Research on cloud edge collaboration technology based on root cause analysis and predictive maintenance of communication station

Ting Fu, Yuxiang Cai, Haosong Sun*
State Grid Fujian Electric Power Co., Ltd., Information & Telecommunication Branch, Fuzhou 350000, Fujian, China

ABSTRACT

Cloud computing has problems such as untimeliness and poor network stability. In order to solve this problem, the predictive maintenance model of information and communication station owners based on edge computing is under in-depth research. On the basis of existing research literature and case description analysis, the technical principles, key technologies and application cases of this model are studied, and the relevant operation and maintenance costs are compared and analyzed. Specifically, through real-time information monitoring and fault prediction technology, it can detect faults at any time and carry out corresponding maintenance in a timely manner, thereby reducing the use of human resources and production downtime. The results show that the maintenance time of this method is about 5-12 minutes, and the predictive maintenance model of the information and communication station based on edge computing has obvious effects and great advantages. It can solve the current problems in cloud computing well and improve the accuracy and efficiency of cloud computing.

Keywords: Predictive maintenance, communication station, support vector machine, cloud edge collaboration, root cause analysis

1. INTRODUCTION

The traditional maintenance model of the information and communication station building is based on regular inspection and emergency maintenance, which has certain limitations. Regular inspections are often carried out at fixed time intervals, and equipment status changes cannot be monitored in real-time, and potential faults are easily missed. While the emergency maintenance model can only be repaired after the fault occurs, which can cause additional downtime of the equipment and increase the risk of business interruption. This paper explores a new maintenance strategy to study the predictive maintenance of information and telecommunication station buildings based on edge computing, aims to improve the operation and maintenance efficiency, reduce the cost, and enhance the business continuity. Through an in-depth study of the theoretical basis, key technologies, and application cases of this maintenance mode, the operating principles and advantages of the predictive maintenance for information and communication station buildings are comprehensively understood. It also provides a theoretical reference and practical guidance for the application of predictive maintenance model.

The first part of this article introduces the importance of information communication station building maintenance and the limitations of existing models, and leads to the research background of the predictive maintenance model of information communication station building based on edge computing. The second part focuses on the significance of this research method, and expounds the potential of predictive maintenance model based on edge computing in improving maintenance efficiency, reducing costs and enhancing business continuity. The third part introduces the principle, key technologies and application cases of the predictive maintenance model of information communication station buildings based on edge computing, so as to better understand its working mechanism and practical application. The fourth part summarizes the research results of this article and looks forward to the future development direction of this field.

2. RELATED WORK

Many people have conducted research on the operation and maintenance of information station buildings. Dai Yanfei stated that the traditional maintenance model can no longer meet the requirements of sustainable development such as high safety, high operational intensity, and high availability of equipment, it was necessary to shift from the original post failure

*553610396@qq.com

International Conference on Optics, Electronics, and Communication Engineering (OECE 2024), edited by Yang Yue, Proc. of SPIE Vol. 13395, 133954E · © 2024 SPIE · 0277-786X · Published under a Creative Commons Attribution CC-BY 3.0 License · doi: 10.1117/12.3048402

maintenance model to the predictive maintenance model of real-time status monitoring equipment[1]. Liu Jianbing proposed a new dimension of network security, further highlighting the importance of boundary management and centralized control. He pointed out that the predictive security network architecture can support the technical, management, and expansion requirements of Level Protection 2.0, and highlighted the innovative technological implementation of new dimensions such as the security management center and security area boundaries of Level Protection 2.0, providing technical support for the implementation of Level Protection 2.0[2]. Cai designed the research route for the predictive operation and maintenance project of Guangzhou Metro Line 11, exploring the architecture and functions of the vehicle integrated system from the aspects of vehicle comprehensive data control layer, vehicle ground data wireless transmission layer, and Suiteng OS cloud platform analysis application layer[3]. Cai used big data precise analysis models as the theoretical foundation to achieve real-time predictive operation and maintenance support for user perception. This plays an important role in identifying problems before they occur, resolving complaints before they occur, and reducing operational costs. It can also provide social services such as real-time monitoring of human traffic[4]. Hu proposed a secure and fast way to achieve large-scale ICT project networking access in the 5G industry, and to detect problems before users, adopt preventive maintenance solutions, and meet the rapid deployment and operation needs of high-quality government enterprise dedicated line services for mobile[5]. Lu analyzed the latest research and industry standard developments that affected BIM and asset management during the operation and maintenance phases[6]. Steffen B found that in energy system planning, modeling, and optimization, it was necessary to consider the dynamic cost reduction potential of operation and maintenance[7]. Wu believed that effective operation and maintenance were crucial for ensuring the good condition of bridges[8]. Sheng reflected the expected development of wind turbine condition monitoring and operation in the US market[9]. Joo proposed a single class learning based anomaly detection method for operation and maintenance data[10]. These studies provide a lot of references for the predictive maintenance of information station buildings through edge computing in this paper.

3. METHODS

3.1 Information and communication station room data

In the data collection and processing of information and communication station buildings, sensors are used to collect data on various environmental and equipment parameters for predictive maintenance and fault prediction. When selecting sensors, factors such as target parameters, accuracy and reliability, communication protocols, as well as durability and adaptability need to be considered[11,12]. The layout of sensors needs to consider factors such as location selection, quantity and density, installation method, and network connection. Through appropriate installation and arrangement, sensors can capture changes in key parameters and cover the monitoring needs of the entire station building. Data acquisition refers to reading data from sensors and transmitting it to edge computing nodes or data collection devices. Then, the raw data is preliminarily processed and cleaned to improve the quality and availability of the data. The steps of data acquisition include data collection and transmission, which require communication with sensors and transmission of data to designated devices through appropriate communication protocols. The steps of data preprocessing include data validation and filtering, data cleaning and denoising, data conversion and standardization, and data storage. There are many redundant data in the collected communication station data, which can be operated through normalization formulas:

$$x_{\mathrm{n}} = \frac{(x-\mu)}{\sigma} \tag{1}$$

Among them, x is the raw data; x_n is the normalized data; μ and σ are the mean and standard deviation of the original data. Afterwards, the data is verified, cleaned, and denoised to eliminate the influence of outliers and noise, improve the accuracy and reliability of the data. At the same time, data conversion and standardization can make the data have a consistent format and range, facilitating subsequent analysis and processing. The processed data are stored in a suitable database or storage medium for future use and reference. Table 1 shows the collected data:

Table 1. Collected data.

Timestamp	Power voltage (V)	Power current (A)	Air conditioner temperature (℃)	UPS output voltage (V)	UPS output frequency (Hz)
04-15 08:00	220	10	25	220	50
04-15 09:00	218	11	26	220	50

Timestamp	Power voltage (V)	Power current (A)	Air conditioner temperature (℃)	UPS output voltage (V)	UPS output frequency (Hz)
04-15 10:00	217	12	27	218	50
04-15 11:00	220	13	28	217	50
04-15 12:00	221	14	29	220	50
04-15 13:00	222	15	30	221	50
04-15 14:00	220	10	25	222	50
04-15 15:00	218	11	26	220	50
04-15 16:00	217	12	27	218	50
04-15 17:00	220	13	28	217	50

Through the reasonable selection and arrangement of sensors, as well as the preprocessing of the collected data, it can provide a reliable data basis for predictive maintenance and fault prediction. The effective implementation of these steps helps to enhance the monitoring capabilities and maintenance efficiency of the station building, and improve the stability and performance of the network[13,14].

3.2 Cloud edge collaboration and edge computing architecture

In cloud edge collaboration, cloud servers undertake the tasks of large-scale computing, storage, and resource scheduling, and can provide high-performance computing power and rich services. The edge device is responsible for processing real-time data, edge analysis, and tasks with high response speed requirements. By flexibly allocating computing tasks and data processing between the cloud and the edge, lower latency, better data privacy protection, and higher extensibility can be achieved. In an information communication station room, an edge computing architecture is designed to realize the predictive maintenance system and improve the reliability and operation and maintenance efficiency of the station room equipment. Selecting multiple edge computing nodes[15,16] in the station building, and make reasonable deployment according to the size and layout of the station building. The edge computing node is a high-performance physical server and virtual machine with sufficient computing and storage capacity. The location distribution of nodes is considered to ensure the efficiency of data collection and processing and reduce data transmission delay. Deploying sensors and monitoring devices to collect real-time operational status data such as temperature, humidity, and voltage of station equipment. Modbus is selected as the communication protocol and transmission method. The data acquisition module transmits sensor data to edge nodes, which can be transmitted through wired or wireless methods. Edge nodes receive and process sensor data for real-time data processing and analysis. Designing a data processing process that includes steps such as data parsing, cleaning, aggregation, and feature extraction. Applying machine learning and data mining algorithms to monitor data in real-time, detect anomalies, and diagnose faults, in order to achieve predictive maintenance functions.

Edge nodes can store historical data and perform offline analysis and model training to improve the accuracy of fault prediction. The fault diagnosis module runs on edge nodes, detecting equipment faults and abnormal situations based on real-time data and pre trained models. This article chooses to use support vector machines for fault diagnosis. Based on the fault diagnosis results, maintenance decisions and alarm notifications are generated to take timely repair measures, reduce equipment downtime and maintenance costs. Partial fault diagnosis and maintenance decisions can be completed at edge nodes, improving response speed and reducing dependence on the cloud. Edge nodes interact with the cloud for data exchange, transmitting critical data and diagnostic results to the cloud for further analysis and long-term storage. The cloud can provide stronger computing and storage capabilities for advanced fault diagnosis, device health analysis, and maintenance decision optimization[17,18].

3.3 Predictive maintenance algorithm development

For the equipment management team of the factory, predictive maintenance can be understood as a predictive maintenance strategy, using advanced tools and technologies to predict and prevent equipment failures. Based on the PreMaint platform, enterprise teams can also identify the process of signs or indicators of impending failure of production equipment. PreMaint's predictive maintenance involves monitoring various parameters, such as temperature, pressure, vibration, noise or electrical signals. Based on platform monitoring algorithms, alarm tools and operation and maintenance management modules, the maintenance team can observe the performance changes of potentially faulty equipment and realize a closed loop of maintenance management.

Tools to help identify root causes are provided in PreMaint, such as a fault case library and a fault knowledge map. Users can further explore the root cause of the problem in the case library, and conduct a comprehensive analysis of factors such as personnel, process, equipment, materials, and environment. In the PreMaint fault knowledge map, users can evaluate the combination of events and conditions that lead to specific undesirable results or failures based on graphical tools, and adopt logical and systematic methods to quickly locate the root cause of the problem and precipitate the enterprise's exclusive knowledge base.

SVM can use sensor data and equipment status parameters in the station building to diagnose equipment faults. By training an SVM model, normal states and various fault states can be classified, enabling timely and accurate detection of potential faults. Assuming we have a training dataset consisting of n samples, each represented by m features. Each sample has a label indicating its category. The training dataset is $\{(x1, y1), (x2, y2), ..., (xn, yn)\}$, where xi represents the feature vector (m-dimensional) of the *i*-th sample, and yi represents the label of the *i*-th sample (normal or faulty). By constructing a hyperplane, the normal and faulty samples are separated as much as possible. Mapping the sample feature vector xi to a high-dimensional feature space, and in the high-dimensional feature space, find a hyperplane so that the normal and fault state samples are on both sides of the hyperplane[19,20]. The equation for a hyperplane is:

$$w * x + b = 0 \tag{2}$$

W is the normal vector of the hyperplane, x is a sample feature vector, and b is the bias term. Maximizing the interval between the hyperplane and normal and fault state samples while minimizing classification error, the objective function can be expressed as:

$$\min\left(\frac{1}{2}\right)*\|w\|^2 + C\sum \max(0, 1 - yi(w * xi + b)) \tag{3}$$

C is a regularization parameter that balances the control interval and classification error. Σ indicates the sum of all samples. Transforming the objective function into a convex quadratic programming problem, and obtain the parameters *w* and *b* of the hyperplane by solving the convex quadratic programming problem. For the new sample feature vector *x*, classify it by determining which side of the hyperplane it is on. If $w * x + b > 0$, it is predicted to be in a normal state; if $w * x + b < 0$, it is predicted as a fault state.

4. RESULTS AND DISCUSSION

4.1 Experimental setup

In order to verify the performance and effectiveness of the predictive maintenance mode, a series of experiments are required. The experimental environment is set as a real information and communication station room, including edge computing equipment, servers, and related sensors and monitoring equipment. By applying a predictive maintenance model based on edge computing in the experimental group and comparing it with the traditional maintenance model in the control group, the differences between the two modes are evaluated. The experiment will focus on performance evaluation indicators such as fault prediction accuracy, maintenance time, and economic cost to comprehensively evaluate the advantages of the predictive maintenance model. During the experiment, it is necessary to ensure the accuracy of data collection, including the accuracy and stability of sensor data, and perform data verification and calibration. Consistent experimental settings and conditions need to be maintained between the experimental group and the control group to ensure the comparability of experimental results. In terms of data analysis, statistical methods are used to analyze experimental data. In order to obtain more stable and reliable results, multiple experiments will be repeated.

4.2 Experimental results

The predictive maintenance model uses edge computing and data analysis technology to predict potential failures and problems in advance through real-time monitoring and analysis of equipment status and sensor data, while the accuracy of fault root cause analysis measures the accuracy and reliability of the predictive model, which has an important impact on the practical application and effect of predictive maintenance. Figure 1 shows the comparison result.

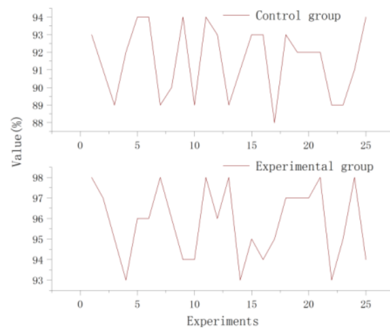

Figure 1. Root cause analysis accuracy rate.

In this test, the experimental group and the control group showed different levels of accuracy. Among them, the accuracy rate of the experimental group was the lowest at 93%, which was obtained from the 4th, 14th, and 22nd experimental tests, and the highest was 98%, which was obtained from the 1st, 7th, 11th, 13th, 21st, and 24th experimental tests. The accuracy rate of the control group is distributed at 88%-94%, it is obvious that the predictive maintenance model designed in this paper has a higher accuracy rate of failure prediction.

The time of root cause analysis can reflect the efficiency of the maintenance team in the troubleshooting process. If the root cause analysis takes a long time, it may mean that the maintenance team has encountered difficulties in determining the root cause of the problem or needs more time to collect and analyze data. Figure 2 is the root cause analysis time test.

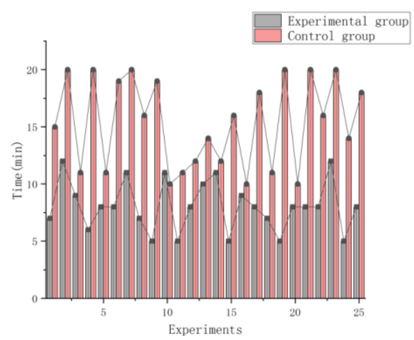

Figure 2. Maintenance time.

In the root cause analysis time test, the maintenance time of the experimental group is between 5-12 minutes, and the problems that arise can be diagnosed and analyzed in a shorter period of time. The analysis time of the control group is between 10-20 minutes, and the maintenance time is longer than that of the experimental group. This is because edge computing technology enables fault detection to be carried out locally on the device without relying on remote servers or cloud platforms. When the analysis results are obtained, the edge device can immediately detect and send an alarm, and the maintenance team can respond quickly.

Figure 3 is a comparison of the economic costs of predictive maintenance.

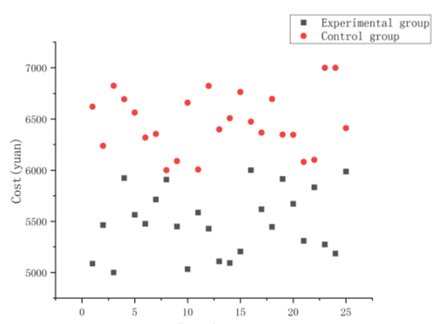

Figure 3. Economic cost.

From the comparison of economic costs, it can be learned that the cost of one-time predictive maintenance of the experimental group designed in this paper is 5000-6000 yuan, while the cost of the control group is 6000-7000 yuan, and the cost of the experimental group is less. The predictive maintenance model combines fault prediction and intelligent scheduling, which can arrange maintenance resources more accurately. By predicting the possibility and priority of failure, the maintenance team can rationally allocate personnel and materials, avoiding unnecessary waste and inactivity of resources, thereby reducing operation and maintenance costs.

5. CONCLUSION

Multiple tests of multiple indicators have found that the predictive maintenance model can reduce maintenance costs through preventive maintenance, avoid further deterioration of failures and lead to higher maintenance costs. It uses real-time monitoring and fault prediction technology to detect faults in a timely manner and take corresponding maintenance measures, reducing the need for manual inspection and troubleshooting, thereby reducing human resource costs. This research provides an innovative operation and maintenance model for the information and communication industry, and provides strong support for the realization of more reliable, efficient and intelligent information and communication station room management. Future development should continue to pay attention to the continuous innovation and improvement of technology, in order to further improve the performance and feasibility of the predictive maintenance model, and promote its widespread promotion and application in practical applications.

ACKNOWLEDGMENTS

This paper is supported by the following fund project: Science and Technology Project of State Grid Corporation of China (Project No. B3130423001P).

REFERENCES

[1] Dai, Y., Zhang, Y. and Wu, M., "Research and application of predictive maintenance technology for health management of signal system," Urban Rail Transit Research 24(11), 32-36 (2021).

[2] Liu, J., Wang, Z., Yang, H. and Ma, X., "Predictive security network architecture and equal protection requirements," Information Security Research 8(1), 28-34 (2022).

[3] Cai, C., Chen, X., Peng, Y., Ye, F. and Li, Y., "Application of Suiteng operating system cloud platform in Guangzhou Metro vehicle predictive operation and maintenance project," Urban Rail Transit Research 26(10), 5-10+35 (2023).

[4] Cai, H., Yang, W., Luo, W., Chen, W. and You, J., "Research on predictive operation and maintenance of network real-time customer perception based on big data," Telecommunications Engineering Technology and Standardization 36(7), 8-15 (2023).

[5] Hu, Y., Gao, Q., Chen, Y., Guo, D. and Feng, G., "Research on ultra-large-scale networking and predictive operation and maintenance based on computing power network," Jiangsu Communications 39(2), 39-43 (2023).

[6] Lu, Q., Xie, X., Parlikad, A. K., et al., "Moving from building information models to digital twins for operation and maintenance," Proceedings of the Institution of Civil Engineers-Smart Infrastructure and Construction 174(2), 46-56 (2020).

[7] Steffen, B., Beuse, M., Tautorat, P., et al., "Experience curves for operations and maintenance costs of renewable energy technologies," Joule 4(2), 359-375 (2020).

[8] Wu, C., Wu, P., Wang, J., et al., "Critical review of data-driven decision-making in bridge operation and maintenance," Structure and Infrastructure Engineering 18(1), 47-70 (2021).

[9] Sheng, S., "NREL's wind turbine drivetrain condition monitoring and wind plant operation and maintenance research during the 2010s: A US land-based perspective," Acoustics Australia 49(2), 239-249 (2021).

[10] Joo, J. H., Nam, J. Y. and Kim, T. H., "Study on damage information management plan for maintenance and operation of river facilities," Journal of the Computational Structural Engineering Institute of Korea 34(1), 9-18 (2021).

[11] Huang, B., Zhang, Y., Huang, B., et al., "Architecture and key technologies of digital-twin-driven intelligent operation & maintenance services for complex product," Journal of Mechanical Engineering 58(12), 250-260 (2022).
[12] Luo, Q., Hu, S., Li, C., et al., "Resource scheduling in edge computing: A survey," IEEE Communications Surveys & Tutorials 23(4), 2131-2165 (2021).
[13] Qiu, T., Chi, J., Zhou, X., et al., "Edge computing in industrial internet of things: Architecture, advances and challenges," IEEE Communications Surveys & Tutorials 22(4), 2462-2488 (2020).
[14] Wang, X., Han, Y., Leung, V. C. M., et al., "Convergence of edge computing and deep learning: A comprehensive survey," IEEE Communications Surveys & Tutorials 22(2), 869-904 (2020).
[15] Deng, S., Zhao, H., Fang, W., et al., "Edge intelligence: The confluence of edge computing and artificial intelligence," IEEE Internet of Things Journal 7(8), 7457-7469 (2020).
[16] Khan, L. U., Yaqoob, I., Tran, N. H., et al., "Edge-computing-enabled smart cities: A comprehensive survey," IEEE Internet of Things Journal 7(10), 10200-10232 (2020).
[17] Kong, L., Tan, J., Huang, J., et al., "Edge-computing-driven internet of things: A survey," ACM Computing Surveys 55(8), 1-41 (2022).
[18] McEnroe, P., Wang, S. and Liyanage, M., "A survey on the convergence of edge computing and AI for UAVs: Opportunities and Challenges," IEEE Internet of Things Journal 9(17), 15435-15459 (2022).
[19] Ranaweera, P., Jurcut, A. D. and Liyanage, M., "Survey on multi-access edge computing security and privacy," IEEE Communications Surveys & Tutorials 23(2), 1078-1124 (2021).
[20] Nguyen, D. C., Ding, M., Pham, Q. V., et al., "Federated learning meets blockchain in edge computing: Opportunities and challenges," IEEE Internet of Things Journal 8(16), 12806-12825 (2021).