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Operation Safety Monitoring of Large Thermal Power Plant Units Based on Edge Computing

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Abstract: In the operation of large thermal power plant, due to various factors, such as the change of fuel quality, load, the aging of equipment. This paper proposes a safety monitoring method of large thermal power plant based on edge calculation. In the system terminal layout sensor sensing in the process of operating status parameters, operating at the edge of the calculation node, pretreatment the original perception of unit operating status parameters, and deployment of lightweight convolution neural network model, input pretreatment state parameters, output unit operation safety test results, implements the large thermal power plant unit operation safety on-line monitoring. The test results show that the design method can accurately detect the actual operation state of the large thermal power plant unit and ensure the operation safety of the unit.

Keywords: Edge computing; Large thermal power plants; Thermal power plant unit; Safe operation; On-line monitoring.

1. Introduction

With the continuous growth of global energy demand, large-scale thermal power plants, as a key component of the power supply system, are being constructed on an increasingly large scale in China. However, the structure of thermal power plant units is complex, and the operating environment is harsh. During operation, they are susceptible to various internal and external factors such as equipment aging, improper operation, and sudden environmental changes. These factors may lead to a decline in the performance of power units or even failures, seriously affecting the stability and safety of the power supply system. The current monitoring methods for the operational safety of thermal power units still have significant limitations. Traditional manual inspections rely on subjective experience and suffer from issues such as delayed response, low efficiency, and high labor costs. Previous studies have attempted to introduce intelligent monitoring methods, but there are significant shortcomings in their technical path and application scenarios. Reference [1] uses k-means clustering algorithm to divide the operating conditions of wind turbines. However, there are significant differences between thermal power and wind power operating conditions, and the complex and changing operating environment makes it difficult to guarantee the accuracy of this method's operating condition identification; Reference [2] implements abnormal state recognition of hydropower units based on AI video technology, but the cost of multimodal data fusion and hardware deployment is too high, making it difficult to promote in resource limited thermal power plant scenarios; Reference [3] uses SCADA data to construct a monitoring model, but it is difficult to obtain heterogeneous data of key equipment in thermal power plants (such as coal-fired boilers and steam turbines), and low-quality data can easily lead to model misjudgment. In addition, although the monitoring scheme based on cloud cloud cloud collaboration can improve computing power, cloud transmission latency and data privacy risks limit its real-time and security.

The above methods generally face two core problems: firstly, the real-time processing capability of multi-source heterogeneous data under complex working conditions is insufficient, making it difficult to meet the high-precision monitoring needs of thermal power plants; Secondly, traditional centralized computing architectures suffer from response latency and resource waste, making them unable to meet the low-power and high real-time requirements of edge devices. In view of these defects, this paper proposes an online monitoring method for unit operation safety based on edge computing. Through distributed computing and lightweight model design, it breaks through the bottlenecks of existing technology in data timeliness, computing efficiency and deployment cost, and provides new ideas for intelligent monitoring of thermal power plants.

2. The Perception of The Unit Operating Status Parameters

In the complex operation environment of a large thermal power plant, the real-time monitoring of the unit status is the key to ensure the safety of power production. In this paper, the key position of a large coal-fired power plant unit deployed diversity of terminal sensor network, these sensors mainly include (but not limited to): voltage transformer, current transformer and temperature and humidity sensor, together constitute a comprehensive, multi-level perception system, can realize the large coal-fired power plant unit running state parameters of comprehensive, real-time capture [4]. In view of the sensing parameters of the operating environment of a large thermal power plant, this paper arranges the temperature and humidity sensor of the sensor inside the sensor senses the temperature and humidity of the unit and the surrounding environment, and outputs the perceived data output in the form of digital signal. According to the perception of power parameters such as operating voltage and operating current of a large thermal power plant unit, the voltage and current signal [5] are measured by installing voltage transformer and current transformer.

Voltage transformer (VT) is installed on key electrical nodes such as generator outlet and transformer incoming line. Using the principle of electromagnetic induction, high voltage is proportionally converted to low voltage signal. The relationship between output voltage and input voltage is as follows:

$$U_0 = \frac{N_2}{N_1} \cdot U_1 \tag{1}$$

Where U0 and U1 are the output and input voltage of the voltage transformer respectively; N1 and N2 are the turns of the primary and secondary edges of the voltage transformer respectively.

Generally, the current transformer (CT) is connected in series in the generator, transformer and transmission line, and the same electromagnetic induction mechanism is adopted to convert the large current into the small current signal output. The expression of the relationship between the output current and the input current is as follows:

$$I_0 = \frac{M_2}{M_1} \cdot I_1 \tag{2}$$

Where:, I_0 is I_1 the output and input current of the current M_1 transformer M_2 respectively; and is the turns of the original and secondary edges of the current transformer respectively.

In this paper, various sensors are arranged in the terminal to sense the voltage, current, temperature and humidity during the unit operation of the state, and provide a data basis for the subsequent safety monitoring of the unit operation.

3. Online Monitoring of The Edge Calculation Nodes for Unit Operation Safety

Generally speaking, the unit in the process of operation, is bound to produce a lot of state parameter data, if directly in the terminal data processing and analysis, not only difficult to ensure the unit operation safety monitoring efficiency, so this paper introduces edge calculation, including the sensor interface unit, calculation and processing unit near the terminal calculation node, to realize efficient online monitoring of unit operation.

3.1. Preprocessing of the unit operating condition parameters

When the edge computing node receives complex multi-dimensional operating state parameters such as voltage, current, temperature and humidity from the terminal-sensing unit, these raw data need to be preprocessed to ensure that the subsequent analysis model can receive high-quality, noise-free input data [6]. In this paper, wavelet denoising technology is used to filter the raw data to eliminate random noise and interference signal and improve the signal to noise ratio of the data. The process is, based on the multi-resolution analysis ability, decompose the original unit operating signal into different frequency components, and conduct soft threshold denoising according to different frequency band characteristics. The expression is as follows:

$$B_\delta = \begin{cases} \left[\operatorname{sgn}(B)\left(|B| - \delta\right)\right], |B| \geqslant \delta \\ 0, |B| < \delta \end{cases} \tag{3}$$

Where:, B the B_δ wavelet coefficient before and after soft δ threshold $\operatorname{sgn}(B)$ processing; set the threshold; the expression is:

$$.\operatorname{sgn}(B) = \begin{cases} 1, B > 0 \\ 0, B = 0 \\ -1, B < 0 \end{cases} \tag{4}$$

After the soft threshold is denoised, the retained wavelet coefficient is reconstructed to obtain the unit operating state parameters after noise removal. After wavelet denoising processing, although the signal to noise ratio is significantly improved, it may still include outliers introduced due to sensor faults, data transmission errors and other reasons. Therefore, the local outlier factor LOF algorithm is used for outlier detection and elimination of [7] in the edge calculation nodes.

Assuming that the data set of unit operating state X parameters x_2 x_1 x_n to be n detected is = { x_i ,...,}, where the total amount of data, the specific expression for the local density measure is:

$$.\eta(x_i) = \frac{|W_d(x_i)|}{\sum_{x_i \in W_s(x_i)} D_d(x_j, x_i)} \tag{5}$$

Where it $\eta(x_i)$ is the sparseness of the data x_i points; the data $|W_d(x_i)|$ set nearest x_i to the d data point; the $D_d(x_j, x_i)$ accessible x_j x_i distance between the data points, and d the closest distance between the two is.

Based on the local density measure of the data point obtained in Equation (5), the discrete factor ld (xi) of the data point to the whole data set can be further calculated to reflect the abnormal degree of the data point. The expression is as follows:

$$.l_d(x_i) = \frac{\sum_{x_i \in W_d(x_i)} \frac{\eta(x_j)}{\eta(x_i)}}{|W_d(x_i)|} \tag{6}$$

Where: $l_d(x_i)$ This is the density difference x_i between the data points and the data set $l_d(x_i)$. The larger the sought discrete factor, the greater the abnormality of the data points relative to the whole data set. Therefore, in the actual detection, according $l_d(x_i)$ to the actual situation of the unit operating state parameters, a reasonable threshold is set, and the data points with the discrete factor exceeding the set threshold are regarded as abnormal data points to eliminate processing.

By pretreatment with wavelet denoising and outlier removal on the edge calculation node, it can provide a more reliable data basis for subsequent operation safety monitoring.

3.2. Lightweight convolutional neural network model for unit operation safety monitoring

As a distributed computing paradigm, edge computing can significantly reduce the data transmission delay by sinking the computing power to the edge of the network, and enhance the real-time and privacy protection ability of data processing. Therefore, this paper processes and analyzes the [8] of the unit running state parameters at the edge computing nodes. After obtaining the pre-processed unit operating state parameters, the operating state category corresponding to the parameters can be detected through deep learning. However, edge computing has disadvantages such as resource limitation, and the conventional deep learning model cannot efficiently analyze the operating state parameters of the unit. Therefore, this paper deploys a lightweight convolutional neural network model in edge computing nodes to conduct data analysis [9].

First build a containing input, convolution, pooling, full connection and output layer of conventional CNN model, input layer mainly unit running state parameters input to the CNN model, convolution layer model input parameter feature extraction, pooling layer to reduce feature dimension, full connection layer to identify the extraction features, by Softmax function mapping category probability distribution, to the category of the largest probability as the corresponding detection results of input parameters, and output from the output layer, and through the parameter quantification compression CNN model, ensure that the model can run [10] on the edge calculation nodes. Parameter quantification is to map the floating point number parameters in the model into integers to reduce the storage and calculation requirements of the model. The specific quantification process is shown in Equation (7):

$$. R_1 = \text{round}\left(\frac{2^m - 1}{Y} \cdot R_0\right) \quad (7)$$

$$. R_2 = \text{clip}\left(R_1, -\left(2^{m-1} - 1\right), 2^{m-1} - 1\right) \quad (8)$$

$$R_3 = \text{clip}\left(R_1, 0, 2^m - 1\right) \quad (9)$$

Formula: R_1 is the model parameters after round the integer operation R_0 ; is the integer function; is the model parameters Y before R_2 the R_3 quantization process; m is the quantization digits; is the quantization threshold; is the cropping operation result of the model parameters in signed and unsigned integer form respectively; clip is a function that limits the model parameters to a fixed range.

After completing the lightweight of CNN model according to the above process, the lightweight model is solidified on the edge calculation node to ensure that the model can run efficiently and detect with high precision under resource-limited conditions. Therefore, to the lightweight CNN model input pretreatment unit running state parameters, when the unit important parameters abnormal, the model not only identify the actual operating status, online monitoring the unit running safety, and can for the abnormal state of the unit running, based on the extraction feature vector, through the reverse propagation algorithm automatically analysis the possible abnormal causes and give feedback, find the abnormal problem in time, improve the decision-making efficiency.

4. Example and Analysis

4.1. Example data

In order to evaluate the performance of the unit operation safety online monitoring method based on edge calculation, the real equipment state parameter data of a large thermal power plant are used for example analysis. From the historical monitoring data of the unit, 10 groups of unit operating parameters with different operating states are randomly selected as the test data of this paper, as shown in Figure 1.

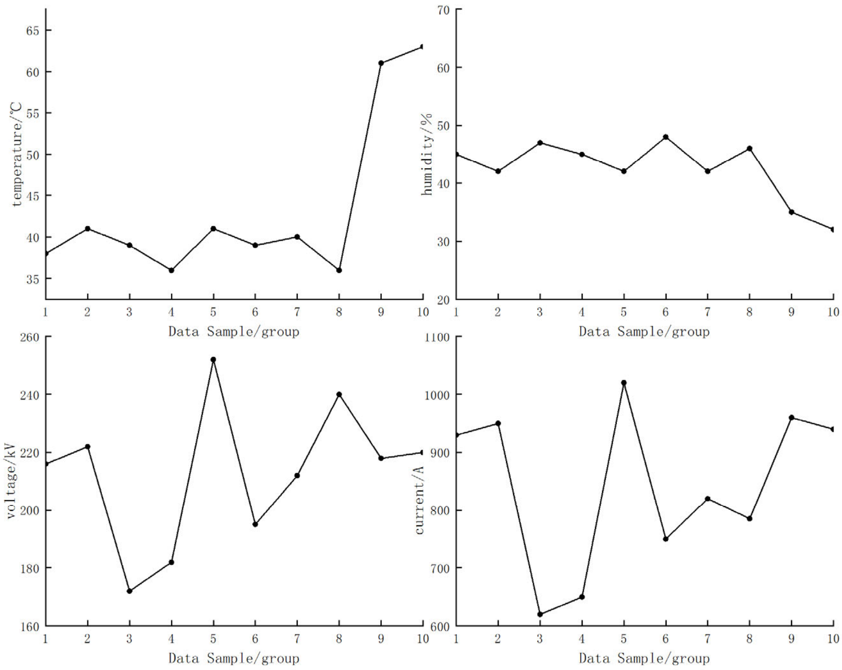

Figure 1. Operation data of a large thermal power plant unit

In the simulated environment of large thermal power plant,MATLAB/Simulink software is used to build the unit operation model to simulate the changes of voltage, current, temperature and humidity of the unit in each operating state. In the process of simulation, respectively, based on edge calculation of large power plant unit operation safety on-line monitoring method, based on cloud synergy large power plant unit operation safety on-line monitoring method and based on SCADA data of large coal-fired power plant unit operation safety on-line monitoring method, respectively, the unit running status monitoring, and the monitoring results are analyzed.

4.2. Comparative analysis of the results

Based on the above case data, the online monitoring results of unit operation safety of large thermal power plants under each method are counted and collated as shown in Table 1.

Table 1. Comparison of on-line monitoring results of unit operation safety of large thermal power plants

sample book	Actual running state	Monitoring results		
		On-line monitoring method of unit operation safety based on edge calculation	Online monitoring method of unit operation safety based on cloud collaboration	On-line monitoring method of unit operation safety based on SCADA data
1	safe in operation	hit the target	hit the target	hit the target
2	safe in operation	hit the target	hit the target	hit the target
3	Drop output	hit the target	Leakage	hit the target
4	Drop output	hit the target	hit the target	Leakage
5	mechanical breakdown	hit the target	hit the target	hit the target
6	mechanical breakdown	hit the target	hit the target	hit the target
7	electrical accident	hit the target	hit the target	hit the target
8	electrical accident	hit the target	hit the target	hit the target
9	temperature anomaly	hit the target	hit the target	Leakage
10	temperature anomaly	hit the target	hit the target	hit the target

According to Table 1, the design method performs the best in the online monitoring of unit operation safety in large thermal power plants. Based on the test samples, the design method in this paper can accurately detect the safety and abnormal operation status of large thermal power plants by 100%, while the hit rates of the two methods in the control group are only 90% and 80%, respectively. The results show the effectiveness of the on-line monitoring method for the operation safety of large thermal power plant, which can realize the high-precision monitoring of the unit running state.

5. Conclusion

This paper proposes an on-line monitoring method of unit operation safety in large thermal power plant based on edge calculation. This method uses the terminal sensor to sense unit operation state parameters, efficiently preprocessing and intelligent analysis of unit operation state parameters, and realizes the real-time monitoring of unit operation safety. In this paper, not only the method improves the real-time and accuracy of monitoring, but also reduces the operation and maintenance cost through the intelligent decision support function, which provides strong support for the safe and stable operation of thermal power plants. With the continuous progress of technology and changing demand, future research will further optimize the algorithm model to improve the robustness and generalization ability of the system; and explore more application of edge computing and artificial intelligence technology in the monitoring field of thermal power plants to promote the continuous improvement of the intelligent level of thermal power plants.

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