'_{obs} \tag{8}$$

$$||X'_{est} - X'_{obs}||^2 = \varepsilon^T \varepsilon \tag{9}$$

Therefore, when $\varepsilon^T\varepsilon$ is minimized, the weight vector W can be calculated using the least squares method. By deriving, we get

$$W = (D_d^T \cdot D_d)^{-1} \cdot (D_d^T \cdot X_{obs}) \tag{10}$$

However, equation (10) has limitations, as it is difficult to ensure the linear in dependence of the column vectors in D_d, and therefore, it is also difficult to ensure the invertibility of the matrix $D_d^T \cdot D_d$. To expand the applicability of equation (10), this paper uses a nonlinear operator $\otimes$ based on Euclidean distance to replace the dot product of matrices. The corresponding weight calculation formula is:

$$W = (D_d^T \otimes D_d)^{-1} \cdot (D_d^T \otimes X_{obs}) \otimes (X,Y) = [\sum_{k=1}^{L}(x_k - y_k)^2]^{0.5} \tag{11}$$

where X and Y are two vectors of length L; x_k and y_k are the k-th elements of X and Y espectively.

After obtaining the weight vector W, the calculation formula for the estimated vector X'_{est} is

$$X'_{est} = D_d \cdot [(D_d^T \otimes D_d)^{-1} \cdot (D_d^T \otimes X_{obs})] \tag{12}$$

After de-normalizing X'_{est}, the actual estimated vector X_{est} of each parameter can be obtained.

3. Application and Verification

The project is implemented based on an Industrial Internet platform, with its functional architecture shown in Figure 1. This platform achieves the modeling, standardization, software implementation, and reuse of industrial technology, experience, and knowledge by building a precise, real-time, and efficient data acquisition and interconnection system. It establishes a development environment oriented towards the storage, integration, access, analysis, and management of industrial big data.

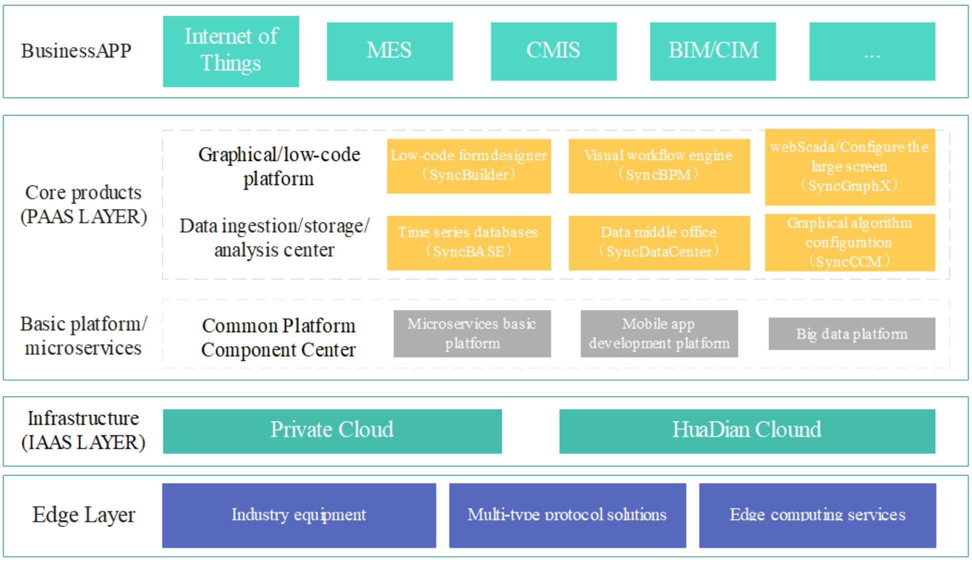


Figure 1: Functional Architecture of the Platform

The platform provides no-code visual configuration and data presentation tools for engineers, aimed at scenarios such as production, monitoring, and business analysis. The intelligent alarm system relies on this platform to achieve data processing, model building, and real-time computation. Additionally, it allows for convenient subsequent functional expansion and customized upgrades.

The platform is built on data servers and analysis servers and uses internationally recognized OPC and modbus communication protocols for data communication with the DCS (Distributed Control System). The specific communication methods are illustrated in Figure 2. The data server reads the measurement point data transmitted from the DCS host system via the OPC communication protocol. Considering the large number of measurement points and the substantial volume of data required for the intelligent alarm system's calculations, the OPC communication method ensures the stable transmission of a large amount of real-time measurement point data to the platform. The analysis server reads operational data from the data server and transmits the calculation results in real-time back to the data server for storage. The data server then uses the modbus communication protocol to write the data back to the lower-level DCS system. The data computed by the intelligent alarm system is characterized by a lower volume but requires high real-time accuracy. The modbus communication protocol effectively ensures the timeliness and stability of data write-back.

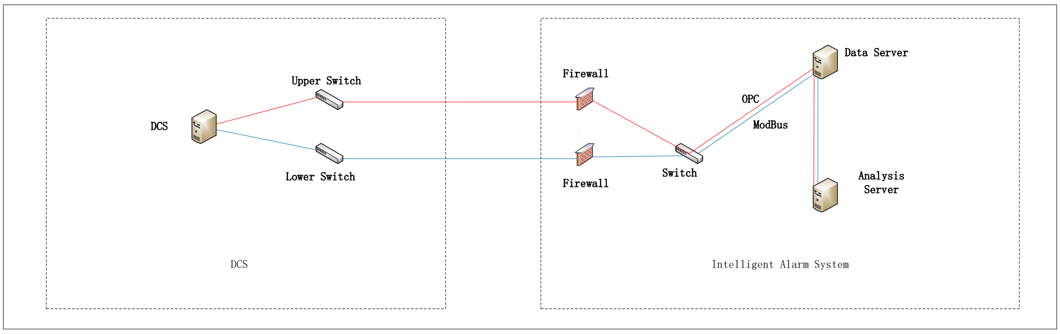


Figure 2: Communication implementation of intelligent alarm system

4. Operational Effectiveness

The intelligent alarm system has established 83 health models for various equipment and processes. Here, we use the turbine body temperature model as an example to demonstrate the effectiveness of the health calculations. This model includes measurement points for inter-turbine temperature, turbine exhaust temperature, and unit load. The predicted health during a specific period of gas turbine operation is shown in Figure 3.

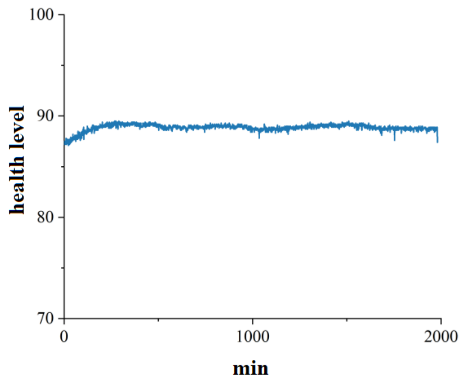
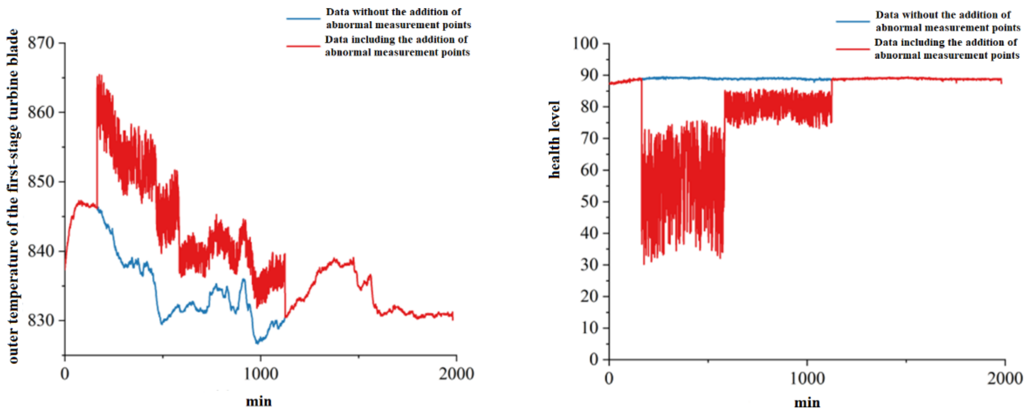


Figure 3: Health curve during stable operation of gas turbine

During stable operation of the gas turbine, its health level also remains high, indicating normal operating conditions, which aligns with the actual situation and is considered reasonable.

An experiment was designed to artificially alter the input measurement data to see if the model can accurately identify anomalies. The selected change point was the first stage turbine blade outer surface temperature. At time point 165, an abnormal value was introduced using the formula $x' = x + 10 + 10 * rand(0,1)$, meaning random noise in the range of [10, 20] was added. At point 585, another abnormal value was introduced using the formula $x' = x + 5 + 5 * rand(0,1)$, meaning random noise in the range of [5, 10] was added. Normal data was restored and random errors removed at point 1124. The altered measurement data is shown in Figure 4(a), and the calculated health level is shown in Figure 4(b).

ISSN 2616-5767 Vol.7, Issue 6: 23-28, DOI: 10.25236/AJETS.2024.070604



(a) Measuring point temperature curve *(b) corresponding health curve*

Figure 4: Measurement point curve and corresponding health curve after the addition of abnormality

At time point 165, significant random noise was added, resulting in a notable health decline at the corresponding point on the health curve. After reducing the noise amplitude at point 585, the health level began to increase but remained below normal operating levels. Once the random noise was removed at point 1124, the health curve returned to match the normal data health curve. This experiment demonstrates that the model accurately identifies the timing of anomaly introduction, increases the health level as anomalies decrease, and returns to normal health levels once anomalies are removed, verifying the model's validity.

After implementation in a power plant, the system detected a lower health level in the gas turbine equipment, traced back to the turbine body temperature's low health level. Inspection of related measurement points revealed a fault in the inter-turbine temperature reading. This shows the system's capability to promptly detect operational faults.

5. Summary

The intelligent alarm system categorizes the gas turbine generator unit into three levels, associating various measurement points and establishing a correlation distribution model. Based on this, it calculates equipment health in real-time using operational data and presents it visually, allowing operators to grasp the overall operational status in real-time. Upon detecting anomalies, the system automatically analyzes which measurement points primarily caused the health decline at the first alarm and identifies the most deteriorated points at the current time, storing relevant data in a database. This helps operators quickly locate the measurement points affecting equipment health and aids in fault diagnosis. The system has the following features:

(1) Integrates isolated analog values into their respective subsystems, performing comprehensive analysis with multiple related variables in conjunction with system operational status, achieving dynamic equipment monitoring and overcoming the risks of false or missed alarms due to isolated threshold settings.

(2) After detecting anomalies, the system can automatically identify the primary and deteriorated measurement points. Combined with real-time stored health data, it assists operators in pinpointing fault locations and determining fault origins, improving efficiency.

(3) The equipment health model covers the main and auxiliary systems and equipment of the gas turbine generator unit, including the gas turbine, heat recovery boiler, and steam turbine, creating a comprehensive plant equipment model.

(4) Leveraging a low-code development platform facilitates further in-depth, customized function expansions and system upgrades, such as excluding non-critical anomalies from health calculations.

References

[1] GE. Accelerating Growth in Natural Gas Power towards a Zero-Carbon Future [R]. GE General Electric Company, 2022.

ISSN 2616-5767 Vol.7, Issue 6: 23-28, DOI: 10.25236/AJETS.2024.070604

[2] Wang Jiandong. Intelligent Industrial Alarm System (First Edition) [M]. China Machine Press, 2021.
[3] Xue Xiaodan. Research on Intelligent Alarm Technology in Intelligent Power Generation Operation Control [D]. North China Electric Power University (Beijing), 2021.
[4] Zhang Mingjun, Han Changlin, Wang Guiping. Research on "Integrated Control" Intelligent Alarm Technology for the Lower Cascade of Jinsha River [J]. Hydropower Station Electromechanical Technology, 2017, 40(07): 9-12.
[5] Ji Hongjin. Multivariate Methods for Geochemical Background and Anomaly Division [J]. Journal of Changchun College of Geology, 1988(03): 311-320.