International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8657-8670

https://doi.org/10.70517/ijhsa463740

Architectural Design of an Intelligent Data Analysis-Empowered Power Information Management Platform

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Abstract the traditional power system monitoring and control methods still have some problems, such as difficult data processing, insufficient robustness, excessive manual intervention and insufficient adaptability. By introducing artificial intelligence (AI) algorithm, this paper aimed to improve the robustness and data processing ability of power system and realize automatic intelligent control to adapt to the modern challenges of power system. In order to meet the need of large quantity and high quality marked image data during the actual training of power system intelligent monitoring method (IMM), this paper constructed the power system intelligent monitoring image data set. In order to analyze the IMM of power system based on AI technology, the E-R Model (Entity-Relationship Model) database was established, and the variational mode decomposition method was used to extract the abnormal state characteristics of power system equipment in the image. The feature was input into support vector machine (SVM) to realize real-time recognition of abnormal state of power system equipment. This paper also analyzed an efficient single-agent reinforcement learning algorithm, Q-learning, to achieve the optimal coordinated control of power system. In this paper, the power system equipment of a power company was simulated. The results show that the false recognition rate and missing recognition rate of the proposed method were both below 0.4%, while some of the false recognition rate and missing recognition rate of the traditional power system monitoring and control method were over 0.4%. Compared with the traditional method, the identification performance of this method has been effectively improved, and the accuracy rate and recall rate of this method have reached more than 80%. The maximum response time of the proposed method was 1477.18 ms and the maximum processing time was 2452.34 ms, both of which were superior to the traditional power system monitoring and control methods. The proposed method has better system performance. Therefore, the IMM of power system based on AI technology is expected to solve traditional problems such as difficult data processing, insufficient robustness, excessive manual intervention, and insufficient adaptability, which can make substantial contributions to the development of intelligent monitoring and control of power system.

Index Terms Power System, Intelligent Monitoring and Control, Artificial Intelligence Technology, Variational Mode Decomposition, Support Vector Machine

I. Introduction

As the demand for electricity continues to grow in modern society, the stable operation and efficient management of the PS (Power System) has become a key element to ensure the normal operation of industrial production, commercial activities and daily life. However, the increasing complexity and scale of PS have brought new challenges to their monitoring, maintenance and control. The traditional PS monitoring and control methods have shown bottlenecks in dealing with complexity, dynamics and uncertainty. As a key infrastructure, the stable operation of PS is very important for the development of social economy. Traditional methods are difficult to satisfy the actual its needs. In order to meet these challenges, AI technology has increasingly become the focus of attention in the field of PS, providing a new way to realize intelligent monitoring and control.

In the past research, many scholars have proposed various methods to improve the monitoring and control of PS, for example, to improve the operating efficiency, reliability and maintenance effect of PS. Bedi G. summarized the important role of the Internet of Things in the monitoring and control of PS, and found that the Internet of Things can provide opportunities for real-time data acquisition, remote monitoring and intelligent control of PS. However, there are still security and privacy concerns, as well as the challenges of large-scale data processing [1]. Butt Osama Majeed summarized the latest advances in smart grid technology and its future prospects in PS. He pointed out that smart grid technology has potential in the monitoring and control of PS, which can realize real-time data acquisition, analysis and prediction, and improve the reliability and efficiency of the system [2]. In order to monitor power consumption, energy usage and equipment status in real time, Shamshiri M pointed out that the Malaysian Technical University Malacca has successfully implemented an Iot-based power energy monitoring system. This IMM provides more information for the management and control of the PS, helping to achieve more efficient energy distribution and fault detection [3]. However, these methods have many limitations in the face of complex PS environment, such as being unable to adapt to the highly variable PS and difficult to handle large-scale data. It also requires stronger protections against unauthorized access and data breaches, which limit the efficiency and stability of the PS.

Recently, some researchers have tried to apply AI technology to the monitoring and control of PS. For example, in order to achieve efficient detection and intelligent analysis of power equipment, effectively improve the maintenance efficiency and reliability of the system, Jenssen Robert combined drone technology and deep learning to achieve intelligent monitoring and inspection of power line components. This can improve the efficient detection and intelligent analysis of power equipment, and effectively improve the maintenance efficiency and reliability of the system [4]. Cheng Lefeng applied AI to the field of intelligent energy and PS, optimizing energy production, transmission and distribution through machine learning technology to improve the efficiency and reliability of PS. However, one of the current challenges is the diversity and complexity of data, which requires in-depth research on how to deal with real-time and large-scale data streams to improve prediction accuracy and decision accuracy [5]. In addition, in order to optimize the energy distribution and network stability of the PS, Zhang Liang used deep deployment neural network to estimate and forecast the state of the PS, providing efficient real-time analysis and prediction methods for the PS [6]. However, although these methods have been successful in some aspects, there are still some challenges, such as large amount of required data, high training complexity, insufficient interpretation, and insufficient data samples resulting in insufficient model generalization ability. It needs to find a balance between performance and interpretability to achieve more reliable and sustainable PS management.

In this paper, AI technology is comprehensively applied to solve the problems existing in the traditional PS monitoring and control methods, so as to realize the intelligent operation of the PS. This paper would explore the application of AI technologies such as deep learning and RL to improve the data processing capability, robustness, automation level and adaptability of PS. Through these methods, new solutions are provided for the stable operation and optimization of PS, which can adapt to the challenges faced by modern PS. This paper not only focuses on technological innovation, but also focuses on how to seamlessly integrate AI technology into the practical application of the PS, so as to promote the development of the power industry in the direction of intelligence and self-adaptation.

II. PS Intelligent Monitoring Image Data Set Construction

II. A.Image Data Set Acquisition

The PS intelligent monitoring image data set constructed in this paper is taken from the CPLID data set published on the Internet. The images included two main categories: ordinary insulator and shock hammer images obtained by unmanned aircraft, and images containing damaged insulators. Figure 1 shows a partial image of the data set, where a is the normal insulator image and b is the damaged insulator image.

a. Image of a normal insulator

b. Image of damaged insulator

Figure 1: Partial image of CPLID data set

Since the training data types of CPLID data sets are not enough, in order to obtain more types of image data to ensure the diversity of data sets, unmanned aircraft are used to take aerial photos of power equipment at different times in a certain area and classify them.

The obtained image size is 840x680 and includes various types of faults. Part of the image is shown in Figure 2, where a is the image of part of the wire slack aging, b is the image of part of the insulator damaged.

a. Image of slack aging of some wires

b. Image of broken insulator

Figure 2: Images of some power equipment faults obtained by aerial photography

II. B.Data Preprocessing

(1) Image fault labeling

LabelMe object annotation tool was used to annotate the unannotated objects in the data set. When there are no detected defects in the image, the image would not be labeled. If the insulator is broken, the wire is loose and aging, etc., it is marked with a rectangular box. Different targets have different location distributions in the image. The target annotation results are output in the form of xml (eXtensible Markup Language) files. Figure 3 shows part of the data image after the markup is completed.

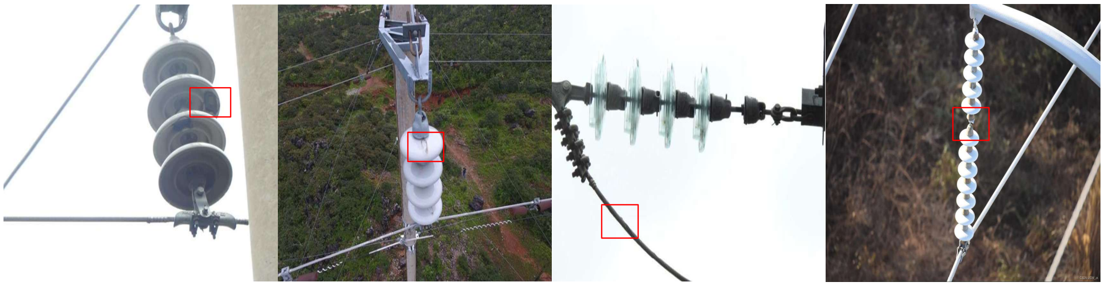

Figure 3: Partial data images after annotation

(2) Data image enhancement

Data enhancement technology is an effective method to improve the robustness of object detection algorithms. Based on the existing data set, this paper would improve the integrity of the data set through data enhancement technology. In specific applications, this paper randomly superimposes various enhancement methods, including the following enhancement methods:

a) It can set the rotation direction and rotation angle of the image, so that the image can be rotated or reversed to enhance the robustness of the angle of view taken by the unmanned aerial vehicle.

b) In the process of image processing, Gaussian, pepper and salt noise is added to improve the anti-interference ability of image processing.

c) In order to prevent objects from gathering in the center of the image, the motion range of the image center can be set, so that the image can be translated horizontally and vertically arbitrarily.

d) The cropping intensity can be set to randomly crop the input image.

e) People can set the scale coefficient and the center shear range to make the image size change.

f) The Value of image HSV (Hub, Saturation, Value) can be adjusted randomly.

By setting the angle range parameter, the input image can be rotated arbitrarily so that the pixels of each image are rotated at the same angle. The pixels of the image before and after rotation correspond to:

$$\begin{cases} \mathrm{x}_0 = \mathrm{r} \cdot \mathrm{c}\alpha \\ \mathrm{y}_0 = \mathrm{r} \cdot \mathrm{s}\alpha \end{cases} \tag{1}$$

$$\begin{cases} x = r \cdot c(\alpha + \theta) = x_0 \cdot c\theta - y_0 \cdot s\theta \\ y = r \cdot s(\alpha + \theta) = y_0 \cdot s\theta - y_0 \cdot c\theta \end{cases} \tag{2}$$

In the formula, (x_0 , y_0) is the coordinate before scaling; (x , y) is the coordinate after scaling, and θ is the rotation angle. The essence of image scale adjustment is to adjust the proportion of each pixel vector in the image.

By setting the image scaling threshold, the input image can be scaled arbitrarily. The lost area in the process of scaling is filled with gray scale, so that the size of the original image is consistent in the process of scaling. The pixels of this image correspond to before and after scaling:

$$\begin{cases} x = k_x x_0 \\ y = k_y y_0 \end{cases} \tag{3}$$

Among them, k_x and k_y are horizontal and vertical scaling ratios. A total of 1328 data sets were obtained. The image data set includes a training set and a test set according to a ratio of 3:1, and a random combination enhancement was selected for each image. Figure 4 shows part of the image enhanced with random combination data, in which Figure 4 (A) is the original image; Figure 4 (B) is the image enhanced with rotation and Gaussian noise data; Figure 4 (C) is the image enhanced with cut and contrast data.

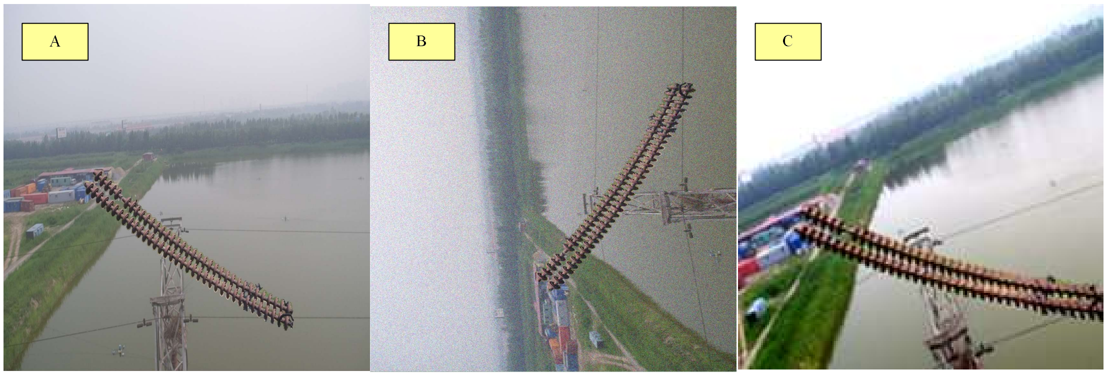

Figure 4: Partial data enhanced image

Figure 4 (A) Original drawing
Figure 4 (B) Rotation and Gaussian noise data enhancement
Figure 4 (C) Clipping and contrast data enhancement

A total of 996 training set samples obtained after pretreatment were trained to train the IMM of PS based on AI technology. The proportion of abnormal states of different equipment in the sample set is shown in Figure 5.

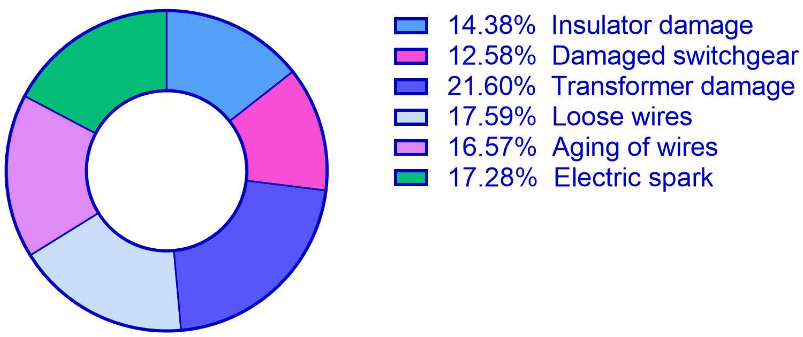

Figure 5: Proportion of abnormal states of different devices in the sample set

III. Intelligent Monitoring Design of PS in View of AI Technology

III. A. Establishing Database

(1) Database design

In order to complete the database design conveniently, quickly and accurately, the first thing to design is the database conceptual model. Its modeling belongs to an abstract process, which can initially realize the modeling of the real world to the computer, and this step is very important. E-R model refers to drawing a diagram of “entity - relationship” through the three concepts of “entity”, “attribute” and “connection”, so as to realize the construction of the model.

Based on the functional requirements of the system, the data conceptual model analyzes the entity attributes of the system and the relationship between different entities from the functional requirements, and then integrates them, and finally obtains the E-R diagram. It can be seen from the system requirements that the system entity includes user information, power equipment information and data information. Figure 6 shows its E-R model diagram.

(2) Database table design

In the data processing of system software, database is the core part. If people can design a reasonable and complete data table structure, they can effectively reduce the redundancy of data and provide fast data reading operation for the system. The database is based on the data table, its main function is to manage the data on the user and the terminal device, and to add, delete, check and change the data. The logical structure of the data table is designed according to the designed database E-R model diagram, so the database should establish three tables: user information table, power equipment information table, data information table. The user and the terminal device is one-to-many relationship, each terminal device and the data returned to the database is one-to-one correspondence. In addition, when designing the structure of the data table, the various fields are also constrained and their types are classified to optimize the space they occupy.

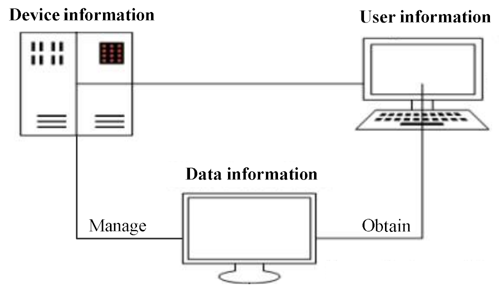

Figure 6: E-R model diagram

a) The user information table is mainly used to save the registered user information, and manage it, login verification and other functions. The user table mainly includes user ID (Identification), user name, password, mobile phone number, mailbox and other information. The user information table is displayed in Table 1.

Table 1: User information table

Field name	Types	Restrictions
ID	Integer	Primary key, self growing
Username	Varchar(20)	Not empty, only
Password	Varchar(20)	Not empty
Email	Varchar(50)	Not empty, only
Phone	Varchar(11)	Not empty, only

b) The equipment information table is used to store the basic information of the power equipment, including the user ID, longitude, latitude, and the time of establishment. Here, the user ID is a foreign key. Table 2 shows the data table structure of the device information table.

Table 2: Device information table

Field name	Types	Restrictions
ID	Integer	Primary key, self growing
Device code	Varchar(20)	Not empty, only
User ID	Integer	Not empty, forergn key
Longitude	Decimal(10, 6)	Not empty
Latitude	Decimal(10, 6)	Not empty
Created time	Datetime	Not empty

c) Data information table is used to store the data collected by the sensing terminal and establish a connection with the relevant sensing terminal, including user ID, device ID, voltage, current, temperature, humidity, and establishment time. The user ID and device ID are foreign keys. Table 3 shows its data table structure.

Table 3: Data information table

Field name	Types	Restrictions
ID	Integer	Primary key, self growing
User ID	Integer	Not empty, forergn key
Decive ID	Integer	Not empty, forergn key
Voltage	Decimal(10, 2)	*Selective filling*
Current	Decimal(10, 2)	Selective filling
Temperature	Decimal(10, 2)	Selective filling
Humidity	Decimal(10, 2)	Selective filling
Created time	Datetime	Not empty

III. B. Composition of Intelligent Monitoring of PS

The intelligent monitoring of PS is composed of multiple parts. The system uses modern control technology, visualization technology, modern communication technology and AI technology, and based on different auxiliary facilities, intelligently monitors the hot spots, power and environment of power equipment [7]-[9]. In addition, the data can also be intelligently analyzed, the data can be comprehensively visualized, and the intelligent linkage alarm can be realized. It can effectively help power equipment informatization, maintenance and operation, and serve the major overhaul, major operation, and whole life cycle management of smart grid. The basic architecture of intelligent monitoring of PS is shown in Figure 7.

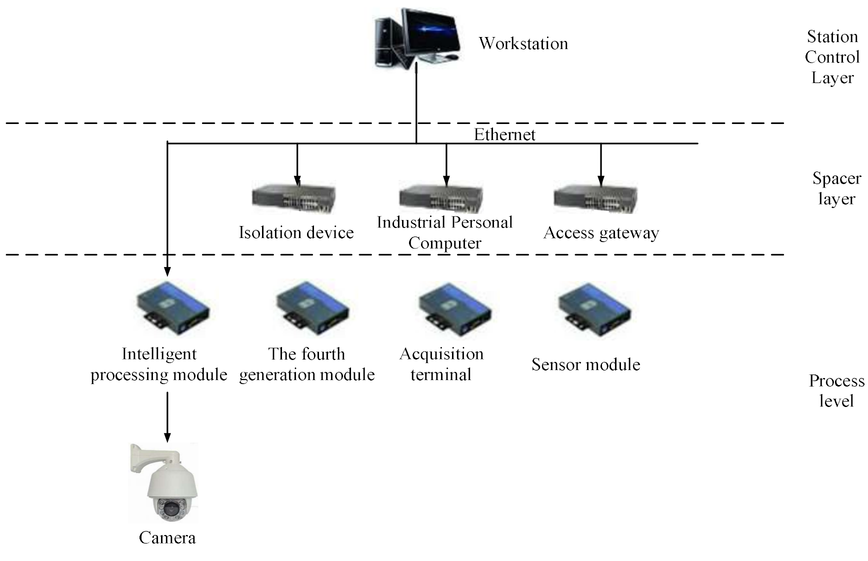

Figure 7: Basic architecture of intelligent monitoring of PS

The working principle of intelligent monitoring of PS based on AI technology is as follows: Intelligent monitoring of PS uses PTZ (pan, tilt and zoom) camera to collect digital images of equipment [10], [11]. The information of digital image is represented by red, green and blue 8-bit luminance values. The acquired images can be transmitted to the remote monitoring center through the network. The computer can capture the device image in the video stream in real time and preprocess it in order to eliminate the noise, interference and difference contained in the image. On this basis, the fault diagnosis method based on vector machine and variational mode decomposition method can be adopted. Finally, the identification results are displayed in real time through the display screen of the workstation.

III. C. Variational Mode Decomposition

The variational mode decomposition technique combines the Lagrange penalty operator and the quadratic penalty factor [12], [13], and replaces the constrained variational method with the unrestricted variational method. The constrained variational method can be solved iteratively, and the frequency and bandwidth of each modal component can be adjusted in real time. This can achieve the effective decomposition of each modal component in the PS, and then extract the abnormal state information of the PS equipment [14], [15].

Frequency modulation is obtained by variational mode decomposition. The modal components of the frequency modulation signal are as follows:

$$v_k(t) = B_k(t) \cdot c[\varphi_k(t)] \tag{4}$$

$$\mu_k(t) = \frac{d\phi_k(t)}{dt} \tag{5}$$

In the formulas, $B_k(t)$ and $\mu_k(t)$ are respectively the amplitude and instantaneous frequency of the harmonic signal $v_k(t)$. $\varphi_k(t)$ phase is a non-negative function and $B_k(t)$ ≥0, $\varphi_k(t)$ ≥0. The variational mode decomposition method is used to separate the harmonic signal, and the discrete mode function $v'_k(t)$ is obtained, among them:

$$\mathrm{k} = 1, 2, \ldots, \mathrm{K} \tag{6}$$

Since $v'_k(t)$ is sparse in the frequency domain, the edge spectrum obtained by the Hilbert transform mode function is:

$$v_k(t) \square (\theta(t) + \frac{1}{\pi t}) * v_k(t) \tag{7}$$

In the formula, $\theta(t)$ represents the unit function of the pulse; $\frac{1}{\pi t}$ is the impulse response of a linearly invariant system under the Hilbert transform, $*$ stands for convolution.

The center band is adjusted to the corresponding basic band, thus obtaining:

$$v'_k(t) = [(\theta(t) + \frac{1}{\pi t}) * v_k(t)]e^{-\mu_k} \tag{8}$$

The square L^2 of the obtained gradient norm of the demodulated signal is:

$$L^2 = \left\| d_a[(\theta(t) + \frac{1}{\pi t}) * v_k(t)]e^{-\mu_k} \right\|_2^2 \tag{9}$$

In the formula: d_a is the differential of the empirical mode component a.

According to the above steps, the following variational restriction model is obtained:

$$\begin{cases} \min\limits_{\{v_k\},\{\mu_k\}} \left\{ \left\| d_a[(\theta(t) + \frac{1}{\pi t}) * v_k(t)]e^{-\mu_k} \right\|_2^2 \right\} \\ s.t. \sum\limits_k v_k(t) = x(t) \end{cases} \tag{10}$$

$$\{v_k\} = \{v_1, v_2, \cdots, v_k\} \tag{11}$$

$$\{\mu_k\} = \{\mu_1, \mu_2, \cdots, \mu_k\} \tag{12}$$

Among them, $\{v_k\}$ has a function set of different modes; $\{\mu_k\}$ is a set of center frequencies; $x(t)$ is a function that puts variational constraints on the input signal, and $s.t.$ represents the constraints.

Formula (10) is converted to an unrestricted model problem by using the Lagrange penalty operator and the quadratic penalty factor:

$$M(\{v_k\},\{\mu_k\},\gamma) = \eta \sum_k \left\| d_a[(\theta(t) + \frac{1}{\pi t}) * v_k(t)]e^{-\mu_k} \right\|_2^2 + \left\| x(t) - \sum_k v_k(t) \right\| \tag{13}$$

In the formula, M represents the Lagrange function and γ represents the Lagrange penalty function. The minimum point of the Lagrange function can be obtained by Formula (13).

Then, these image signals are converted into a mode function with a number of K, thus realizing the recognition of abnormal state of PS equipment [16], [17].

III. D. SVM

SVM can effectively process high-dimensional data and maintain a good classification effect when there is less training data [18], [19]. By finding a hyperplane to classify the data, it is possible not to intersect the data at the same time, and the distance between the two types of data is maximized. In the intelligent monitoring and control method of PS based on AI technology [20], [21], the collected abnormal state features are input into the SVM, and the trained model is used to identify the abnormal state of PS equipment in real time. Therefore, SVM is one of the key algorithms to realize the intelligent recognition of abnormal state of PS equipment. By using variational mode decomposition method to extract the abnormal state features of PS equipment in images, the classification accuracy and efficiency of SVM can be effectively improved, so as to achieve accurate recognition of PS abnormal state.

The abnormal state characteristics of PS equipment obtained by the above process are set as the training sample of SVM, and expressed as the following formulas:

$$D=\left\{(m^1,m^1),\cdots,(m^l,n^l)\right\} \tag{14}$$

$$m\in R^n \tag{15}$$

$$n\in\left\{-1,1\right\} \tag{16}$$

The above training sample exists in a primitive input space R^n, mapped from a nonlinear function J to a high-dimensional feature space:

$$\min \mathrm{J}(\zeta_{\mathrm{i}})=-\frac{1}{2}\sum_{\mathrm{i,j=1}}^{1}\zeta_{\mathrm{i}}\zeta_{\mathrm{j}}n(h(m_i),h(m_j))+\sum_{\mathrm{i=1}}^{1}\zeta_{\mathrm{i}} \tag{17}$$

In the formula, $\min \mathrm{J}(\zeta_{\mathrm{i}})$ is the optimal structure on the high-dimensional plane, and $n(h(m_i),h(m_j))$ are the classification result of high-dimensional features.

Add Gaussian radial basic core function $K(m_i,m_j)$ to Formula (17) :

$$\min \mathrm{J}(\zeta_{\mathrm{i}})=-\frac{1}{2}\sum_{\mathrm{i,j=1}}^{1}\zeta_{\mathrm{i}}\zeta_{\mathrm{j}}n(K(m_i,m_j))+\sum_{\mathrm{i=1}}^{1}\zeta_{\mathrm{i}} \tag{18}$$

The following formula can be used to obtain the optimal separation hyperplane:

$$V\sum_{\mathrm{i,j=1}}^{1}\zeta_{\mathrm{i}}n(K(m_i,m_j))+g=0 \tag{19}$$

In the formula: V is the support vector. The optimal nonlinear SVM classifier y thus obtained is shown as follows:

$$y=s(V\sum_{\mathrm{i,j=1}}^{1}\zeta_{\mathrm{i}}n(K(m_i,m_j))+g) \tag{20}$$

Finally, anomaly detection of PS equipment can be realized by Formula (20).

III. E. Single-agent RL

Q learning is a single-agent reinforcement learning (RL) algorithm used to make decisions in uncertain environments [22], [23]. In the intelligent control of PS, the operating state and external environment of the PS may change, and the intelligent control system can make corresponding decisions according to the current state and environmental changes to achieve the optimal control of the PS. Q learning represents the mapping relationship between state and action by establishing Q tables and Q functions. In the PS, the different running states are taken as the state space, and the possible control actions are taken as the action space. Then according to the objective function of the intelligent control system, the Q-learning algorithm is used to constantly update the Q table and Q function to realize the intelligent control of the PS. Through Q learning algorithm, the intelligent control system can choose the best control action according to the current state, so as to realize the optimal control of the PS. Because the state space and actions of RL algorithms are discrete and limited, a table is used to record the value function, which records each state and action pair in the table. Moreover, during each iteration, the reward value would affect the update of the value function, which is equivalent to the agent checking every behavior, so that the convergence of Q learning can be ensured.

The optimal objective function $\mathrm{V}^{\pi^*}(\mathrm{s})$ and Q learning strategy π^* are:

$$\mathrm{V}^{\pi^*}(\mathrm{s})=\max_{\mathrm{a}\in\mathrm{A}}\mathrm{Q(s,a)} \tag{21}$$

$$\pi^*(\mathrm{s})=r\max_{\mathrm{a}\in\mathrm{A}}\mathrm{Q(s,a)} \tag{22}$$

In the formulas, $Q(s,a)$ is the Q function in the state behavior, and A is the behavior set. When the body iterates, the error of the Q-value function can be obtained by Formula (23) and Formula (24) :

$$\rho_k = R(s_k, s_{k+1}, a_k) + \gamma Qk(s_{k+1}, a_g) \tag{23}$$

$$M_k = R(s_k, s_{k+1}, a_k) + \gamma Qk(s_{k+1}, a_k) \tag{24}$$

In the formulas, $R(s_k, s_{k+1}, a_k)$ is the iterative reward function, and a_g is the greedy action strategy; ρ_k is the error of the value function, M_k is the error estimate of the Q function. $Qk(s_{k+1}, a_g)$ is the Q function under the greedy action strategy.

IV. PS Intelligent Monitoring Simulation Experiment

In this paper, 200 sets of 20 kinds of PS equipment in A power company in A city are selected as experimental objects. From January 1, 2022 to December 31, 2022, it used the traditional PS monitoring and control method and the PS IMM based on AI technology analyzed in this paper to identify six equipment abnormal states of insulator damage, switchgear damage, transformer damage, wire slack, wire aging, and spark. This paper divides the obtained data into two groups. The data of the traditional PS monitoring and control method is the control group, and the data of the PS IMM based on AI technology designed in this paper is the experimental group. The two sets of data are analyzed and compared to evaluate the performance and effect of the PS IMM based on AI technology.

IV. A. Identification Performance

The recognition performance has an important influence on the IMM of PS based on AI technology. In PS, accurate identification of key information is the key to realize intelligent monitoring. The reliability and accuracy of monitoring system are directly determined by the level of false identification rate and missing identification rate. If the identification performance of IMM is not good, it may lead to misjudgment or missing judgment of critical events, and then affect the operation safety and stability of PS. Therefore, in order to improve the level of intelligent monitoring of PS, it is necessary to continuously optimize the recognition algorithm, and comprehensively consider the data quality, feature extraction, algorithm parameters and other factors. Only on the basis of effectively improving the recognition performance, it can realize the accurate monitoring and rapid response of the PS, so as to ensure the reliable operation and optimal control of the PS. The results of different equipment abnormal states identified by the method presented in this paper at different times are shown in Table 4. The false identification rates and missed identification rates of the control group and the experimental group are recorded, and the comparison results are shown in Figure 8.

Table 4: Abnormal status identification results of different devices (times)

Data sequence number	1	2	3	4	5	6
Insulator damage	146	136	218	117	206	116
Damaged switchgear	176	174	107	148	143	172
Transformer damage	184	192	143	214	122	125
Loose wires	240	120	126	150	129	135
Aging of wires	169	220	236	242	127	238
Electric spark	181	142	112	129	196	194

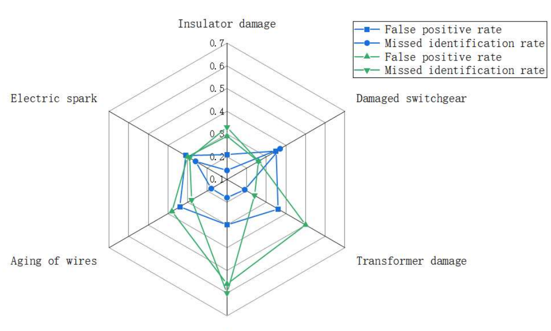

Figure 8: Data of false recognition rate and missed recognition rate of control group and experimental group (%)

Figure 8 describes the data of misrecognition rate and missed recognition rate of the control group and the experimental group. Blue represents the data of misrecognition rate and missed recognition rate of the experimental group, and green represents the data of misrecognition rate and missed recognition rate of the control group. It can be seen that the false recognition rate and missing recognition rate of the experimental group were below 0.4%, and even the lowest was below 0.2%; in the control group, the misrecognition rate and missing recognition rate were more than 0.4%, and there was no data less than 0.2%.

IV. B. Classification Accuracy

As a complex engineering system, the safety and stability of PS is of great significance to energy supply and social development. The accurate identification of various states and events in the PS is one of the core tasks to realize intelligent monitoring. The level of classification accuracy directly determines the credibility and accuracy of the monitoring system. If the classification accuracy is low, the monitoring system may have misjudgments and false positives, resulting in the neglect or wrong processing of real anomalies. Therefore, in order to improve the intelligent monitoring level of PS, it is necessary to continuously optimize the classification algorithm, and comprehensively consider the data quality, feature selection, model training and so on. Only on the basis of effectively improving the classification accuracy can people achieve accurate monitoring and fine management of the PS, provide reliable guarantee for the power operation, effectively prevent the occurrence of various hidden dangers and accidents, and promote the sustainable development of the PS. This paper records the accuracy rate and recall rate of the analyzed PS IMM based on AI technology. The results are shown in Figure 9. The horizontal axis is the accuracy rate and recall rate, and the vertical axis is the abnormal state of 6 kinds of equipment.

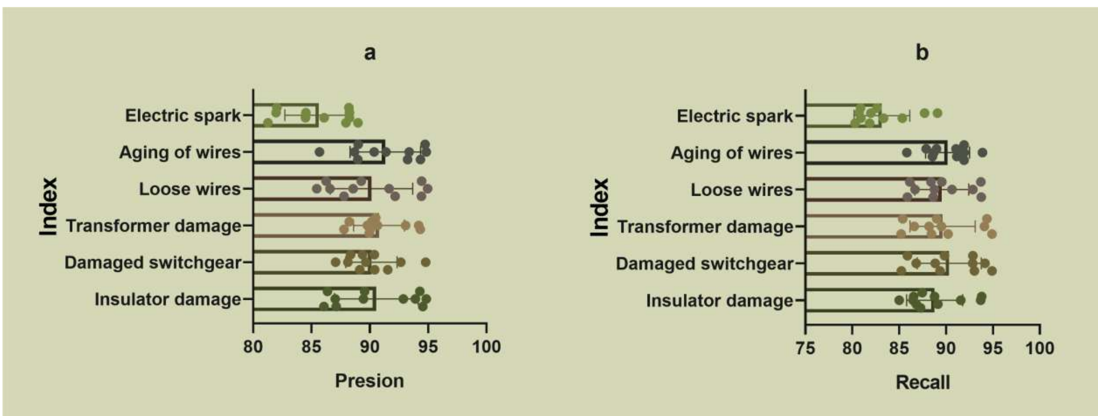

Figure 9: Accuracy rate and recall rate data of IMM of PS (%)

Figure 9(a) Accurate rate data of IMM of PS
Figure 9(b) Recall rate data of IMM of PS
Figure 9(a) described the accurate rate data of the IMM of PS, in which the maximum value was 94.95%. Figure 9(b) described the recall rate data of the IMM for PS, where the maximum value was 94.91%. Generally speaking, for the intelligent monitoring task of PS, the accuracy rate and recall rate can reach more than 80, or even more than 90% was relatively superior, so the IMM of PS based on AI technology analyzed in this paper was more accurate and credible.

IV. C. Degree of Weather Influence

Weather conditions is important in the operation and safety of the PS, and different weather conditions, such as strong winds, heavy rain, snow, etc., would have a certain impact on the equipment and lines of the PS. It may lead to equipment failure, line breakage or power load increase, and affect the accurate identification of the IMM of the PS based on AI technology, and then adversely affect the security and stability of the system. Under different weather conditions, this paper records the average value of F1 of the analyzed IMM of PS in view of AI technology. The results are shown in Figure 10. The horizontal axis is the abnormal state of 6 kinds of equipment, and the vertical axis is the value of F1.

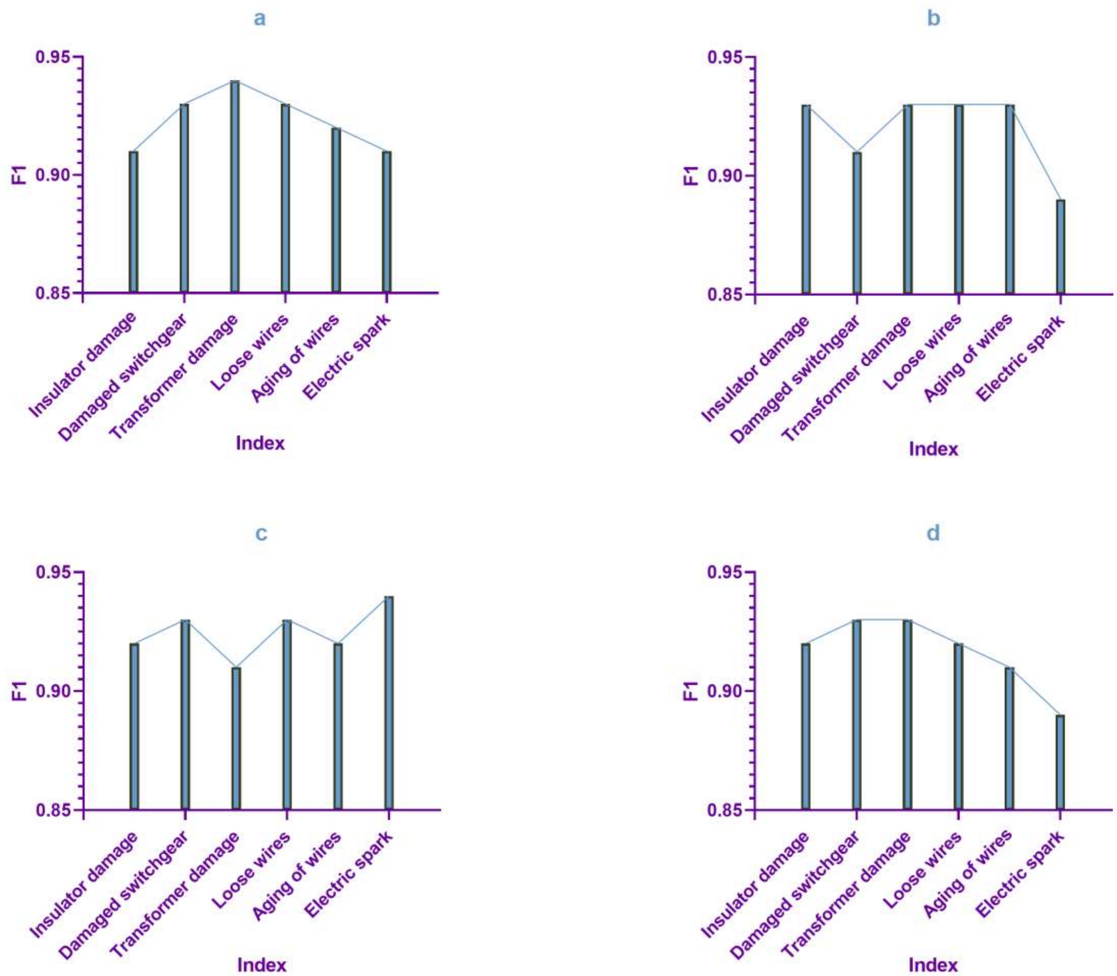

Figure 10: Average F1 data of IMM of PS

Figure 10(a) F1 average data of IMM of PS under normal weather
Figure 10(b) F1 average data of IMM of PS in snowy weather
Figure 10(c) F1 average data of IMM of PS under strong wind weather
Figure 10(d) F1 average data of IMM of PS in rainy days

Figure 10(a) described the average F1 data of the IMM of PS under normal weather, where the maximum value was 0.94. Figure 10(b) described the average F1 data of the IMM of PS in snowy weather, where the maximum value was 0.93. Figure 10(c) described the average F1 data of IMM of PS under strong wind weather, where the maximum value was 0.94. Figure 10(d) described the average F1 data of the IMM of PS in rainy days, where the maximum value was 0.93.

The IMM of PS based on AI technology analyzed in this paper is less affected by weather. In snowy and rainy days, F1 value may decrease slightly due to unclear picture shooting and other reasons, but in general, the IMM of PS based on AI technology analyzed in this paper has a good monitoring effect.

IV. D. System Performance

As a complex and huge engineering system, the safety and stability of PS is very important to the development of economy and society. The IMM based on AI technology, as a key means to ensure the operation of the PS, its performance has a decisive role in the effectiveness and reliability of the monitoring system. The system performance directly affects the accuracy, operability and response time of the monitoring system. If the system performance is good, the monitoring system can efficiently identify abnormal conditions and fault events, and quickly respond accordingly, providing accurate early warning and protection strategies. However, if the system performance is not good, it may lead to identification errors, missing critical events and response lag, which ultimately affect the safe operation of the PS. This paper recorded the response time and processing time of the control group and the experimental group. The comparison results are shown in Figure 11. The horizontal axis is the 11 groups of data, and the vertical axis is the values of response time and processing time.

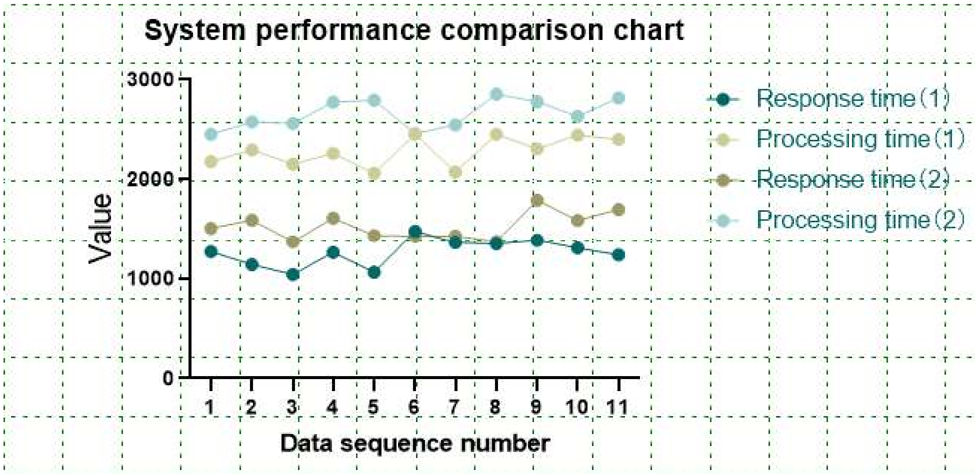

Figure 11: Response time and processing time of control group and experimental group (milliseconds)

Figure 11 describes the response time and processing time data of the control group and the experimental group. Response time (1) and processing time (1) represent the data of the experimental group. The maximum response time of the experimental group was 1477.18 milliseconds, and the maximum processing time of the experimental group was 2452.34 milliseconds. Response time (2) and processing time (2) represent the data of the control group, with a maximum response time of 1788.34 ms for the control group and a maximum processing time of 2850.53 ms for the control group.

V. Discussions

In Figure 8, the PS IMM based on AI technology analyzed in this paper performs better than the traditional PS monitoring and control methods in terms of false recognition rate and missing recognition rate, thus improving the overall recognition performance. This conclusion further proves the feasibility and superiority of using AI technology for intelligent monitoring of PS, and also confirms that the method analyzed in this paper has high practical value in practical application.

In Figure 9, the accuracy rate and recall rate of the PS IMM based on AI technology analyzed in this paper are all above 80%, indicating that the method has a high classification accuracy when detecting PS anomalies. At the same time, this high-precision anomaly detection capability can help PS managers find and solve the problems in the PS more quickly, and ensure the safety and stability of the PS. Therefore, this method has the potential of practical application, and can be used as a new idea and technical means for the intelligent upgrade of PS.

By observing Figure 10, the F1 value of the PS IMM based on AI technology analyzed in this paper is above 0.8 under different weather conditions (including snow, rainy day and strong wind). It shows that the method has good detection performance under different weather conditions, and has high accuracy and reliability for the identification of PS anomalies. This shows that the method has strong robustness and can maintain high recognition performance in different environments. At the same time, the IMM of PS based on AI technology can realize timely detection and processing of abnormal conditions of PS under different weather conditions, and has important application prospects in the field of PS monitoring and control.

According to the results in Figure 11, compared with traditional PS monitoring and control methods, the PS intelligent monitoring and control method based on AI technology analyzed in this paper performs better in response time and processing time, that is, the method can respond to and deal with PS anomalies more quickly, and improve the real-time and efficiency of the system. Since the abnormal situation of the PS may have a serious impact on the operation of the system, the rapid response ability and efficient processing ability of this IMM based on AI technology are of great significance to ensure the operation efficiency and reliability of the PS.

VI. Conclusions

Based on AI technology, this paper discussed the research of intelligent monitoring and control technology of PS, and analyzed the IMM of PS based on AI technology. As the scale of PS continues to expand, the traditional monitoring and control methods can no longer meet the actual needs, so it is necessary to introduce AI technology to solve the problem of PS monitoring and control. In this paper, the application of AI technology in PS monitoring and control was discussed from the aspects of data preprocessing, database establishment and abnormal state recognition of PS equipment. It put the analyzed IMM of PS based on AI technology into practical application and conducts experiments, so as to conclude that the application of AI technology can improve the security and stability of PS and enhance the monitoring and control ability of PS. With the increasing scale and complexity of PS, the intelligent monitoring and control technology of PS would be developed and improved continuously. In the future, with the continuous development of AI technology and cloud computing technology, the degree of intelligence of the PS can be further improved. Intelligent technology would be verified and improved in large-scale applications, focusing on energy conservation and sustainable development.

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