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RESEARCH ARTICLE

Design and Optimization of an Intelligent Monitoring System for Overhead Lines Based on Common Information Model

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ABSTRACT Overhead lines act as the basic media for electricity transmission, and their stable operation remains really important to the whole power systems. As a result, real-time monitoring towards the operation status and fast discovery towards the device fault are in urgent demand. To deal with such issue, this work presents design and optimization of an intelligent monitoring system for overhead lines based on common information model (CIM). Firstly, tree format data structure is established using CIM, and analysis of CIM-XML data files are completed based on CIM. Then, the necessary relational tables without affecting database performance are established, in order to ensure that the mapped relational database can fully express all kinds of relationships in CIM. Finally, the abnormal temperature rise at the connection of overhead lines in traction power supply systems is selected as the object. And some simulation is conducted to evaluate performance of the designed prototype system. The results show that the system can accurately detect the voltage value from normal working state to the limit state of human safety voltage, with relatively small errors (about 3%-6%). Compared with inductive high-voltage detection technology, this system has higher detection capability. The intelligent monitoring of overhead lines based on the Common Information Model (CIM) optimizes the combined contact force characteristic values of pantographs and dynamic schemes of overhead lines, reducing the average risk loss.

INDEX TERMS Intelligent monitoring, database development, optimal design, common information model.

I. INTRODUCTION

Before or after running a railway, the locomotive needs to be prepared, and OL (Overhead lines) residual voltage detection step is a necessary step before climbing to the summit in the preparation process [1]. The use of autotransformer and other reasons make the short-circuit current constantly increase [2]. At the same time, the short-circuit current changes with the running state of the switch [3]. And the short-circuit current on the circuit breaker may approach or exceed its interrupting capacity at any time, which becomes a serious hidden danger for the safe operation of the power grid [4]. In order to overcome the deficiency of traditional artificial fault identification efficiency and accuracy, the OL non-contact image detection and monitoring system of high-speed railway based on deep learning has been widely used in high-speed railway operation and maintenance [5].

With the rapid development of electrified railway, it is urgent to realize long-distance centralized monitoring of load switches and electric disconnectors scattered in stations and sections [6]. Theodosoglou et al. can judge the abnormal temperature of this part by observing the change of the color-changing paint on the clamp or the attached temperature measuring piece through telescope or naked eyes, and this method has many limitations [7]. Li et al. introduced the design and application of unmanned aerial vehicle autonomous detection system for high-voltage transmission lines. By using an infrared thermal imager to detect the circuit and analyzing the temperature distribution in the image, it was found that there was a heating fault at the joint of a certain section of the circuit. In response to this issue, maintenance personnel promptly replaced and repaired it [8].

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Luo et al. explored the application of drones in transmission line detection, as well as the development of related technologies and algorithms. By performing preprocessing, feature extraction, and other operations on the images captured by drones, important information such as the appearance damage of the line and insulator contamination can be extracted.

In recent years, with the development of deep learning technology, some advanced convolutional neural network (CNN) models have also been applied in image processing, greatly improving the accuracy and efficiency of detection [9]. In addition, the framework can also be used to monitor and manage renewable energy generation facilities, as well as evaluate and manage the performance of power networks [10]. Mei proposed a joint simulation method of finite element model and multi-body model based on continuous contact force model, which comprehensively considered the simulation requirements of each subsystem [11]. Xiangchao et al. think that the interaction between pantograph and catenary mainly depends on the static geometric parameters of suspension device. The maximum entropy principle and maximum likelihood method are used to solve the statistical inverse problem, and the selection method of relevant geometric parameters is determined according to statistical information [12]. Lee et al. analyzed the dynamic characteristics of the pantograph when it passed through through OL modeling, and proposed that the service life of the pantograph can be predicted according to the influence of vehicle speed, pantograph-catenary system parameters on the fatigue life of the pantograph [13].

In order to ensure the safety of railway traffic, an intelligent monitoring system is necessary [14]. How can the object-oriented nature of CIM model be combined with the relational database that is popular all over the world at present, so that the universality and expansibility of CIM model can be truly realized, and the data access efficiency can meet the requirements of power production [15], [16]. In addition, CIM unified semantic standard is adopted to describe the power grid, which makes it possible to transfer information and share data across the network, and can realize the interoperability and splicing of power grid models. Combining sensor technology, embedded technology, mobile communication technology and Internet technology, this paper puts forward an intelligent monitoring system and optimization method of OL based on CIM algorithm, and realizes the remote online monitoring of the state of OL compensation device.

As an abstract model based on object-oriented technology, CIM unifies the power entity model, and the component interface regulates the standard way of information exchange and access to common data interfaces between applications/components and other applications/components. CIM is extensible. As CIM covers most fields of power system, it is only necessary to implement the CIM model of his concerned fields for applications [17]. With the appearance of new devices and devices in the description objects, CIM can be extended by itself before the CIM standard of these new devices comes out. The reserved application software is encapsulated to complete the exchange of existing data model and CIM model, so as to ensure the data to interact with other applications in CIM form.

This article can improve the real-time performance of the system by optimizing data processing processes and algorithms, thereby monitoring the status of overhead lines in real time, discovering problems in a timely manner, and taking corresponding measures. Can accurately detect the voltage value from normal working state to safe voltage limit state. Innovation contributions include:

1. This article studies an OL intelligent monitoring system based on the CIM algorithm. The system can accurately detect the voltage value from normal working state to the limit state of human safety voltage, with relatively small errors. Compared with inductive high-voltage detection technology, this system has higher detection capability.

2. Based on the CIM model and data standards, the system can integrate multiple sources of data, including electrical parameters of the line, environmental factors, etc., to provide comprehensive background information for the analysis of abnormal temperatures. Through a single objective optimization algorithm, the system can automatically identify patterns and trends of abnormal temperatures, issue early warnings, and reduce the likelihood of accidents.

3. Compared with traditional monitoring systems, the intelligent monitoring system for overhead lines based on CIM has stronger adaptability and intelligence capabilities. It can automatically adjust monitoring parameters, optimize warning thresholds, and even perform remote control and operation based on actual situations. This intelligent capability greatly enhances the flexibility and adaptability of the system. It helps to reduce the demand for manual inspections, reduce energy consumption and maintenance costs, and is in line with the development trend of green power grids.

Section I of the article elaborates on the background of remote monitoring of load switches in stations and sections under the rapid development of electrified railways. Section II provides a summary of intelligent power equipment fault diagnosis and more optimized customer management. Analyzed the design and application of autonomous detection systems for some high-voltage transmission lines. Section III provides an overview of the CIM model. Solved the problem of difficult real-time measurement of OL wear in OL wire breakage faults. Section V validated the multi-user response capability of the system and tested the response performance from a single task request to 150 concurrent tasks. Section 5 summarizes the entire text, and the results indicate that the system's functionality should be able to monitor the accuracy of data in real-time and detect and process erroneous data in a timely manner.

II. RELATED WORK

Each CIM package contains multiple classes, and UML's classes illustrate all the classes in the package and their relationships. When a class has a relationship with classes in other packages, those classes will also be displayed with an annotation to show which package they belong to [18] and [19]. Classes have properties that describe the characteristics of objects. Each class in CIM contains attributes that describe and identify a specific instance of the class. However, there are many additional data types in CIM. The capacitor bank has the property of maximum voltage, and its data type is voltage. The definition of this data type is in the domain package. The existing TFL modeling methods almost all rely on the load data monitored by the motion weighing system (WIM system).

However, the WIM system has natural defects such as unsatisfactory low-speed measurement accuracy and inability to measure the length and lateral position of vehicles on the lane, which limits the improvement of TFL simulation accuracy. For this purpose, Ge et al. developed a TFL monitoring system that integrates machine vision and WIM system functions. In this system, a deep learning method is applied to accurately detect vehicles and wheels in the video, and key parameters for TFL modeling are extracted based on the detection results [20]. The successful application of integrated circuits in road construction is still plagued by the accuracy and stability of their quality assessment. Ma et al. proposed the AICV acceleration intelligent compaction value, which is a new harmonic intelligent compaction quality evaluation index with higher accuracy than the commonly used CMV compaction measurement value [21].

Intelligent power equipment fault diagnosis and more optimized customer management, among which power grid automation is one of the most important issues to ensure the safe operation of the power grid. In recent years, intelligent scheduling methods based on big data analysis have been applied to power intelligent scheduling and have been significantly promoted. However, intelligent scheduling for big data analysis requires a large amount of historical data, which is sometimes not easily obtainable. Xiao proposed a new intelligent scheduling model based on reinforcement learning, which is more robust, secure, and efficient [22], [23]. The development time is different, the hardware and software adopted may come from different manufacturers, and the data and report formats may be incompatible with each other [24].

In the years after the publication of the draft standard, electric power workers all over the world have done a lot of in-depth research on it [25]. And they have completed the experimental verification of data import and export based on CIM (Common Information Model) [26]. For example, combined with CIM, some graphic support platforms with certain openness can be designed. This is expected to complete the integration of power system graphic drawing and topology structure [27]. With the rapid development of the power industry, the detection and maintenance of high-voltage transmission lines have become particularly important. Traditional manual detection methods have problems such as low efficiency and safety hazards, therefore, unmanned aerial vehicle autonomous detection systems have become a new solution [28].

The power management system framework based on cloud computing is a platform that can process and analyze large amounts of data in a short period of time, providing more effective decision support for the energy industry [29]. This system framework adopts distributed computing and storage technology, which can quickly process and analyze data from different sources, such as operational data of power companies, market data, and weather data [30]. Currently, many power companies have adopted a cloud based power management system framework for big data analysis [31]. For example, some companies use this framework to predict electricity demand, optimize energy consumption, and improve operational efficiency [32]. The overhead line intelligent monitoring system of the public information model can use multiple databases to store and manage data [33]. Real time database is a database used to process real-time data, which can quickly process and store real-time data, and provide real-time query and analysis functions [34].

Structured databases typically support one or more query languages, such as SQL (Structured Query Language). These query languages allow users to query and filter data based on specific conditions, such as searching for data from specific devices during specific time periods. Common real-time databases include Oracle Real Time Database and SQL Server [35]. In summary, some studies may not fully utilize the advantages of public information models, resulting in limited data processing capabilities and inability to process large amounts of data or achieve real-time monitoring. This may lead to unsatisfactory monitoring performance or delay issues. The design and research of intelligent monitoring systems for overhead lines based on public information models may lack real-time performance. They may not be able to quickly process and analyze data, thus preventing timely detection of problems and taking corresponding measures. The lack of necessary security measures and encryption technology makes data vulnerable to attacks and leaks.

Failure to consider the scalability of the system makes it unable to adapt to the needs of business development and technological progress. This may limit the future application and development of the system. In the past, it was difficult to fuse overhead line monitoring data, and data from different sensors needed to be fused to provide more comprehensive and accurate monitoring information. But the format, precision and frequency of data collected by different sensors are different, which leads to difficulties in data fusion. Although cloud computing and IoT technology are currently being used, further optimization may be needed in large-scale data transmission and processing. When integrating systems, compatibility issues between different systems may be encountered. Based on this research, this article utilizes a public information model to achieve standardization and consistency of data, improving the accuracy and reliability of the data. The introduction of advanced data fusion

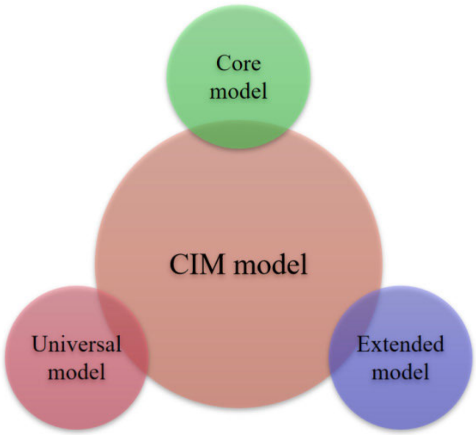

FIGURE 1. CIM model category.

technology has improved the comprehensiveness and accuracy of monitoring. Adopting a modular design facilitates system expansion and maintenance, while reducing system complexity.

III. RESEARCH METHOD

A. CIM MODEL OVERVIEW

Using UML (Unified Modeling Language), the entity type of power system is abstracted as a group of packages containing one or more class diagrams, and all classes in the package and their relationships are represented graphically. Then, according to the attributes of classes and their relationships with other classes, each class is defined in words, and the attributes of specific instances of classes are described and identified. According to the class used in the short-circuit current program defined by CIM, the short-circuit current real-time monitoring software based on CIM model runs after responding to the trigger. Firstly, the required data is read from the memory base based on CIM, and the zero-sequence electrical island is formed according to the network topology; The solution to this problem is to analyze the topology of zero-sequence network of the whole network before solving admittance matrix, and establish the relationship between nodes and zero-sequence electrical islands, which can improve the running speed of the program.

CIM model is a collection of computer system classes, which defines the relationships among systems, constructs an abstract framework that is easy to understand by designers, and forms tiny information. At present, there are three types of CIM models. Figure 1.

Core model: Analyze and describe the basic vocabulary of the management system, define each management field on the system platform, which is the part of functional association under the basic category, and extend the feasible starting point of the public model based on the basic vocabulary within the system.

General model: by defining the general model of a specific management domain, the related technologies independent of the system can be realized, which is helpful to develop management applications.

Extended model: as a technical extension of a general model, it is mostly used in a specific environment.

Aggregation relationship indicates that the relationship between classes is global and local. The global class "consists" of local classes, or the global class "contains" local classes. The local classes are part of the global class, and the local classes are not inherited from the global class as in generalization relationship. A composite aggregate belongs to its own part. As shown in Figure 2. Sharing is used to simulate the whole relationship, where the composite diversity is greater than 1. A shared aggregate is shared by several aggregates. Through generalization, a more specific class can inherit all attributes and relationships from a more generalized class at the upper level. Generalization or inheritance is a powerful technique to simplify the object graph.

B. OVERALL DESIGN OF OL INTELLIGENT MONITORING SYSTEM

This system is designed to solve the problem that OL wear is difficult to measure in real time in the solution of OL disconnection fault. Because of the large coverage of OL, low power consumption, low cost and safety must be given priority. This system also applies the idea and characteristics of Agent technology, which makes the system more intelligent and easy to modify and maintain. In the process of system design, everything from a complete device to a component is an Agent, and these agents are combined together to form a multi-agent system through mutual connection. Router Agent not only has the function of terminal node, but also has the function of forwarding data.

This system can correctly judge whether the OL pull-out value or conduction height exceeds the limit. The amount of data measured by geometric measuring equipment is very large, and it is impossible to send all these data by wireless communication. Therefore, it is necessary for the vehicle-mounted system to have the ability to judge the overrun, and only transmit the judged overrun data. Vehicle-mounted equipment needs to meet the requirements of automatic operation and unmanned operation. On-line monitoring can't be equipped with enough on-board operators, so the system should be able to work completely independently.

Along the railway line, the router/terminal equipment of this system is installed on each pillar, and the distance between adjacent pillars of OL is less than 65 meters. ZigBee wireless technology can be used for data transmission, and a small ZigBee network with about 31 nodes can be established by two kilometers. And transmits the collected parameters to coordinator agent in real time through ZigBee network. The online monitoring system of OL compensation device consists of monitoring terminal, GPRS data transmission platform and monitoring center. The monitoring terminal mainly includes data acquisition unit, control unit, trans-

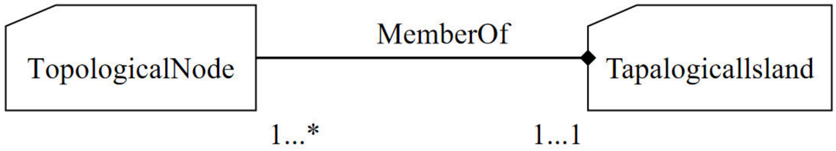

FIGURE 2. Example of composite polymerization.

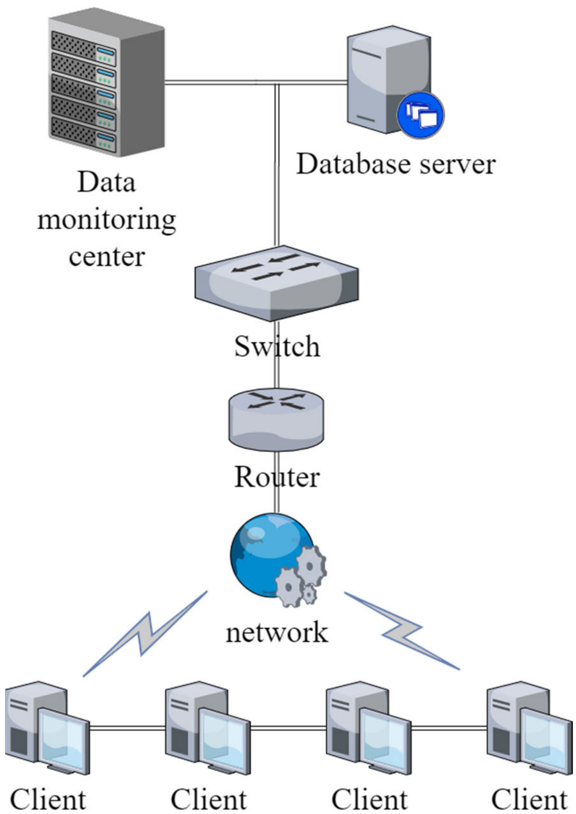

FIGURE 3. The overall structure of the system.

mission unit and power supply. The overall structure of the system is shown in Figure 3.

Monitor the environmental temperature of the terminal fixed-size dyeing site, and process the collected data separately for storage. In case of disconnection fault, take the initiative to send the report information to the monitoring center. The monitoring center stores, analyzes and displays the received data. The monitoring center sequentially sends telemetry commands to each monitoring terminal for data acquisition. The network topology of the whole system is star topology. There is no data interaction between monitoring terminals, and communication only takes place between the monitoring center and each monitoring terminal. The monitoring terminal doesn't send any information when it doesn't receive the inquiry information or when there is no over-limit disconnection fault.

The equipment in the testing part of the system is portable and mobile, and the testing personnel can connect it with the OL line according to their needs. Before the high-voltage electricity inspection, the self-checking function of the system can be used to judge whether the whole circuit is qualified, and the performance of the OL residual voltage detection can be improved through auxiliary measures such as nonlinear temperature compensation technology and instantaneous overvoltage protection technology. After the signal processing operation, the input analog signal is converted to analog.

The theoretical analysis and calculation are carried out in the plane perpendicular to the OL distribution. In the study, the height L is set to within 10 m. In the field of power frequency electromagnetic field, there are the following physical relations:

$$\omega \leq \frac{1}{\tau_s} \tag{1}$$

where ω is the angular frequency, τ_s is the propagation time of electromagnetic wave within the scope of the research object. If τ_s is much smaller than t, the delay effect can be ignored and the propagation time of electromagnetic wave can be ignored.

As an interference source, the contact system can influence the biological and engineering systems of adjacent railways through various coupling. According to the length of unit impulse response, digital filters are divided into two types: infinite unit impulse response digital filters and finite unit impulse response digital filters. The unit impulse response lengths of the two digital filters are different, so the system function forms and implementation structures are different, and the design methods are fundamentally different.

The difference equation of a N-order recursive digital filter is:

$$y(n) = \sum_{i=0}^{M} b_i x(n-i) - \sum_{i=0}^{N} b_i x(n-i) \tag{2}$$

The corresponding system function is:

$$H(z) = \frac{\sum_{r=0}^{M} b_r z^{-r}}{1 + \sum_{k=1}^{N} a_k z^{-k}} \tag{3}$$

It can be seen that the recursive digital filter has feedback from the output to the input, and the system function $H(z)$ has poles in the finite z plane.

The monitoring device is in the OL high voltage and strong electric field, and the opening and closing of the relay in the circuit will cause certain electromagnetic interference to the circuit, so it is necessary to design a low-pass filter circuit to reduce the interference to the sensor monitoring signal. The monitoring system adopts the second-order Butterworth filter, which gradually drops to zero in the stop band, and the filtering result is relatively stable. When calculating negative entropy, because the probability density function of the signal is unknown, the approximate calculation formula is usually adopted:

$$J(y) = \{E[g(y)] - E[g(y_{Gauss})]\}^2 \tag{4}$$

where y_{Gauss} is a Gaussian random variable with the same mean and covariance matrix as the variable y, g is a nonlinear function, and E is the mean operation.

The router/end node Agent of the system uses strain sensors to measure the tension. Strain sensor is mainly used to measure the strain of an object. The commonly used sensing element is resistance strain gauge, which can convert the strain of an object into the change of its own resistance.

For a metal wire with resistivity ρ, length L, radius R and cross-sectional area A, its resistance value R can be expressed by the following formula:

$$R = \rho\frac{L}{A} = \rho\frac{L}{\pi R^2} \tag{5}$$

As long as the resistance change R of the strain gauge is measured, the strain value of the wire rope can be obtained. According to the relationship between strain and stress, the stress value can be calculated as follows:

$$\sigma = E \cdot \varepsilon \tag{6}$$

The stress σ is proportional to the strain ε, and the strain ε of the wire rope is proportional to the resistance change, so the stress σ is proportional to the resistance change. This is the basic principle of measuring the strain of an object with a strain gauge. In practical application, the change of resistance can be converted into the change of output voltage by bridge measuring circuit.

C. SYSTEM OPTIMIZATION METHOD

The characteristics of grid monitoring are multi-source, high-dimensional, prior and heterogeneous. Nowadays, OL intelligent monitoring system mainly collects information monitoring data for power grid monitoring, and constructs integrated intelligent alarm to realize the diversification of technical monitoring, so as to ensure the reliability of application system. Optimize multiple systems to form an aggregate, ensure comprehensive regulation and control of relevant data, and unify data sharing, so as to ensure that the optimized power grid monitoring system built on CIM model can be compatible with various formats and realize high-quality regulation and control; Generally, it is handled manually by power grid management personnel on site; If the equipment is complicated and abnormal, the relevant maintenance workers should be informed to carry out supporting investigation and treatment. And record detailed abnormal conditions and alarm data, and after the abnormal problems are disposed, carry out matching updating and archiving operations for abnormal conditions again.

Similar to CIM model's abstraction of actual power system objects into classes, Java programs also abstract each component into classes, encapsulate the characteristics of each component in Java classes using private data members, and define their own methods for other classes or users. While each actual element in CIM/XML (extensible markup language) file is represented by a class object, and the data is also stored in the corresponding object. In this way, the analysis of all power system elements in CIM/XML file has been completed, and the Java program has obtained all the information.

In this way, after learning CIM Model, analyzing CIM/XML file structure and 7-layer tree data structure, CIM/XML file analysis is completed through three main classes: Model, ModelFactory and Plant. The specific work of the three classes is shown in Figure 4. CIM model is just an abstract model, which neither defines the specification of data in the model nor the format of data exchange. In engineering application, it is necessary to make clear and feasible regulations on the implementation of CIM model. The emergence of XML has solved this problem. The definition of RDF syntax based on CIM model standardizes the structure/markup definition of the corresponding XML document, so that it can be understood consistently in different environments. This makes XML widely used, which can simplify data sharing, data transmission and data upgrading of the system, and can also broaden the application fields of data.

CIM/XML language needs to deal with a very huge data pattern, so it will be problematic to express CIM pattern directly with DTD (Document Type Definition) definition. CIM is an object model established by object-oriented method. Classes are connected by the relationship between classes, while XML provides a hierarchical structure. In addition, Schema supports namespaces, built-in many simple and complex data types, and supports custom data types. Because there are so many advantages, Schema has gradually become a unified specification for XML applications. CIM/XML language defined by CIM RDF Schema can describe the power grid well, and its description language based on RDF (Remote Distribution Frame) framework can conveniently realize data transmission on computers.

The lifting force on the pantograph can make the pantograph head closely contact with the contact wire, and continuously provide power for the train. The coupling vibration of pantograph -OL system will occur due to the interaction between the pantograph-OL system and the pantograph-OL system. The tension of the string itself, the gravity of the string and the gravity of the clamp. Therefore, its expression can be written as:

$$F_{md,i} = \sigma\left(x - x_{d,i}\right)\left(\frac{1}{2}m_{d,i}g + m_{cl,i}g + f_{d,i}\right) \tag{7}$$

$$F_{cd,i} = \sigma\left(x - x_{d,i}\right)\left(\frac{1}{2}m_{d,i}g + m_{cl,i}g - f_{d,i}\right) \tag{8}$$

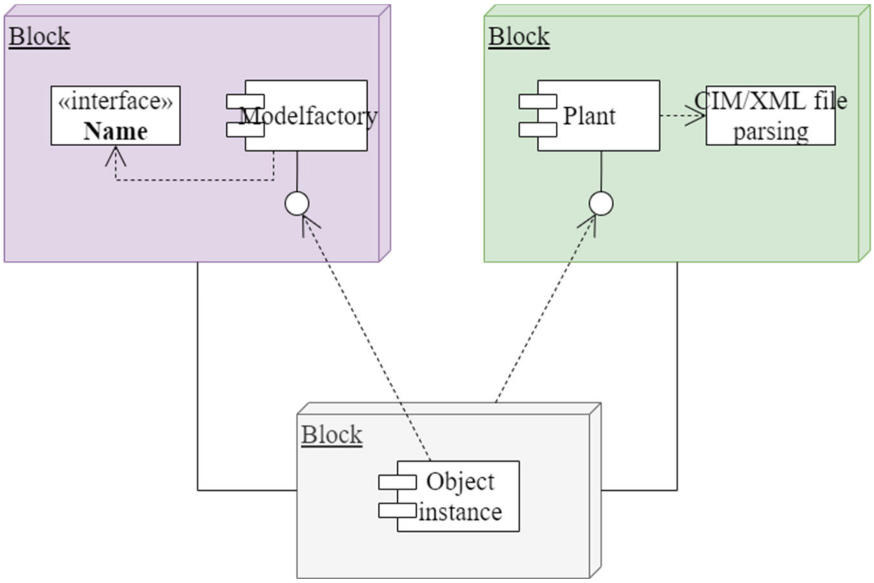

FIGURE 4. Schematic diagram of parsing program.

where $x_{d,i}$ represents the position of the ith hanger on the x axis, $m_{d,i}$ represents the mass of the ith hanger, $m_{cl,i}$ represents the mass of the ith clamp, g represents the acceleration of gravity, and $f_{d,i}$ represents the tension of the hanger.

Replacement and preventive maintenance are the main ways of OL system maintenance. In order to be more targeted, this paper divides preventive maintenance into minor repair and major repair. Minor repair refers to the improvement of the external working environment of the equipment. Improve the operation condition of the equipment, but it will not restore the equipment as new; Maintenance refers to the overall replacement of equipment. This kind of maintenance requires the most maintenance resources, which will restore the equipment state to a new initial state. In each maintenance cycle, it is limited by railway materials, funds, manpower and technology, and the maintenance plan in each cycle is bound by maintenance resources.

The maintenance resources in the k maintenance cycle of the system are the sum of the maintenance resources required by all equipment in different maintenance modes, as shown in formula (9):

$$M_k = \sum_{i=1}^{m} u_{i,k} \tag{9}$$

where $k = 1, 2, \cdots, N_p$, $u_{i,k}$ is the maintenance mode variable of equipment i in the kth maintenance cycle: no maintenance is 0, preventive minor repair is 1, preventive overhaul is 2, and replacement maintenance is 3.

When the vibration encounters a non-uniform particle, it will reflect, which will not increase the amplitude of the passive contact suspension. But when this reflected wave meets the pantograph running at high speed along the contact line, the situation will be completely different. This kind of interaction, restriction and interaction between pantograph and catenary caused by vibration waves is called Doppler effect, which is expressed by Doppler coefficient α. Doppler factor α is a coefficient related to wave propagation speed and running speed, and its theoretical calculation formula is:

$$\alpha = \frac{C_p - v}{C_p + v} \tag{10}$$

It can be seen that the propagation and reflection of waves along the contact line will change the contact force of pantograph and catenary, and the ratio of the contact force between adjacent times is usually expressed by γ.

$$\gamma = \frac{r}{\varepsilon} \tag{11}$$

If $\gamma > 1$ is used, the contact force increment of pantograph-catenary will be larger than the original contact force and jump; if $\gamma < 1$ is used, the vibration of the contact line will gradually ease. When $\gamma = 1$, the amplitude will neither increase nor decrease, and the contact force will remain the same.

Figure 5 shows the receiving data processing flowchart. Monitoring messages typically consist of a single transmission control character or a single transmission control word guided by several other characters. The guiding characters are collectively referred to as prefixes, which contain identifier sequence numbers, address information, status information, and other required information. The monitoring terminal receives the query req command sent by the center and responds to the command to upload data. The sending method completes the upload of alarm information: the monitoring terminal determines the fault, sends the alarm information to the center, and waits for confirmation from the upper computer. The communication establishment is initiated by the remote data concentrator, and the central communication server is in a waiting state. After the link is established, the data concentrator first sends its ID number to the central server for registration. The communication server will only send commands to read data after successful registration. The design of the service software adopts multi-threaded processing and event driven technology.

When the pantograph and OL are not off-line, the coupling between pantograph and catenary is realized by static lifting force F_0 in static state and contact force F_{pc} in dynamic state. At this point, the vertical displacement of the bow head is equal to the vertical displacement of the contact point on the contact line, namely:

$$w_h = w_c(x, t)\,|_{x=Vt} \tag{12}$$

It should be emphasized that at this moment, the velocity and acceleration of the pantograph head are not equal to those of the contact point on the contact line. The formula (12) is used to obtain the first-order and second-order full differential of time t, and the additional constraint relationship of velocity and acceleration between the bow head and the contact point on the contact line is obtained, namely:

$$\dot{w}_h = w_c' V + w_c'\,|_{x=Vt} \tag{13}$$

$$\ddot{w}_h = \ddot{w}_c + 2V\dot{w}_c' + w_c'' V^2\,|_{x=Vt} \tag{14}$$

In the iterative process of the algorithm, the w can be dynamically adjusted to ensure that the algorithm can search for a better area in the global range at a faster speed in the early stage, and can perform fine optimization near the extreme point in the later stage.

The strategy of linear decreasing dynamic inertia weight is adopted, as shown in formula (15):

$$w = w_{\max} - \frac{(w_{\max} - w_{\min}) \times T}{T_{\max}} \tag{15}$$

where $T_{\max}$ is the maximum number of iterations, $w_{\max}$ is the maximum inertia weight, $w_{\min}$ is the minimum inertia weight, and T is the current number of iterations. The research shows that the initial population has great influence on the optimization effect, and the better the diversity of the initial population, the better the optimization effect. In this paper, a chaotic initial population method is proposed, which uses chaotic Logistic model to generate the initial population. The model is expressed as:

$$x_{k+1} = \lambda x_k (1 - x_k) \tag{16}$$

where λ is the control parameter, and when $\lambda = 3$, x_k is in a completely chaotic state between [0,1].

IV. RESULT ANALYSIS

Based on the results of the requirements analysis, the structure of the database can be designed in this article. The intelligent monitoring system for transmission lines analyzes various device information stored on overhead lines, such as device type, location, manufacturer, etc. Store sensor information installed on the device, such as sensor type, location, measurement range, etc. While storing data, we also consider how to extract useful information from the data. Use the Pandas library in Python for data cleaning and processing, and use the matplotlib library for data visualization. When storing data in a database, this article considers data integrity. Ensure the accuracy and consistency of data, for example, each device should have only one corresponding sensor, and each sensor should have only one corresponding measurement value. To improve query efficiency, create indexes for commonly used query fields. For example, query fields for timestamp, device ID, and sensor ID.

The upper computer that meets the system requirements is used to display and control the output of the development interface. Compared with the direct output of ordinary liquid crystal displays, the test equipment is used to take the voltage output source as the detection signal. Figure 6 shows the residual voltage output data during stable operation with relatively appropriate contact time. The relative fluctuation of data is small, and the system can accurately detect the voltage value from the normal working state to the limit state of human safe voltage, with the relative errors of 5.70% and 3.37%, respectively. Compared with the inductive high-voltage detection technology, this system has higher detection performance. Experimental data show that the monitoring system can effectively detect the existence of dangerous residual voltage source, and its working accuracy and stability are good.

In the task of OL image detection, it is often faced with the situation of identifying and reasoning a large amount of image data, which will consume a lot of resources of the background operation server. TF Serving is an open-source software for deploying machine learning models, which provides high-performance inference services, supports multiple types of models, and can be easily extended. Its distributed computing function can help allocate computing tasks between multiple servers, effectively utilizing system resources and improving processing speed. This system realizes the computing service through the distributed computing function of TF Servicing component. To verify the multi-user response capability of the system, the response performance from single task request to 150 concurrent tasks was tested respectively, and the results are shown in Figure 7. It can be seen from the figure that, for different concurrent task requests, the system can respond to tasks well, and there is no system request blocking. The average response time of a single task is less than 12 ms and 25 ms on cluster server and embedded system, respectively.

For the performance test of the monitoring system, the key point is to run with the help of the functions of the host, thus reflecting some key performance of the system. If the power monitoring system is faced with corresponding risks and problems in the working stage, it will transmit signals in the shortest time, and study the fault types through professional

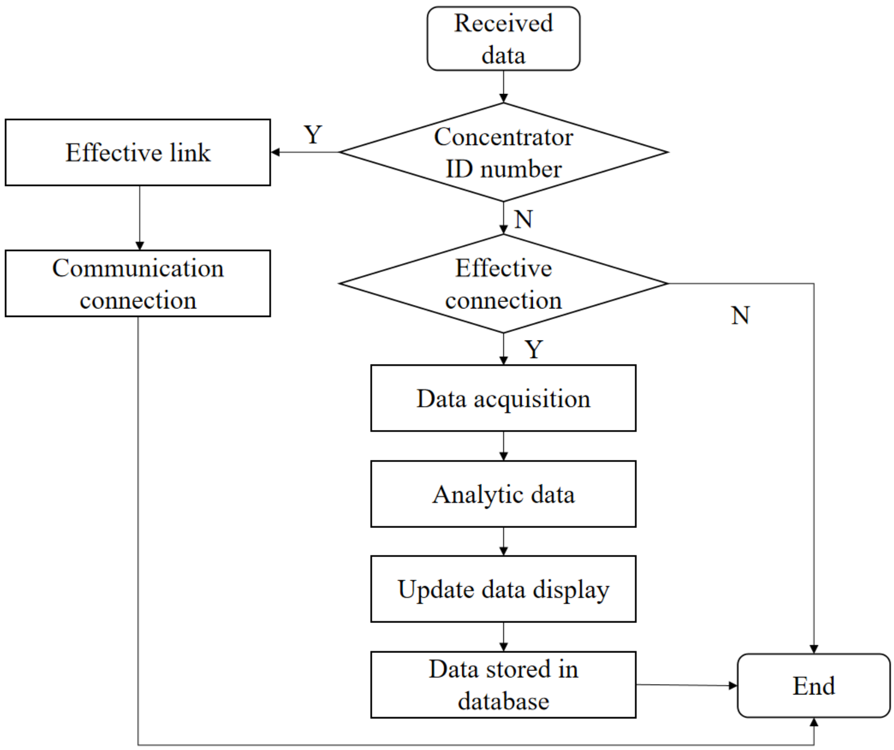

FIGURE 5. Flow chart of receiving data processing.

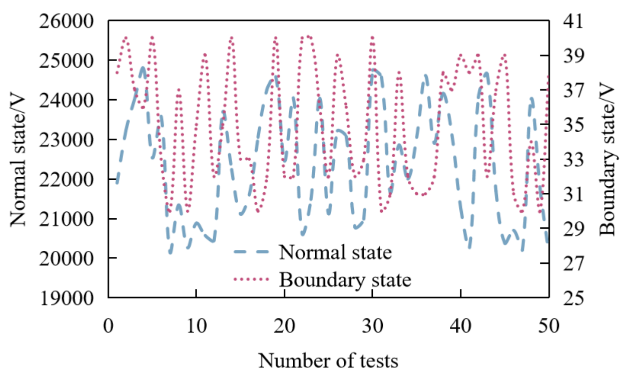

FIGURE 6. Residual network voltage data curve.

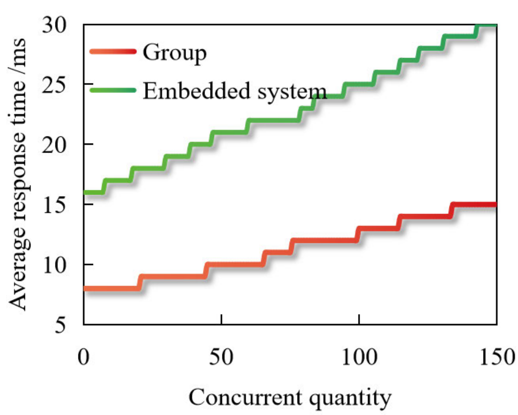

FIGURE 7. Multi-user concurrent testing.

systems and staff. In addition, some measures are taken to ensure the safety and stability of the working system. The performance test results of the monitoring system refer to Table 1, which provides the general response time of different processing links under different concurrency and user scale, and has been carefully sorted out at the same time. The unit is seconds.

In terms of response time, it is considered as meeting the expectation. In addition, in terms of performance requirements, the limit user concurrency scale that the system needs to deal with is 100. Combined with the contents of Table 1, it can be observed that when dealing with 100 users, it can still meet the actual demand of response time, so it is considered that the detection of this part meets the conditions. For intelligent monitoring systems, real-time performance is crucial. The monitoring data of overhead lines needs to be processed and analyzed quickly in order to promptly identify problems and take corresponding measures. Therefore, the system adopts efficient algorithms and data processing techniques to reduce processing latency.

In addition, network latency is also a factor that needs to be considered, and it should be reduced by optimizing network communication protocols and reducing data transmission volume. To ensure the accuracy and reliability of monitoring data, the system has error rate monitoring function. This

TABLE 1. Monitoring system performance test results.

Number of concurrent users	Add information	Report creation	Information inquiry
10	0.2239	0.0508	0.1459
20	0.2956	0.0549	0.4519
30	0.3304	0.0608	0.48
40	0.3785	0.1904	0.4886
50	0.436	0.1985	0.5534
60	0.4522	0.3335	0.5803
70	0.4934	0.4771	0.6223
80	0.5335	0.5152	0.6577
90	0.638	0.5201	0.7746
100	0.7171	0.6709	0.7844

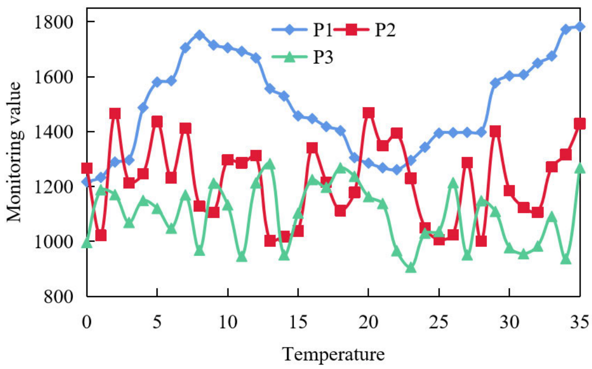

FIGURE 8. Predicted value monitoring results.

function should be able to monitor the accuracy of data in real-time and detect and process erroneous data in a timely manner. Use reliable communication protocols to transmit data, verify and inspect data, and regularly maintain and inspect equipment. As is shown in Figure 8, P1 is the predicted value of the compensation device falling from the forecast air temperature, P2 is the predicted value of the compensation device falling from the measured air temperature, and P3 is the predicted value of the compensation device falling from the field monitoring.

It can be seen that although there are some differences between the field monitoring values and the values fitted according to the measured air temperature, the differences are not significant. Combined with the analysis of the actual situation, besides the error of the monitoring device itself and the fitting error, it is considered that it is influenced by pantograph-catenary vibration and natural wind speed when high-speed rail is running, and this error can be continuously corrected by averaging a large number of data.

In this paper, the single-objective optimization algorithm is also used to calculate the maintenance plan. The characteristic of single objective is that only one objective is optimized, the other objective is taken as a constraint condition, and only one optimal result can be obtained in each calculation. The optimization with maintenance cost as the constraint condition and the optimization with maintenance cost as the optimization target and OL system reliability as the constraint condition are compared with the results of double-objective optimization of system reliability using multi-objective optimization algorithm. The results are shown in Figure 9.

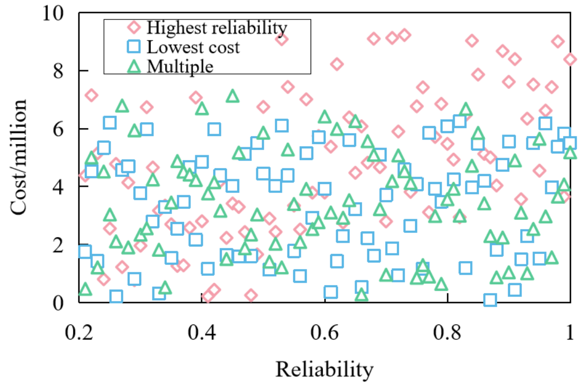

FIGURE 9. Comparison of optimization results.

Figure 9 compares the validation results of the target optimization algorithm with the highest reliability and lowest cost. For optimization constrained by maintenance costs, this means minimizing maintenance costs as much as possible while meeting other conditions. In optimization with maintenance costs as the optimization objective, the goal is to minimize maintenance costs as much as possible. In optimization with OL system reliability as a constraint, it is necessary to minimize maintenance costs while meeting system reliability requirements. The results of using multi-objective optimization algorithms for dual objective optimization of system reliability can consider two or more objectives simultaneously, such as minimizing maintenance costs while meeting system reliability requirements. This optimization method can find a relatively optimal equilibrium point, rather than optimizing only one objective while ignoring other objectives.

It can be seen that the result of multi-objective optimization gives the limit boundary of single-objective optimization. The optimization result with the lowest cost for a given reliability is very close to the multi-objective optimization result, while the optimization result with the highest reliability for a given maintenance cost approaches to the multi-objective optimization result from a poor direction. In addition, the multi-objective optimization algorithm can get the complete distribution of the optimal front-end once, while the single-objective optimization algorithm can only get one optimal solution each time, so it must be calculated many times. Therefore, the multi-objective optimization algorithm has great advantages over the single-objective optimization algorithm in computational efficiency.

Single objective optimization problem is the most common optimization problem, which aims to minimize or maximize a specific objective function. This algorithm is simple and clear, easy to understand and apply. The disadvantage is that it can only handle a single goal and cannot balance multiple goals. For complex multivariate functions, finding the global

TABLE 2. Risk loss value under different maintenance calculation schemes.

MAINTENANCE CYCLE	SINGLE TARGET VALUE AT RISK (TEN THOUSAND YUAN)	MULTI-OBJECTIVE VALUE AT RISK (TEN THOUSAND YUAN)
1	85.071	124.618
2	155.101	122.601
3	109.612	99.128
4	151.428	75.894
5	108.413	142.888
6	116.492	79.448
7	117.022	53.999
8	80.061	156.388
9	133.638	148.682
10	120.304	121.225

optimal solution may require a significant amount of computational time and resources. Multi objective optimization problems are even more complex, involving multiple conflicting objectives that require simultaneous optimization and finding a relatively optimal solution. Multiple objectives can be considered simultaneously to achieve more comprehensive optimization. For complex problems with multiple conflicting objectives in practical applications, multi-objective optimization is more practical. The disadvantage is that there are multiple optimal solutions and no global optimal solution. It is necessary to balance the conflicts between different goals and provide additional decision-making basis. For large-scale multi-objective optimization problems, the computational complexity is usually high.

The maintenance cost of multi-objective optimized maintenance plan is obviously lower than that of single objective, because the multi-objective maintenance plan gives full play to the value of different maintenance methods during the operation period. It shows that more preventive minor repairs are adopted for the power supply equipment in OL system, and the preventive overhaul and replacement maintenance times of some power supply equipment with low risk loss such as insulators and positioners are reduced. The specific risk values obtained from 1-10 maintenance cycles are shown in Table 2.

The average risk values of the two models are similar, but the multi-objective optimization model takes the average risk loss of the system as the target, which makes the fluctuation of optimization results smaller and the optimization strategy of maintenance plan more reasonable. There are many factors that affect the dynamic performance of pantograph-catenary system, such as contact suspension type, thread tension and material, span, length and tension of elastic sling, etc. In order to improve the significance of the target parameters, the train running speed is increased to 330 km/h. Firstly, the level table of pantograph factors is established. The pantograph factors include: equivalent mass and stiffness of pantograph head, equivalent mass and stiffness of upper frame, equivalent mass and damping of lower arm. Through pantograph-catenary dynamic simulation, statistical test, original scheme and optimal combination contact force characteristic values, see Table 3.

Through orthogonal test analysis of several pantograph parameters, it is concluded that the equivalent mass of pantograph head is the most sensitive parameter of pantograph-catenary dynamic response, and the optimal combination parameters of pantograph can obviously improve the dynamic performance, and the test index does not linearly change with single pantograph factor. The pantograph-catenary contact force of the pantograph with the optimal horizontal combination parameters obtained from the experiment fluctuates less than that of the pantograph with the original parameters. The orthogonal test results show that changing the parameters of pantograph can improve the dynamic performance of pantograph-catenary, and this conclusion can provide theoretical basis for the optimal design of pantograph.

The optimized model may find a more stable level of pantograph coefficient. This means that the power system will not experience significant fluctuations in its pantograph coefficient when dealing with power loads, responding to emergencies, or under various operating conditions, thereby enhancing the stability of the power system. The model will find a coefficient level that improves the efficiency of pantograph use. This means that under the same operating conditions, the optimized model can better utilize the pantograph, keeping it in working condition for more time, thereby improving the operational efficiency of the power system. The optimized model may find a safer level of pantograph coefficient. This is reflected in less damage to the contact network or less wear on the pantograph itself. In either case, this is a positive impact on the entire power system, as it can extend the service life of the overhead contact system and pantograph. At the same time, the model will find a more adaptable pantograph coefficient level. This means that in the face of different operating conditions, such as temperature changes, wind changes, etc., the model can better adjust the working status of the pantograph, thereby better responding to these changes.

Based on the above, the system can provide decision-makers with more accurate and comprehensive information support by collecting and analyzing a large amount of real-time data. This data-driven decision-making method can improve the accuracy and reliability of decision-making. Compared with traditional monitoring systems, the intelligent monitoring system for overhead lines based on CIM has stronger adaptability and intelligence capabilities. It can automatically adjust monitoring parameters, optimize warning thresholds, and even perform remote control and operation based on actual situations. This intelligent capability greatly enhances the flexibility and adaptability of the system. The system adopts a modular and scalable design concept, which can be customized and expanded according to actual needs. This means that the system is not only suitable for monitoring overhead lines in traction power supply systems, but can also be applied to other types of overhead line monitoring

TABLE 3. Comparison of statistical eigenvalues of contact force.

Scheme	Standard deviation of contact force/N	Minimum contact force/N	Maximum contact force/N
Original scheme	30.32	99.68	255.24
Experimental scheme	20.88	136.93	287.26
Combination scheme	21.69	140.57	228.71

scenarios. The intelligent monitoring system for overhead lines based on CIM fully considers the principles of sustainability and green environmental protection in the design and implementation process. It helps to reduce the demand for manual inspections, reduce energy consumption and maintenance costs, and is in line with the development trend of green power grids.

V. CONCLUSION

With the continuous development of high-speed railway traction power supply system intelligence, this paper studies OL intelligent monitoring system and optimization method based on CIM algorithm. Because of the existence of virtual classes in CIM, some virtual tables will be generated in relational database correspondingly, and there are many foreign keys in relational tables, which makes it troublesome and inefficient for programmers to operate the database. At the same time, it also realizes multi-task concurrency and distributed computing services of user clusters, which increases the expansibility of the system and can flexibly adapt to various application scenarios.

The system can accurately detect the voltage value from the normal working state to the limit state of human safe voltage, with the relative errors of 5. 70% and 3. 37%, respectively. Compared with the inductive high-voltage detection technology, the system has higher detection performance. The system can accurately detect the voltage value from normal working state to the limit state of human safety voltage, with relatively small errors. Compared with inductive high-voltage detection technology, this system has higher detection capability. The intelligent monitoring of overhead lines based on the Common Information Model (CIM) optimizes the combined contact force characteristic values of pantographs and dynamic schemes of overhead lines, reducing the average risk loss. This article proposes that changing the parameters of the pantograph can improve its dynamic performance, providing a theoretical basis for optimizing the design of the pantograph.

However, research still has certain limitations. Real time monitoring of overhead lines requires efficient communication and data processing technologies. While processing large amounts of data, ensuring the real-time and stability of the system places high demands on both hardware and software. In the future, it is necessary to improve the compatibility between different systems and reduce the difficulty of integration through standardized and open architecture design. At the same time, explore new integration methods to achieve more efficient information sharing and system linkage.

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