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Design of Power Cable Data Monitoring and Forecasting System for Utility Tunnel Based on Edge Computing

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Abstract. Urban underground comprehensive pipe galleries are gradually replacing traditional underground pipe galleries due to their advantages of strong safety, easy maintenance and monitoring. In order to monitor the power system facilities in the underground pipe gallery, and collect and process the collected power system data effectively, this paper designs and builds the overall hierarchical structure of the power detection system and the sub function modules of the power system monitoring and control system, and improves the corresponding data sensor layout scheme at each acquisition node. Then, combined with edge computing technology and cloud processing technology, it strengthens the processing and analysis level of the collected power data. Finally, based on edge cloud collaboration, a real-time monitoring model for the power system in the pipe gallery is developed. Convolutional neural networks are used to extract targets from power data. In order to enhance the ability to extract the main targets, attention mechanisms are integrated into the neural network. The model is trained using labeled multi time series data such as environmental temperature and humidity, protective layer grounding current, and fused data as datasets to infer the current state of the power system, achieve real-time monitoring of the power system status, and evaluate its operational status.

Keywords: operating systems, edge computing, neural network, underground pipe gallery

1 Introduction

Underground comprehensive pipe gallery is a public tunnel space used underground in cities for centralized laying of municipal pipelines such as power, communication, water supply and drainage, and gas. The construction of underground comprehensive pipe galleries is conducive to coordinating the planning, construction, and management of various municipal pipelines, solving problems such as repeated excavation of road surfaces, dense overhead line networks, and frequent pipeline accidents. It is an effective means to ensure urban safety, promote intensive and efficient urban transformation and development, and improve the comprehensive carrying capacity and urbanization development quality of cities. Currently, major cities are increasing the construction of underground comprehensive pipe galleries, which is a high-yield and beneficial project for the people.

Urban underground pipe gallery has centralized functions, wide coverage, large construction length and buried underground, complex interior, even harmful gases appear in some sections, and it is impossible to realize frequent manual daily patrol for the management of the pipe gallery. Therefore, the operation of various facilities is monitored through corresponding sensors. Therefore, discussing how to use various sensing equipment and

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executive electronic equipment to improve the centralized scheduling and comprehensive operation capacity of various facilities and resources in the pipe gallery is the main way to realize the informatization and intelligence of the pipe gallery [1]. The foundation of a smart grid is the Internet of Things, especially the sensor network in the Internet of Things. Sensor networks are a crucial part of modern power equipment information perception, mainly responsible for the overall information perception of smart grids, such as power grid operation and maintenance, status monitoring, parameter collection, safe power supply, and equipment maintenance. In the organic integration process of smart grid and Internet of Things, the concept of power Internet of Things has gradually formed and played an indispensable role in the construction of modern smart cities. With the integration of Internet of Things with emerging information processing technologies such as artificial intelligence and big data computing, IoT applications have become diversified and intelligent, and the complexity of real-time IoT data flow and computing tasks has also rapidly increased. Edge computing is a good solution to the contradiction between device side data acquisition and computing data processing. edge computing architecture aims to build a distributed application platform with computing and storage capabilities close to the terminal device side, so that real-time data of the Internet of Things does not need to be uploaded to the centralized cloud computing platform, and the monitoring of power system data can be completed with maximum efficiency.

The research object of this article is the power facilities and systems in the pipe gallery. In the comprehensive pipe gallery, the power facilities are generally at the bottom layer. In the actual operation process, it is necessary to supervise the power facilities and collect data on the power facilities, mainly collecting electricity quantity, power system operation status, power system fault points, etc. Summarizing the actual operation experience of underground pipe galleries, the data collection of power facilities in underground pipe galleries has the following characteristics:

1) Circuit data collection should have the characteristics of “multiple points and wide coverage”, that is, the sensor layout should be scattered and dense, and the collection range should be as full as possible. At the same time, there should be some time redundancy in responding to real-time data, so the requirements for real-time data collection and transmission rate are relatively low.

2) The main functions of the power monitoring section should include collecting electricity information for underground pipe galleries, detecting abnormal environmental conditions in power warehouses, and monitoring electricity consumption. The pipe gallery should also include asset equipment monitoring systems, environmental monitoring systems, pipe gallery monitoring systems, warning systems, etc. In addition, it should also include environmental data monitoring, such as methane, carbon monoxide and other gas detection, temperature and humidity monitoring, water level monitoring, etc. inside the pipe gallery [2].

To sum up, in order to monitor the power system facilities in the underground pipe gallery and effectively collect and process the collected data, this paper designs a data acquisition framework for the underground pipe gallery power system, and arranges corresponding sensors at each acquisition point. Then, combined with edge computing technology, it improves the ability to process and analyze data. Finally, it designs the underground pipe gallery power monitoring system. The detailed work of this paper is as follows:

1) Completed the overall architecture design of the underground pipe gallery power system, including hierarchical structure and physical functional level structure design, as well as communication scheme design between various levels;

2) Completed the design of edge end architecture, and starred in the research of edge server deployment, cloud communication, edge computing and other issues;

3) We have completed the selection and layout design of data collection equipment, and then implemented the prediction system design for power faults and power dispatch based on the data design.

2 Related Work

There are many high-quality research results on edge computing and power monitoring system framework. First of all, in terms of physical architecture, Jing Zhao of Yunnan Power Grid Company, in order to improve the effectiveness of power system monitoring, first established a distribution network security risk map, calculated and analyzed the security risk through potential functions, obtained node potential energy values and key node data, and then built a smart grid multi-source heterogeneous data monitoring model based on edge computing, which can realize the timely perception and real-time response of distribution network faults. Finally, the efficiency in grid fault diagnosis was verified in the real environment [3].

Xinhua Yang from Lanzhou University of Technology has designed a power IoT intelligent terminal acquisition system based on LoRa radio to address the issues of wired communication faults and unstable communication between power equipment data acquisition devices in the field of intelligent distribution. This system solves the problem of reliable communication in data acquisition and information transmission of voltage and current in distribution areas, and has stable and reliable performance in practical applications [4].

The research content of Xianggui He from Hunan University focuses on the issue of energy consumption and electricity theft monitoring in urban road lighting. A two-step wireless communication and time-sharing synchronous collection of power data from all monitoring nodes is proposed, and a centralized controller is used to calculate the lighting power and energy consumption of the lighting line. Real time lighting energy consumption and electricity theft monitoring strategies for identifying electricity theft behavior are also introduced. The hardware module design of the centralized controller is introduced, and software construction is implemented [5].

In the research of edge computing, Yuancheng Chen proposed a method of edge computing terminal deployment and service allocation. After clarifying the terminal service processing architecture and data node division, a two-layer model considering terminal deployment and service allocation is established. The outer model solves the problem of service allocation at edge computing terminals, and the inner model solves the problem of edge computing terminal deployment. Then, based on the inherent coupling relationship between the two-layer models, a model optimization method is proposed to verify the feasibility of the proposed method in numerical examples [6].

Nan Yao focused on the efficiency and energy consumption of edge computing, proposed a computing task unloading strategy based on deep reinforcement learning algorithm and a resource allocation optimization algorithm, established a delay, energy consumption and energy efficiency model of edge cloud collaboration, and studied the impact of the number of user devices, task volume, task priority, etc. on delay, energy consumption and energy efficiency [7].

Huina Wei, of North China Electric Power University, proposed a joint optimization algorithm of power control and spectrum resource allocation based on bilateral matching for massive data in power system edge computing. By transforming the optimization problem into a one-to-one matching problem, the network throughput can be maximized while ensuring the transmission rate. The simulation results show that compared with traditional energy efficiency first algorithms, the proposed algorithm can improve throughput by 6.24% [8].

Zhichao Lin of Guangdong Power Grid used edge computing to solve the power monitoring problem of power dispatching. In order to better meet the real-time requirements of distribution network protection business, he proposed a container based distribution network protection microservice modeling and computing resource scheduling method. Firstly, the distribution network protection business was decomposed into multiple microservices, and a microservice temporal logic model for distribution network protection business and a container based microservice architecture for distribution network protection business were established; Then, a computing resource scheduling model for microservices was established, and the results of microservice computing resource scheduling with minimum business delay were obtained through improved differential evolution algorithm; Finally, the simulation example compares the results of different microservice computing resource scheduling strategies, and the application scenario of edge computing provides a new idea [9].

The above research results provide ideas for the formation of the content and innovation points of this article. Based on the various research results, this article summarizes and innovates to achieve data detection and system design for the power system.

3 Overall System Architecture

The main detection object of the underground pipe gallery power system is power cable facilities. This article first designs and implements intelligent monitoring of power cables. The power cable intelligent monitoring system mainly includes cable edge intelligent terminals, cable body monitoring, pipe gallery environment monitoring, security environment monitoring, and IoT management platform [10]. The overall hierarchical structure of the intelligent detection system is shown in Fig. 1.

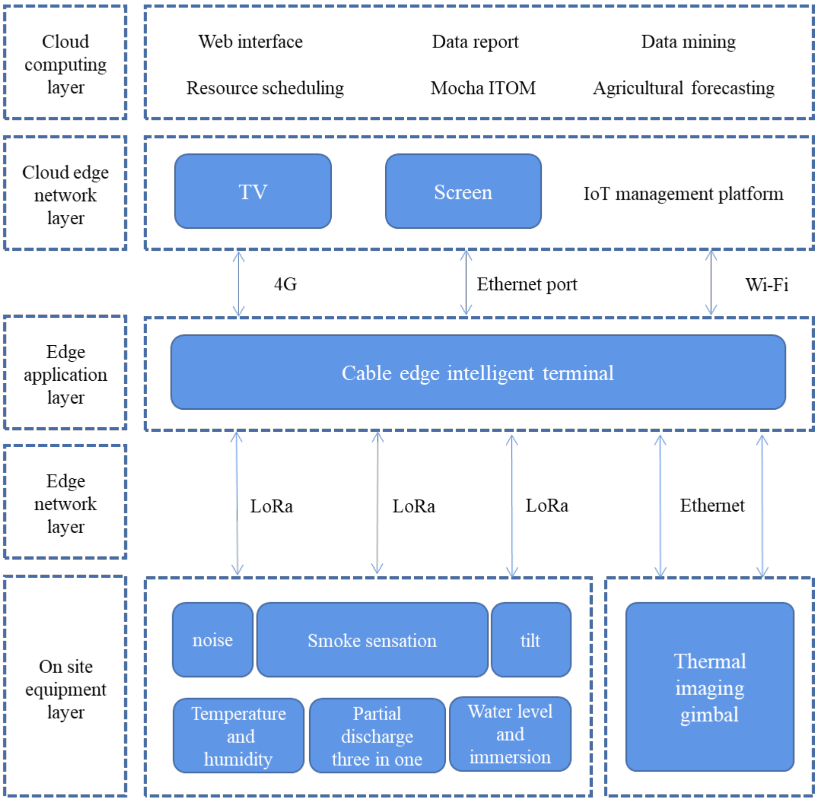

Fig. 1. Schematic diagram of system hierarchical architecture

The hardware of the IoT network layer mainly includes communication cables, short distance wireless communication modules, etc., responsible for network transmission between on-site devices, between on-site devices and edge nodes, and between edge nodes and sensors; Responsible for transmitting massive data generated by on-site equipment and sensors to the edge application layer, and returning decision instructions to the cloud computing layer and edge application layer.

The edge application layer preprocesses the raw perception data and runs some model calculation tasks, such as state analysis, electricity consumption analysis, etc; According to the task results, control instructions are issued, and data analysis and processing results are sent to the cloud computing center.

The cloud edge network layer is responsible for the network transmission between the edge application layer and the cloud computing layer. The network transmission distance between the edge application layer and the cloud computing layer is relatively long, which has certain limitations on the amount of data transmitted; The sensor perception data and partial data analysis results preprocessed by the edge application layer can be uploaded to the cloud computing layer, and decision instructions from the cloud computing layer can be returned.

The cloud computing layer is mainly responsible for computing global, non real-time, and long-term big data analysis tasks, such as urban electricity consumption big data analysis and data mining, power grid scheduling decisions, etc., and distributing relevant results to edge nodes [11].

Therefore, the monitoring and control system design of the entire power system is shown in Fig. 2.

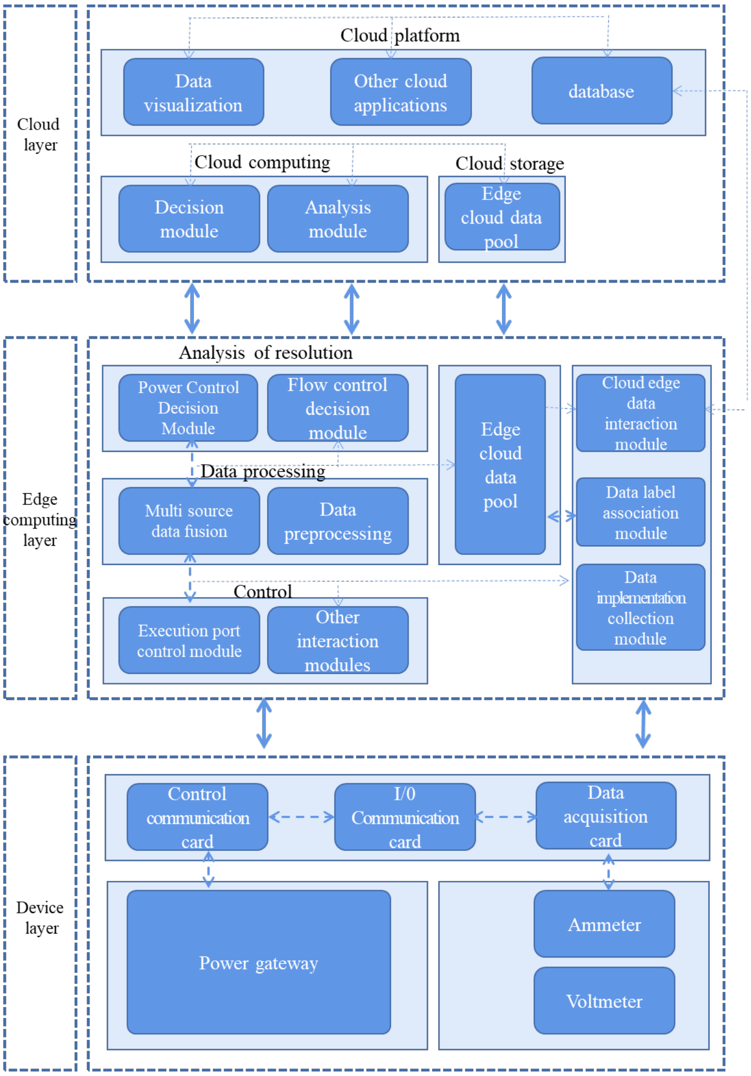

Fig. 2. Functional diagram of monitoring and control system

Considering the possible failures in the actual operation process, all microservices in the edge computing gateway may fail. Based on this reality, this paper adds the circuit breaker mode to improve the operational flexibility of the edge computing gateway. The circuit breaker mode ensures that failed services are not repeatedly called to ensure that poorly performing services do not exhaust all resources.

The circuit breaker mode is shown in Fig. 3. There are three scenarios for using the circuit breaker mode in the edge computing gateway. The first scenario is when microservices can be called normally. Microservice A calls microservice B, and at this time, the circuit breaker uses a timer. If the call to microservice B is completed before the specified time of the timer expires, it is considered that the call process is smooth and microservice A can continue to work normally. The second scenario is when the called service fails. Microservice A calls microservice B, but this time microservice B runs slowly and cannot complete the call to the remote service before the timer on the circuit breaker maintenance thread times out. The circuit breaker will cut off the connection to the remote service. Then microservice A will receive an error from the issued call, but microservice A will not occupy resources to wait for microservice B to complete the call. If the call to microservice B is interrupted by a circuit breaker timeout, the circuit breaker will start tracking the number of faults that have occurred. The third scenario is that the called microservice B has already experienced enough errors, and the circuit breaker will quickly “trip” the circuit. Without calling microservice B, it is determined that all calls to microservice B will fail. A circuit breaker trip will result in the following three outcomes:

1) Microservice A now immediately knows that there is a problem with microservice B, without waiting for the circuit breaker to time out.

2) Microservice A can now choose to either fail completely or execute alternative code to take action.

3) Microservice B has a chance to recover because microservice A will not call it after the circuit breaker trips. This provides microservice B with an opportunity for recovery and helps prevent cascading deaths in the event of service failure.

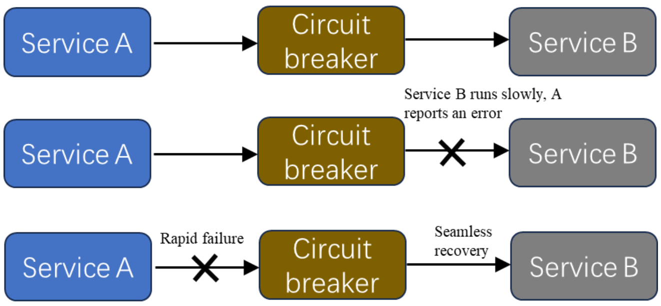

Fig. 3. Classification of usage scenarios for circuit breakers

In the edge computing gateway, multiple microservices are required to complete a function together. The remote invocation of microservices is likely to fail, or the microservices are suspended without any response until timeout. In circuit breaker mode, microservice A delegates the actual call to microservice B to the circuit breaker, which takes over the call and wraps it in a thread. The circuit breaker monitors the thread and can stop the call if it runs for too long.

In summary, by monitoring the partial discharge, sheath circulation, and temperature of key nodes in power facilities, the monitoring of the pipeline environment is achieved, which includes monitoring the water level, water immersion, temperature and humidity, and smoke of cable ducts; Security environment monitoring mainly monitors the status of fire doors, personnel intrusion, fires, etc; On site sensors send monitoring data to cable edge intelligent terminals through LoRa wireless communication or network cables. After cloud computing processing, end users can real-time query the operation status of power cables on their PC.

In combination with the reference architecture of edge computing, the equipment and functions in each level are divided. The specific levels of the proposed architecture are as follows:

1) The main modules of the device layer are: control execution module as an edge node, power equipment monitoring and control ontology module, and perception module. Control execution module: including short distance communication module, hardware devices as edge nodes, etc. Commonly used edge node devices include field programmable logic gate arrays, Raspberry Pi, intelligent mobile terminals, Nvidia Jetson embedded chips with AI functions, etc; It is a hardware device that runs edge computing layer related models and data preprocessing tasks.

2) The edge computing layer includes data processing module and control module: responsible for information interaction with the control execution module of the device layer, and transmitting the state information of the power system device fed back by the control execution module to the data processing module, and carrying out the closed-loop process from “device working state awareness - state analysis - device control - device working state awareness”. It generally includes sensors (such as temperature, humidity, pressure, current, voltage, etc.), smart meters (used to measure energy consumption), data acquisition terminals, etc.

3) The cloud layer is divided into cloud computing, cloud storage, and cloud platform modules. The edge computing layer can call cloud computing resources according to actual needs.

This section introduces the concept and characteristics of edge computing, and analyzes the application scenarios of edge computing in the power system monitoring of underground pipe gallery. Secondly, according to the actual production requirements of power system monitoring and the development of information technology, the functional requirements of power system data detection system based on edge computing are analyzed and the overall architecture of intelligent control system based on edge computing is proposed. The intelligent control system designed in this article can collaborate with the computing resource advantages of the cloud layer to achieve the application of intelligent functions such as massive data perception, intelligent analysis, intelligent decision-making and control. It can provide a theoretical basis for the research work in subsequent chapters.

4 Deployment and Construction of Edge Computing Platform

After the analysis of the data acquisition framework and data acquisition in Chapter 3, the collected multi-source heterogeneous data needs to be processed on the edge computing platform arranged on the terminal side. This chapter mainly focuses on the software deployment and implementation of each layer of the hierarchical architecture of the edge stream data processing platform, the data access layer of the Internet of Things, the data forwarding layer, and the big data processing layer. As shown in Fig. 4, the edge computing cluster designed in this paper is mainly composed of a master node, three working nodes, a database server and multiple Internet of Things gateway servers, which conduct high-speed data communication with each other and complete distributed tasks such as big data real-time stream computing.

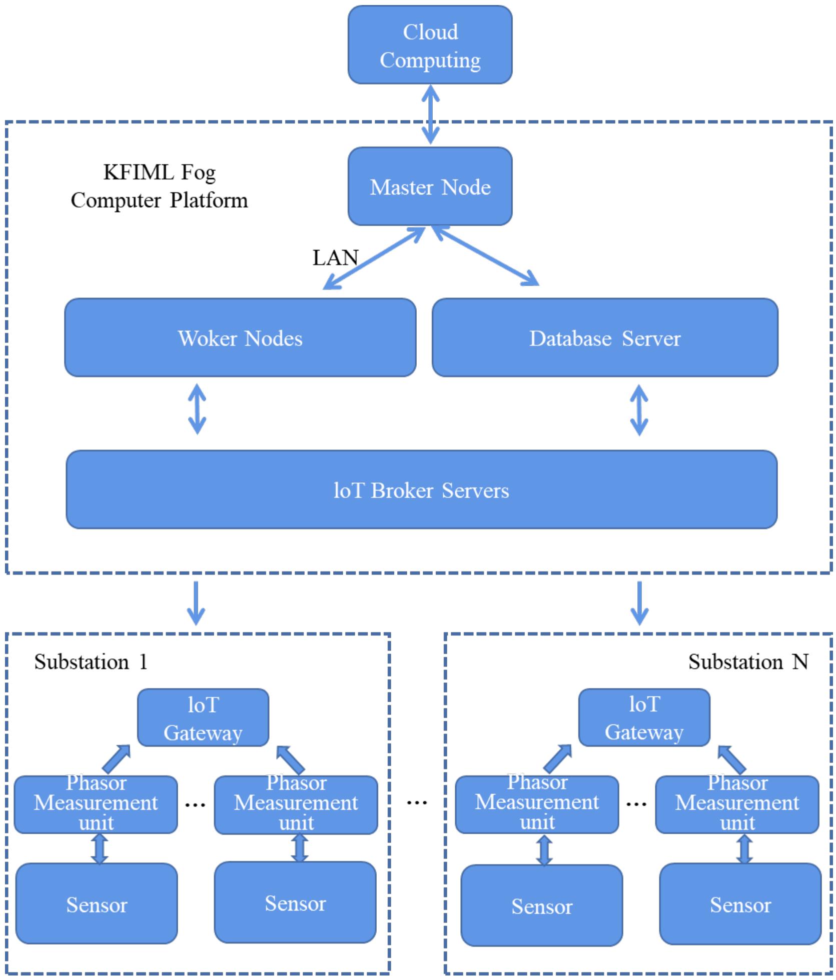

Fig. 4. Edge computing cluster function diagram

The edge master node, working node and database server in the heterogeneous edge computing cluster are all 64 bit host servers of X86 architecture, and the IoT gateway server is a lightweight raspberry pie board computer server node based on ARM architecture. Each server node is connected to the local LAN through a 1Gbps Ethernet cable.

The IoT Data Access Layer uses distributed IoT access components, which are containerized and deployed on lightweight edge computing nodes such as ARM architecture servers. At the same time, it provides message parsing services and data rule engines for protocol data such as MQTT, directly connects data streams reported by IoT terminal devices, and supports data forwarding services with various distributed message middleware. The Data Transfer Layer mainly deploys distributed message middleware Kafka and ZooKeeper clusters, providing caching services for the data forwarded by the IoT data access layer, achieving decoupling between the original data access of the IoT and the big data computing engine, and improving the stability of the platform system. The Big Data Processing Layer deploys the streaming computing data processing engine Flink, providing big data processing capabilities for real-time IoT data, including streaming computing, sliding window computing, and batch processing. The real-time computing results are then stored in downstream data repositories [12].

In the physical layer, the edge gateway used in this article is the LC-DAQ810 comprehensive data acquisition gateway produced in Huizhou, Guangdong. This gateway adopts a high-performance CPU processor, which has the characteristics of supporting high-frequency operations, floating-point operations, and supporting secondary development; And it has 256MB of memory, 4GB of EMMC, and can be equipped with external TF cards, USB, extended storage, etc. Its specific parameters are shown in Table 1.

Table 1. Main technical parameters of the comprehensive data collection gateway

Parameter	Detailed information
Working voltage	24VDC
Voltage input range	12VDC-36VDC
Rated working current	100mA@24VDC
Communication interface	Wifi\LoRa\NB-Iot\ZigBee
Wireless interface	2-way Ethernet 10/100M: 3-way RS485 interface: 1-way TTL information debugging
Networking Protocol	MQTT\HTTP\WebService
CPU main frequency	ARM Cortex-A87800MHz
RAM	256Mb
Power dissipation	<=5W
Environment condition	-25℃—65℃
Extreme operating temperature	-40℃—80℃

The edge gateway architecture is shown in Fig. 5.

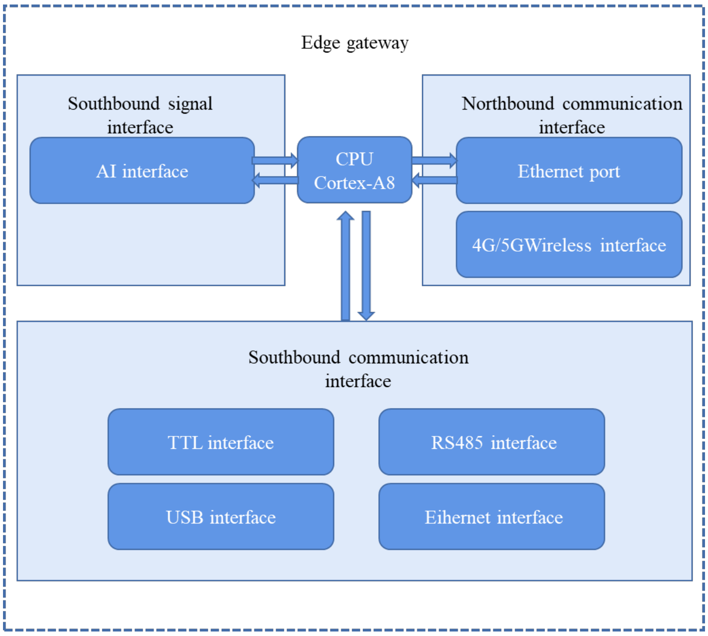

Fig. 5. Edge gateway

The peripheral equipment mainly consists of three major parts: north communication interface, south communication interface, and south signal interface. The northbound communication interface mainly undertakes the communication between the server and the edge gateway, while the southbound communication interface and the southbound signal interface undertake the communication between the edge gateway and devices or sensors. The edge gateway can collect data from devices supporting USB, TTL, RS485, AI, Ethernet and other communications, and support edge computing for data preprocessing and data feature extraction, and upload the calculated data to the server in TCP/IP mode.

The edge gateway will collect raw data on the operating status of the air compressor, which will be preliminarily processed and calculated, and then sent to the cloud server for storage and corresponding calculations. In addition, the server also bears the responsibility of accessing the computer side and needs to process real-time requests from the computer side. Therefore, it is necessary to select cloud servers based on the actual technical requirements of the entire system. The selection criteria for servers are generally determined by the following important parameters:

(1) CPU: The CPU of a cloud server represents the computing power of the host. Based on the actual situation, this article selects CPUs with 4 cores or more.

(2) Memory: According to the architecture designed in this article, the system needs to run a database, which consumes a lot of memory. Therefore, 8GB or more of memory needs to be selected.

(3) Hard disk: In order to ensure system operation speed and meet data storage requirements, a 500G SSD solid-state drive is selected

(4) Bandwidth: Bandwidth represents data transmission capacity, and the larger the bandwidth, the greater the supported traffic and the faster the website's response speed. To ensure the system's response speed, a network bandwidth of 2Mbps is selected.

After the above process, the system data collection and the layout of the edge computing platform and cloud computing layer are completed.

5 Design of Power Monitoring and Prediction System in Pipe Gallery

The real-time monitoring of the power system inside the pipe gallery is the core function of the system. It has good applications in quickly identifying anomalies in power systems, real-time control, and optimizing power supply processes. Based on the edge cloud architecture constructed in this article, a real-time monitoring model for the power system in the pipeline corridor is established based on edge cloud collaboration. At the same time, BP neural network and attention mechanism are applied to improve and optimize the feature extraction performance of the model. Through the multi temporal data of environmental temperature and humidity, protective layer grounding current, and historical state of the power system, fusion data labels are obtained to reflect the current state of the power system [13]. At the same time, the multi temporal data and fusion data labels that represent the power system state are used as the training data for the evaluation model, realizing the monitoring of the real-time state of the power system and the evaluation of its operation status.

5.1 Design of Data Collection Nodes

When collecting information from the power grid, it is necessary to collect data from all nodes as much as possible. If a collection module is installed at a certain node, the voltage phasor of that node and the branch current phasor connected to that node can be directly measured. The voltage and branch current of the node where the collection module is installed can be directly measured. If some nodes in the power grid are equipped with acquisition modules, and the voltage or branch current of the nodes or branches without data acquisition modules can be calculated based on the voltage ampere characteristics of the nodes and branches in the system, Kirchhoff's law, and the known voltage and current phasors of the system, then the data of that node or line can also be obtained. The network node design is shown in Fig. 6.

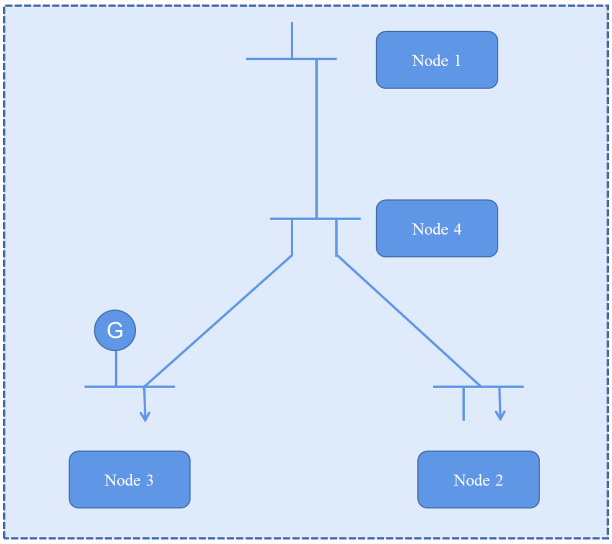

Fig. 6. Network node design

The monitoring system arranges data collection nodes, and its mathematical model is:

$$\min \sum_{j \in T} c_j k_j . \tag{1}$$

T -All nodes of the collection module need to be configured;

c_j -All expenses for installing the acquisition module for node j;

k_j - Boolean representation of node state, when installing the acquisition module $k_j = 1$, when not installed $k_j = 0$.

The design goal of the collection system is to achieve direct or indirect measurability of voltage and current data at all nodes within the system. A constraint function is introduced, expressed as:

$$g_i = \sum_{j \in T} f_{ij} k_{ij} . \tag{2}$$

In the formula, f_{ij} is the correlation function between node i and node j. The return value of the same correlation function is 0 or 1. When two nodes are related, the return value is 0, and when there is no correlation, it is 1, g_i represents the data collection status of node i after installing the data collection module according to the assembly plan, and the defined constraint conditions are:

$$g_i \geq 1, i \in T . \tag{3}$$

Consider the special nodes within the system separately, which are characterized by the absence of input and output power. The data collection of these nodes needs to consider the data collection status of their neighboring nodes. Therefore, the update constraint function is defined as:

$$g_i = \sum_{j \in T} f_{ij} \left(k_j + d_j h_j \right), i \in T. \tag{4}$$

In the formula, d_j indicates whether the node is a special node and returns a value of 0 or 1. h_j represents the availability of data for the special node and returns a value of 0 or 1. When both function values are 1, it indicates that the data for the special node is available [14].

When considering a failure of one of the data collection modules in the system, and still ensuring that the system data can be collected, the constraint conditions for defining system nodes are:

$$g_i = \sum_{j \in T} f_{ij} \left(k_j + d_j h_j \right) \geq 2, i \in T. \tag{5}$$

The above constraints ensure that all nodes can still collect data when any data collection module fails. When there is a line interruption in the power grid, the constraint conditions are:

$$f_i^k = \sum_{j \in T} f_{ij}^m \left(k_j + d_j h_j \right) \geq 1, i \in T, m \in M. \tag{6}$$

In the formula, m is the number of the faulty line, M is the set of line numbers between all busbars in the power grid, f_{ij}^m represents the faulty line m between nodes i and j. When a fault occurs, the value of f_{ij}^m is 0.

5.2 Electricity Consumption Prediction

Electricity consumption is an important economic indicator for power supply enterprises, reflecting their sales capacity and comprehensive management level. At the same time, the forecast of electricity sales plays an important role in power supply enterprises' reasonable determination of the total quota of electricity sales, decomposition of electricity sales indicators, mastery of electricity market, formulation of orderly electricity use plans, guidance of the rational operation of power plants and transmission and distribution networks, and promotion of the healthy development of the electricity market. Therefore, this part of the content forecasts electricity consumption based on the results of edge computing. This paper forecasts the current and voltage data in the data acquisition node, and first normalizes the data [15]. The processing method is as follows:

$$C_i^{'} = \frac{C_i - (1+\delta) C_{i\max} - (1-\delta) C_{i\min}}{(1+\delta) C_{i\max} - (1-\delta) C_{i\min}}. \tag{7}$$

In the formula, $C_{i\min}$ and $C_{i\max}$ are the minimum and maximum values of electricity, respectively, $C_i^{'}$ is the result of data conversion, and δ is the percentage of training sample target size.

This article uses a BP neural network to predict electricity sales. The number of nodes in the input and output layers of the BP neural network is the actual situation. Taking into account the factors that affect electricity sales forecasting parameters, the input layer nodes and output layer nodes are ultimately determined. On the basis of ensuring the necessary data for the BP neural network prediction model, the system size should be minimized as much as possible. The network structure is shown in Fig. 7.

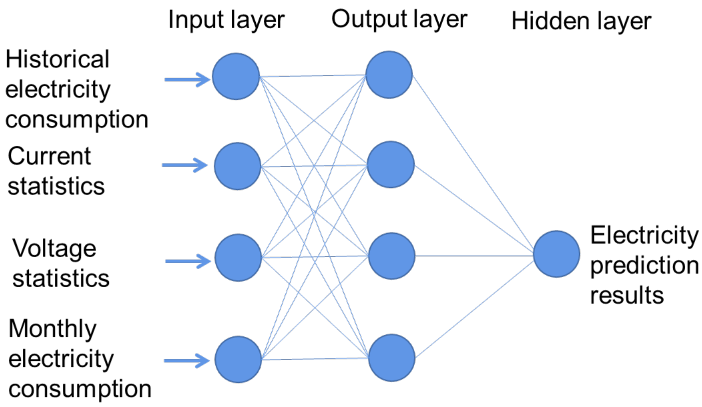

Fig. 7. BP neural network structure

The main characteristic of BP neural network is that the signal propagates forward, while the error propagates backward. Specifically, for neural network models with only one hidden layer, the process of BP neural network is mainly divided into two stages. The first stage is the forward propagation of the signal, passing through the hidden layer from the input layer and finally reaching the output layer; The second stage is the backpropagation of errors, from the output layer to the hidden layer, and finally to the input layer, adjusting the weights and biases from the hidden layer to the output layer, and from the input layer to the hidden layer. The training process of BP neural network is as follows:

1) The initial values of weights and thresholds are set to $\omega(0)$ and $\theta(0)$;

2) Input learning sample: Input vector X_P, output target T_P;

3) Select the sigmoid function for the excitation function setting, and the expression is as follows:

$$Sigmoid = 1/\left(1+\exp\left(1-x\right)\right). \tag{8}$$

4) Calculate training error

Output layer:

$$\Delta\delta = O_{pj}\left(1-O_{pj}\right)\left(t_{pj}-O_{pj}\right). \tag{9}$$

Hidden layer:

$$\Delta\delta = O_{pj}\left(1-O_{pj}\right)\sum_k \delta_{pk}\omega_{jk}. \tag{10}$$

In the formula, represents the expected output value of each output node; k is the node number of the upper layer where node j is located.

5) Modify weights and thresholds.

6) When P experiences $1-P$, determine whether the indicator meets the accuracy requirements; If the requirements are met, go to (7); otherwise, go to (3).

(7) Stop, end.

The number of nodes in a hidden neural network is determined by the following formula:

$$n_h = \sqrt{n_i + n_0} + l. \tag{11}$$

In the formula, n_h represents the number of hidden layer nodes, n_i represents the number of input layer nodes, and n_0 represents the number of input layer nodes. Then, select the initial weight value, with the weight range being a random number between $(-1,1)$. The selection of learning rate η, when η is large, the amount of weight modification is large, which accelerates the learning speed but may result in non-convergence. When η is small, the learning process is smooth, but the learning speed is slow. Generally, it is preferred to choose a smaller learning rate. $\eta \in [0.05, 0.8]$. The adaptive adjustment method for learning rate in the learning process of neural networks is as follows:

$$\eta(k+1) = \begin{cases} 1.2\eta k & Ep(k+1) < Ep \\ 0.8\eta k & Ep(k+1) > 1.2Ep \\ \eta k & other. \end{cases} \tag{12}$$

In actual operating environments, in order to improve prediction accuracy, BP neural network is combined with mathematical models. In this paper, multiplication and neural network are combined to predict electricity consumption. The combined network structure is shown in Fig. 8.

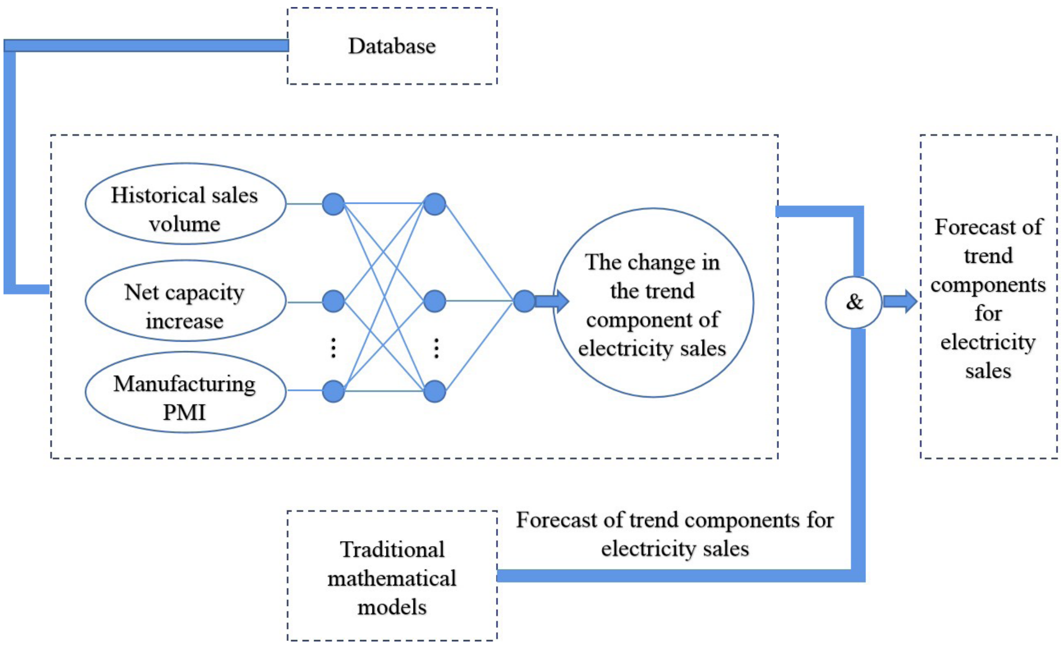

Fig. 8. Improved BP neural network structure

For the calculation of the trend component of electricity sales, the electricity prediction model is as follows:

$$P_i = P_{oi} + \phi_\Delta . \tag{13}$$

P_i is the predicted result of the trend component of electricity sales, P_{oi} is the traditional mathematical model's electricity sales component, and ϕ_Δ is the change in the trend component of electricity sales predicted by the BP network. The prediction process of the entire network is shown in Fig. 9.

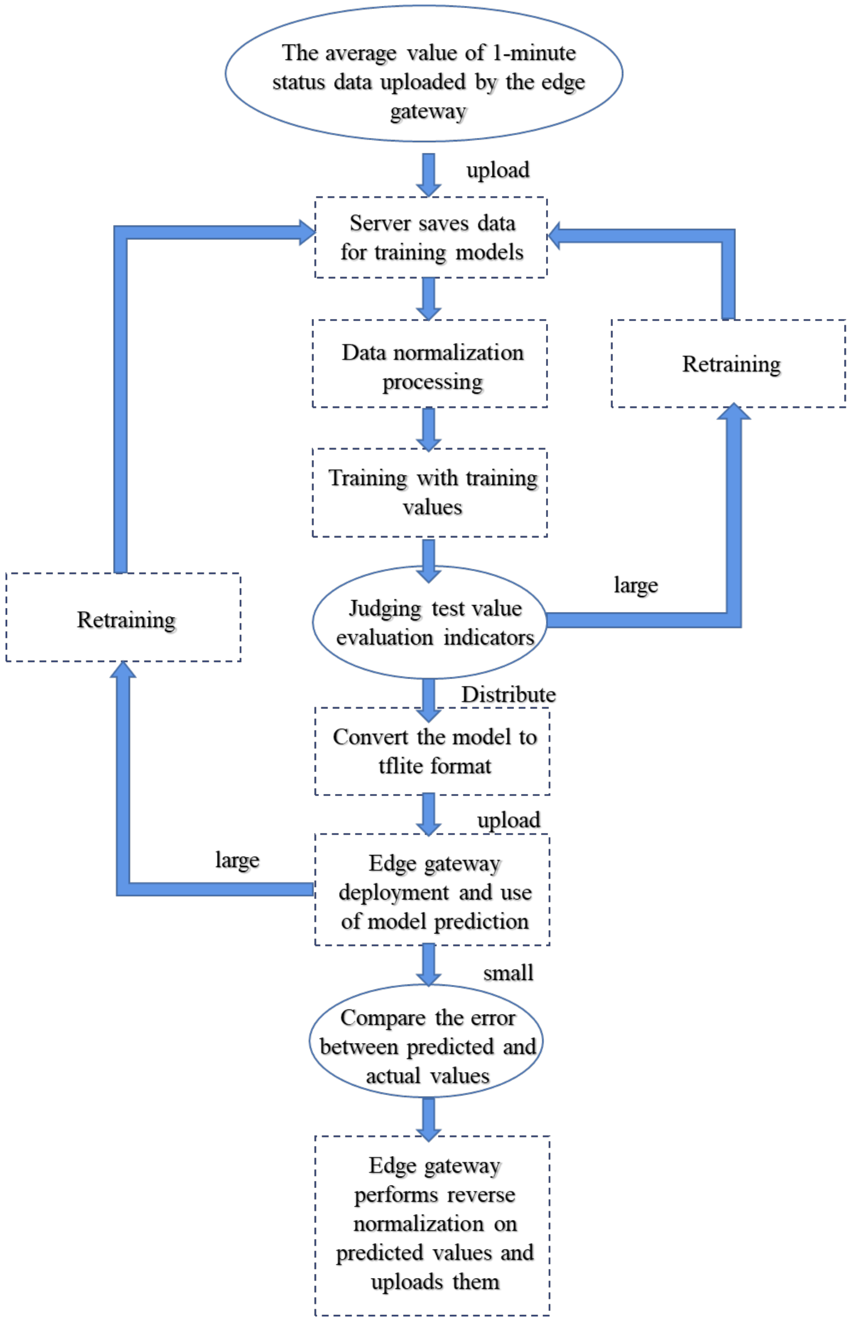

Fig. 9. Predictive function flowchart

The above model can be used to analyze the prediction of electricity in underground official doctors, and the output is the prediction result. At the same time, the output data serves as the display value of the prediction system, which can be displayed in the system.

5.3 Design of Power System Monitoring and Prediction Software System

The functional requirements of the air compressor status data monitoring and anomaly prediction system based on edge cloud collaboration designed in this article mainly include user management and registration, real-time monitoring of power system status, data prediction function, and visual display function.

The user design of the user management and registration system mainly includes two parts. One part is ordinary role users, who can view monitoring data through the login page and be promptly notified of device abnormalities or impending abnormalities. Relevant personnel can then take corresponding measures.

The traditional operation of the power system requires manual regular and scheduled inspections, which is labor-intensive, and monitoring feedback is often slow. The real-time monitoring function of the power system status is based on the edge cloud collaborative power system status data monitoring and anomaly prediction system, which can effectively solve this problem. Staff can view the equipment status in real time by browsing the system interface. Due to the use of edge cloud collaborative architecture, the system has a higher response speed compared to traditional cloud service systems. The real-time and stability of the edge cloud collaborative architecture can ensure that the collected data can be monitored in a timely manner, thereby ensuring the reliable operation of the power system.

The data prediction function uses the BP neural network algorithm to predict power usage data, with the aim of facilitating power scheduling based on electricity consumption.

The visualization display function is designed to visually display predicted data through curves and other forms, while also displaying the monitored data objects in the interface.

All front-end display interfaces of the system are implemented using the Bootstrap framework, and the back-end business logic is implemented using the Django framework. Bootstrap is a front-end page framework that can create elegant front-end interfaces and only consume a small amount of resources. The designed system includes a user login interface, a power system management and monitoring interface, a power system data monitoring and display interface, and a monthly electricity forecast display interface [16]. The login interface is shown in Fig. 10.

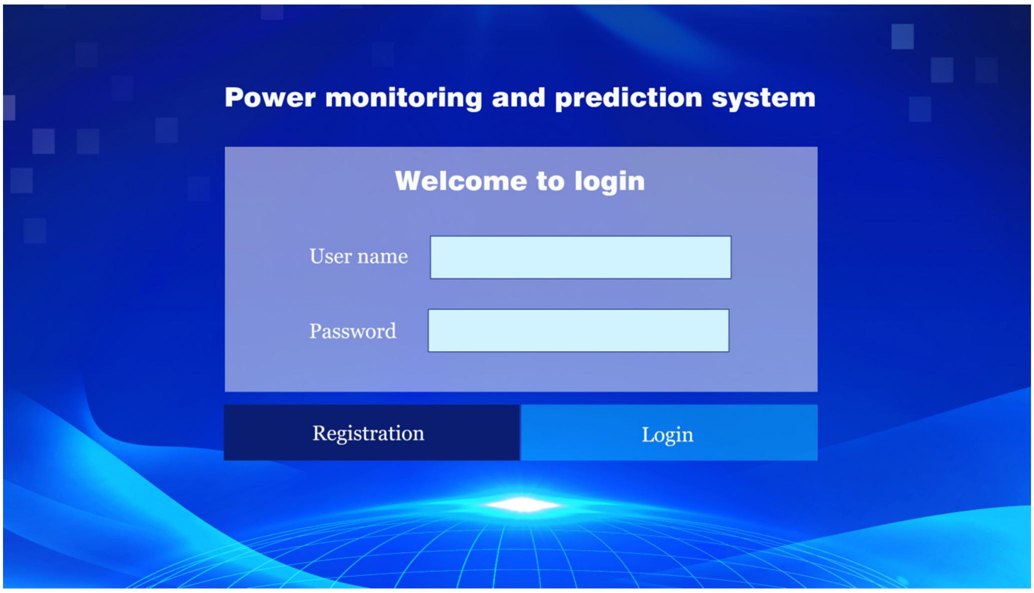

Fig. 10. Login interface

The power system management monitoring interface is used to monitor the data operation status of various nodes in the power system, mainly manifested in three states: normal equipment operation, abnormal equipment operation, and equipment disconnection; Each sheet is composed of device name, device status, device type, device number, and device location, which can help management personnel understand the detailed status and information of the device in a timely manner. The interface is shown in Fig. 11.

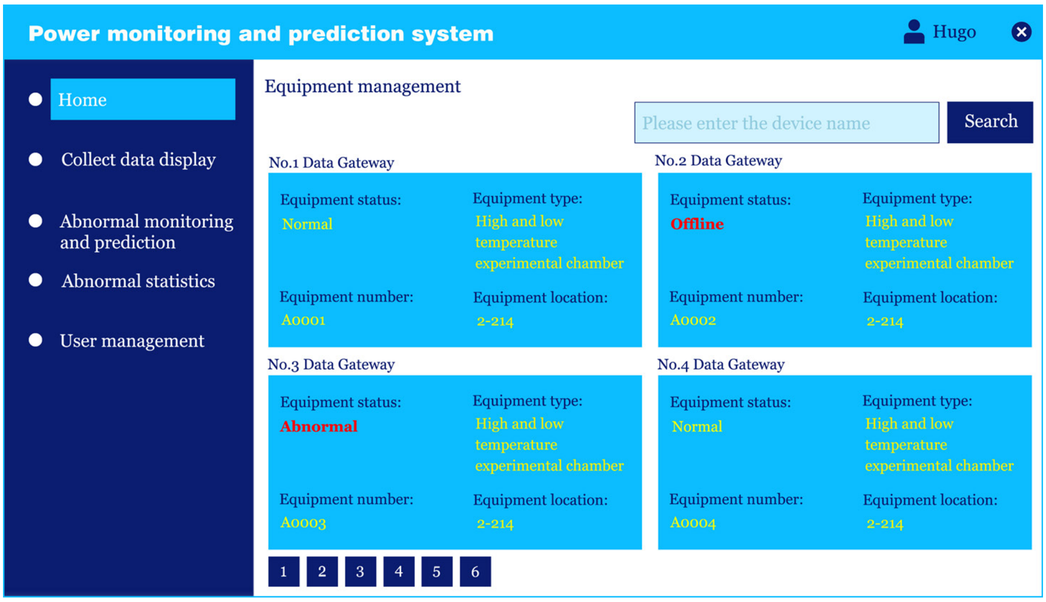

Fig. 11. Monitoring management interface

This interface can display the monthly electricity consumption values in the power system by selecting devices, thereby achieving the prediction of the consumption of electricity for the next month and year; And real-time and predicted values can be collected by clicking the corresponding collection button. The prediction interface is shown in Fig. 12.

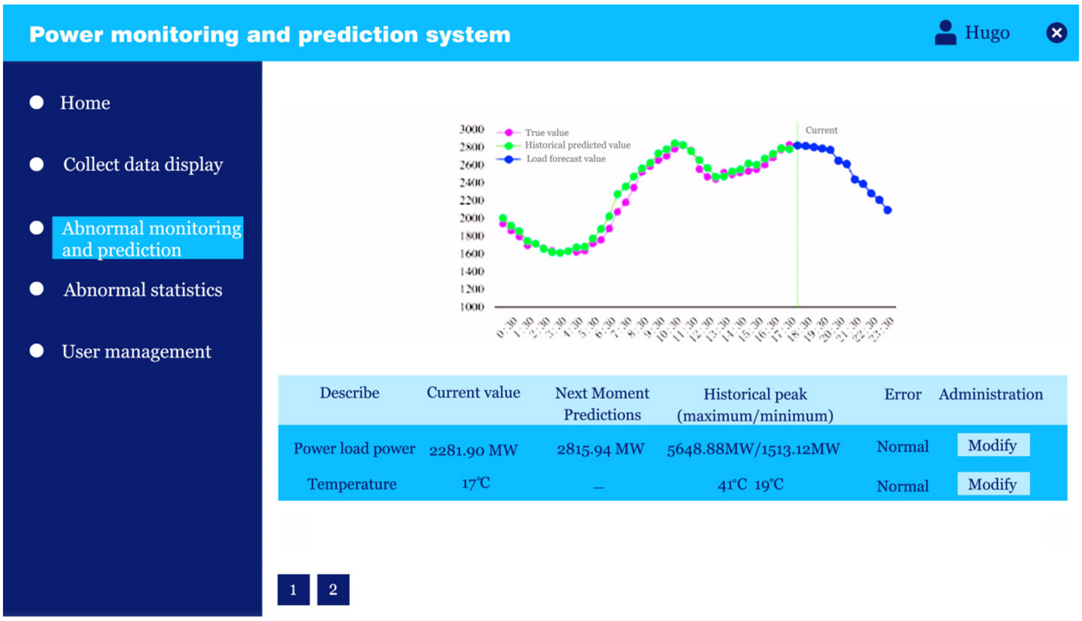

Fig. 12. Electricity prediction interface

This section mainly completes the power system's power fault monitoring and power consumption prediction functions, and then designs an intelligent monitoring and power prediction system based on functional prediction and data processing.

6 Conclusion

This paper realizes the monitoring of the power system facilities in the underground pipe gallery, while effectively collecting and processing the collected data, designs the monitoring and control system functional modules that can detect the overall hierarchical structure of the system and the power system, and describes the corresponding sensor layout scheme at each acquisition point. Then, it designs the real-time monitoring model of the power system in the pipe gallery combining edge computing technology and cloud processing technology. At the same time, it applies BP network and attention mechanism to improve and optimize the model feature extraction performance, and realizes the monitoring of the real-time status of the power system and the evaluation of the operating status through the tagged data such as environmental temperature and humidity, sheath grounding current, etc.

1) We have selected a gateway with IoT functionality for the layout design of collection nodes, completed the physical level data collection electromechanical layout, and preliminarily formed a data collection network;

2) Analyzed the functions of cloud computing and configured a cloud computing framework for this article

3) The power prediction system requires a simple and intuitive monitoring system interface. Combined with an improved data feature extraction network, a basic power system prediction system was designed, and the basic UI interface was provided

At the same time, this article also has many shortcomings and has become a further research direction. The summary is as follows:

1) Regarding the issue of data collection delay, it is necessary to reduce the collection cycle of sensors and the power consumption of gateways, while ensuring a high sampling frequency and reducing power consumption.

2) The system software is relatively basic, and the development of the software system should be further refined on the existing basis, with more user-friendly functional settings added.

Based on edge computing and swarm intelligence optimization and other technologies, this paper has made some research on the task allocation optimization of the power Internet of Things. However, due to the limited research time, some aspects in this paper still need to be further improved, including but not limited to:

1) The combination of intelligent optimization algorithms and the latest technologies. According to extensive literature review, the fusion of intelligent optimization algorithms and machine learning has flourished in recent years, such as the combination of genetic algorithms and deep neural networks in machine learning methods. In the future, I will consider using some machine learning algorithms to enhance the performance of intelligent algorithms in solving task allocation problems, in order to obtain more reasonable task allocation schemes.

2) Design aspects of the system UI interface. In the process of designing the power Internet of Things data monitoring system, the primary consideration of this article is the implementation of the core objective function, which is to calculate monitoring and prediction data through intelligent optimization algorithms. However, there are some imperfections in the system interface design. Therefore, this article will further optimize the UI interface of the system in the future.

3) In terms of hardware testing of the system. Although this article has conducted extensive system testing on the designed power Internet of Things monitoring system, including system functional testing and task allocation scheme effectiveness testing, these tests are all at the software level. Due to device limitations, this article is unable to use real wireless sensor nodes, power IoT edge devices, edge servers, and high-precision measurement tools for more convincing system hardware testing in a short period of time. In the future, with the improvement of experimental equipment, this article will supplement the hardware testing part of the obtained task allocation plan.

4) Lack of research on the positioning of power monitoring equipment makes it difficult to quickly locate the fault point after a fault occurs, and further research focuses will also include fault diagnosis.

7 Acknowledgement

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