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Research on the Construction Method of an Intelligent Operation and Maintenance System for Power Pipeline Equipment Based on Digital Twins and AI-Driven Health Assessment

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Abstract This paper conducts a reconstruction analysis of the intelligent maintenance system for power transmission equipment from the perspectives of digital twins and artificial intelligence. After constructing the intelligent maintenance system, the technical architecture of the system is established using technologies such as multi-source heterogeneous databases. Additionally, the paper explores the integration of artificial intelligence technology into the maintenance management of power systems to achieve precise assessments of the system's health status and tests the performance of the proposed evaluation method. In terms of system health assessment, the relative error of the proposed method does not exceed 0.012, with an average assessment accuracy of 99.39% and an average assessment time of 150.63 seconds. Among all assessment methods, the proposed method achieves the highest accuracy and fastest speed, demonstrating significant advantages in power equipment health assessment.

Index Terms digital twin, artificial intelligence, intelligent maintenance system, health assessment, power equipment

I. Introduction

With the advancement of technology and the development of society, power systems have become an indispensable part of our daily lives [1], [2]. Intelligent maintenance of power equipment has emerged as a critical factor in enhancing the operational efficiency and stability of power systems [3], [4]. In traditional power equipment maintenance, challenges often arise due to the subjective judgment and lack of experience among maintenance personnel [5], [6]. With the development and application of digital twin and artificial intelligence (AI) technologies, intelligent maintenance of power equipment has introduced advanced technologies such as the internet and big data to enable remote monitoring, fault prediction, and proactive maintenance of power equipment, significantly improving the reliability and safety of power systems [7]-[10].

Digital twin technology refers to a technique that simulates and monitors the real world by creating virtual, digital models [11], [12]. In the intelligent operation and maintenance of power production line equipment, by creating virtual copies of power production line equipment, real-time monitoring and analysis of key indicators such as the power environment, equipment status, and energy consumption can be achieved. Through the integration of business systems and interfaces for collaborative command and decision-making, the true challenges of intelligent operation and maintenance of power production line equipment can be addressed, thereby enhancing the reliability, safety, and efficiency of the system [13]-[16]. AI-driven health assessment is also widely applied in the intelligent maintenance of power transmission and distribution equipment to enhance the safety, stability, and efficiency of power systems [17]-[19]. AI image recognition technology can quickly and accurately identify potential fault points or abnormal conditions by analyzing sensor data or photos captured by surveillance cameras. Additionally, it can mine and analyze large amounts of historical data to detect potential abnormalities and predict potential faults in advance [20]-[23]. These anomaly detection and prediction models can help power maintenance personnel take timely measures to prevent accidents.

This paper first establishes an intelligent maintenance system for power transmission and distribution equipment, comprising perception layer, communication layer, platform layer, and application layer. It employs multi-source heterogeneous databases and data+knowledge+model-driven modeling techniques to construct a technical framework for an intelligent maintenance system for power equipment based on digital twins. Second, artificial intelligence technology is introduced into power system maintenance management, applied to areas such as power system component failures, fault diagnosis, equipment health assessment, and equipment inspections. Finally, the health assessment results of power equipment are quantified using equipment health index models and dual-branch convolutional neural network models to evaluate and predict equipment risks and health. Simulation experiments validate the superiority of the methods proposed in this paper for power system health assessment.

II. Overall Architecture and Key Technologies of Intelligent Operation and Maintenance Systems

II. A. Overall Architecture of Intelligent Operation and Maintenance System

To effectively address the current issues in power equipment maintenance, such as incomplete monitoring, fragmented data, and delayed responses, it is imperative to build an intelligent maintenance system that integrates "sensing, communication, analysis, and decision-making" [24]. The system should be based on digital sensing and integrate edge computing, artificial intelligence, cloud platforms, and expert knowledge systems to form a closed-loop management mechanism from data collection to early warning diagnosis to maintenance decisions. The intelligent maintenance system can be broadly divided into four functional layers: perception layer, communication layer, platform layer, and application layer. The overall architecture of the intelligent maintenance system is shown in Figure 1.

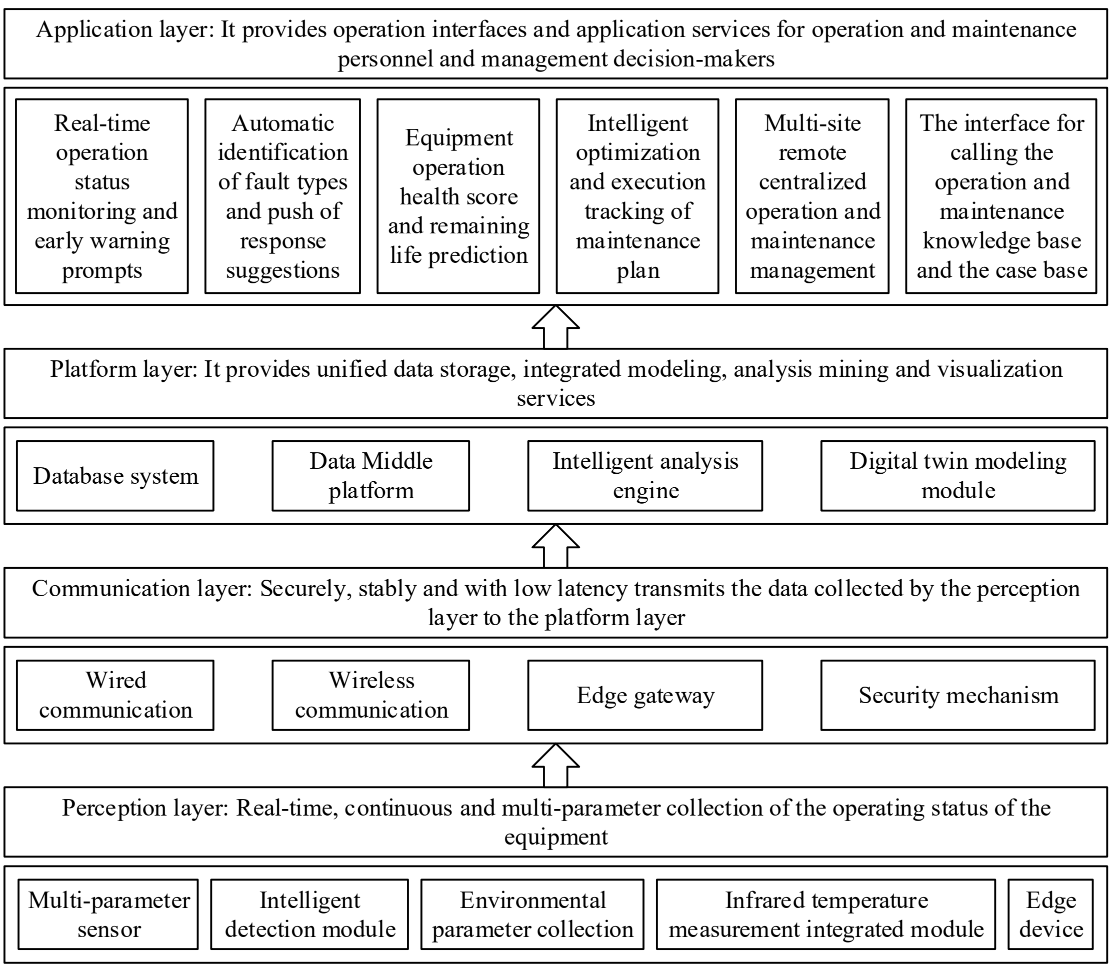

Figure 1: The overall architecture of intelligent operation & maintenance system

II. A. 1) Perception layer: Multi-source data collection and status monitoring

The perception layer is the foundation of the intelligent operation and maintenance system, responsible for real-time, continuous, and multi-parameter data collection of the operational status of power equipment. By installing sensors such as temperature, vibration, pressure, current, voltage, and oil level at critical locations, and deploying intelligent detection modules on equipment such as hydroelectric generators, switchgear, excitation systems, and governors, the system can comprehensively obtain equipment operational data. Additionally, the perception layer includes the collection of environmental parameters such as head, water temperature, humidity, and indoor dust, as well as video image monitoring and infrared temperature measurement integration modules to achieve comprehensive monitoring of the equipment operating environment. Based on equipment operational characteristics, data sampling frequencies at critical locations should meet high-frequency collection requirements of 1 Hz or above, while ordinary signals maintain a periodic update interval of 5 to 10 minutes.

II. A. 2) Communication Layer: Stable and Secure Transmission System

The communication layer is responsible for securely, stably, and with low latency transmitting the data collected by the perception layer to the platform layer. In a stable environment within the factory, wired methods such as industrial Ethernet and CAN bus are used for data transmission. To improve data transmission efficiency and response speed, the system introduces edge gateways and edge computing nodes to perform local preliminary processing and compression, thereby alleviating the pressure on central computing. At the same time, the communication layer has built-in encryption and authentication mechanisms to ensure data integrity and security during communication.

II. A. 3) Platform layer: Data storage, integration, and analysis processing

The platform layer is the core of the intelligent operations and maintenance system, aggregating various data resources and providing unified data storage, integrated modeling, analysis and mining, and visualization services. This layer mainly includes:

(1) Database system: used to store structured monitoring data and unstructured images, logs, and videos.

(2) Data middleware: Performs data cleansing, format standardization, and standardized processing on multi-source data.

(3) Intelligent analysis engine: Utilizes machine learning, expert systems, and fault databases to conduct state identification, trend prediction, and fault diagnosis.

(4) Digital twin modeling module (optional): Constructs virtual models of electromechanical equipment to support fault simulation and emergency response scenario simulation.

II. A. 4) Application Layer: Operations Decision Support and Visual Interaction

The application layer is designed for operations personnel and management decision-makers, providing an operational interface and application services. Common features include real-time operational status monitoring and early warning alerts, automatic identification of fault types and push notifications with recommended responses, equipment operational health scoring and remaining useful life (RUL) prediction, intelligent optimization of maintenance schedules and execution tracking, centralized remote operations management across multiple sites, and access to operations knowledge bases and case libraries. Through these features, the application layer enables efficient management and intelligent decision support for power plant equipment.

II. B. Key Technologies

II. B. 1) Multi-source heterogeneous database construction technology

Data serves as the foundation and basis for conducting simulation and decision-making in digital twin power engineering projects. The quality and management of data directly impact the success of digital twin system development.

The digital twin power engineering project based on multi-source heterogeneous databases integrates multiple related database systems through a heterogeneous database system, enabling data sharing and transparent access. This allows for the consolidation and sharing of data information resources, hardware device resources, and human resources across different databases, effectively addressing the issue of data silos and laying a solid foundation for the business applications of digital twin power engineering projects. The information exchange topology structure between the heterogeneous database system and various information subsystems is shown in Figure 2. The exchange process for real-time information pushed by various information subsystems to the heterogeneous database includes:

(1) The heterogeneous database initiates a business request.

(2) The distribution hub verifies the correctness of the username and password.

(3) After the distribution hub verifies the credentials, it forwards the business request to the information system platform.

(4) The information system performs user validity verification.

(5) The information system processes the business request.

(6) The information system returns the business processing message to the distribution hub.

(7) The distribution hub returns the processing results to the heterogeneous database.

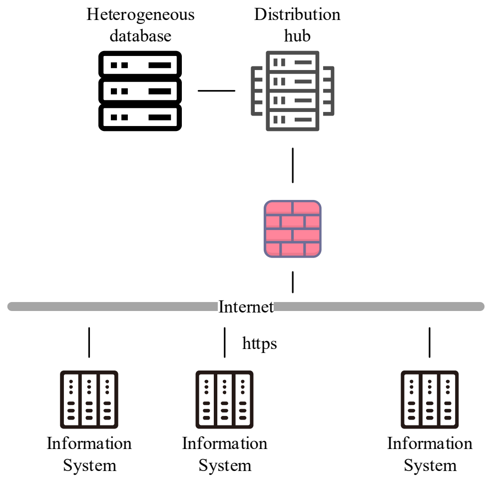

Figure 2: Topological structure of heterogeneous database information exchange

The data architecture of the smart maintenance management platform for power equipment based on digital twin technology is primarily divided into major data modules such as data connection, data mapping, twin models, and data decision-making, thereby connecting object data between the physical and twin spaces. The data architecture of the smart maintenance management platform for power equipment based on digital twin technology is shown in Figure 3.

(1) Data connection. This includes data collection, sensing, and feedback control based on a big data platform.

(2) Data Mapping. This includes functional modules such as data interconnection, information interoperability, and model interoperability. These functional modules can interact with each other to achieve the management of data, information, and models.

(3) Twin Model [25]. This includes model construction, fusion, correction, and verification.

(4) Data Decision-Making. This includes the description, diagnosis, prediction, and handling of data decision-making applications.

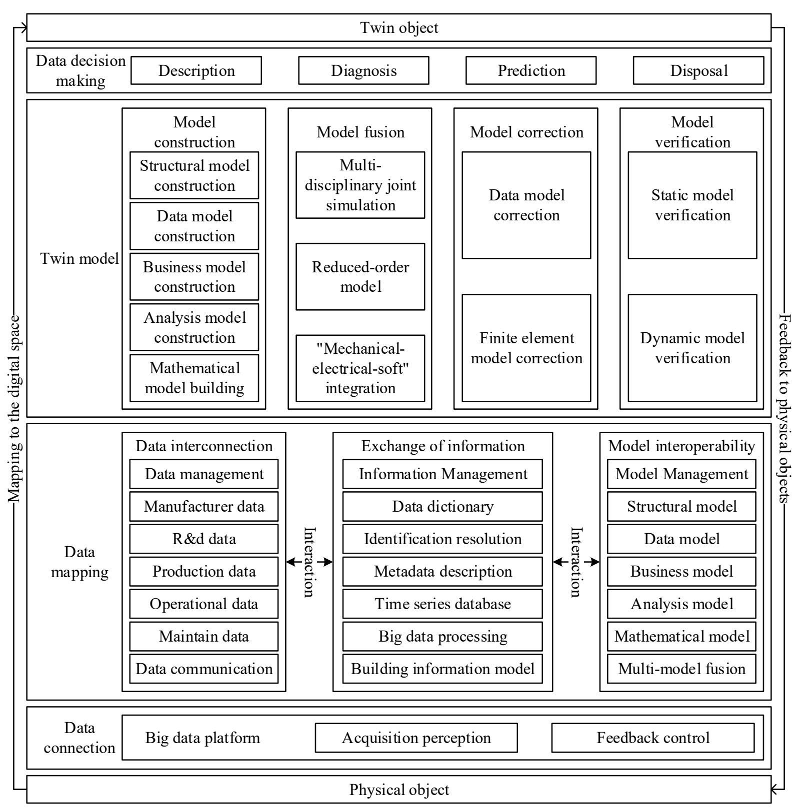

Figure 3: Intelligent operation & maintenance platform based on data twin technology

II. B. 2) Modeling technology driven by "data + knowledge + models"

Digital twin modeling technology can be divided into three types based on the model update mechanism: data-driven, knowledge-driven, and model-driven modeling technologies.

(1) Data-driven modeling technology: Based on underlying data analysis, it does not require knowledge or model establishment, and is highly versatile and widely applicable.

(2) Knowledge-driven modeling technology: Based on intermediate-level mechanisms and laws, it does not require precise modeling and is suitable for scenarios where the underlying principles are well-established.

(3) Model-driven modeling technology: Based on existing upper-level models, it requires existing models to be known and is suitable for scenarios where models are mature.

Power plant equipment maintenance often involves complex scenarios with multi-source heterogeneous data, multi-physics field coupling, and incomplete maintenance mechanism models. A combined modeling approach of "data-driven + knowledge-driven + model-driven" can be adopted.

Data-driven modeling employs machine learning algorithms such as deep learning and reinforcement learning, as well as various evolution-inspired computational methods. Model/knowledge-driven modeling focuses on domain-specific rule-based knowledge, human-in-the-loop operational experience knowledge, and existing model and algorithm knowledge.

Through "data + knowledge + model" driven modeling technology, a comprehensive twin model of mechanical and electrical equipment maintenance is constructed, covering both the visual and acoustic domains. Data, knowledge, and model-driven modeling enriches and improves the full-spectrum and full-sound-domain twin models of electromechanical equipment from different technical scenarios and dimensions, enhancing model accuracy and completeness. The "data + knowledge + model" driven modeling technology serves as the foundation for digital twin models while also incorporating feedback from twin model applications to continuously refine and improve the models, forming a positive feedback loop between modeling and application.

II. C. Application of Artificial Intelligence Technology in Power System Operation and Maintenance Management

II. C. 1) Artificial Intelligence-based Parts Failure and Fault Diagnosis

Before the application of artificial intelligence technology to power system operation and maintenance work, power system maintenance personnel had to manually assess and analyze the power system before they could formulate power system operation and maintenance plans.

The application of artificial intelligence to the fault diagnosis and identification of power system equipment uses effective methods to test power transformers, high-voltage switches, and other power devices to ensure that problems with power devices can be detected in a timely manner, thereby enabling rapid handling of problems with power devices. Since artificial intelligence can efficiently collect big data, power system operation and maintenance personnel can analyze this data to more quickly and accurately identify the root cause of faults, thereby proposing targeted diagnostic methods.

II. C. 2) Artificial Intelligence-based Evaluation of Electrical Equipment Health Status

When maintaining and repairing power systems, it is essential to evaluate their operational status in order to better prevent accidents and ensure stable operation of the power system.

The introduction of artificial intelligence into power systems can not only improve the efficiency of fault diagnosis but also enhance the accuracy of operational status monitoring. This has significant implications for reducing maintenance cycles and improving the operational efficiency of power systems.

II. C. 3) Intelligent technologies used for equipment inspection and testing

By leveraging artificial intelligence (AI) technology, more precise information can be obtained during power equipment inspections, thereby enhancing the efficiency of power equipment maintenance and repair operations. The integration of AI with advanced methods such as image recognition in power system patrols and inspections enables comprehensive visualization and precise control of power system operations. AI technology can also be used to comprehensively analyze information from multiple sources, enabling efficient synchronized monitoring of multiple substations, distribution rooms, and other facilities, thereby improving operational management efficiency and maximizing the stable operation of power systems. Additionally, AI-based analysis can provide timely warnings about potential hazards during operation, further reducing losses caused by power system accidents and ensuring the safe and stable operation of power systems.

II. D. Power Equipment Risk Assessment

II. D. 1) Equipment Health Assessment

Equipment health assessment is a method for quantifying the comprehensive operating status of power equipment [26]. The cloud computing layer constructs an equipment health index model to assess the health status of equipment. The calculation method for the health index model is expressed as:

$$EHI = \sum_i [W_i \cdot f_i(X_i)] \tag{1}$$

In this context, EHI denotes the Equipment Health Index, X_i represents different types of monitoring data, W_i denotes the corresponding weighting coefficient for the monitoring data, and f_i denotes the evaluation function for the corresponding monitoring data.

The health index ranges from 0 to 1, with higher values indicating better equipment health. Specifically, the evaluation function f_i depends on the specific monitoring parameters and evaluation requirements. These functions are typically derived from empirical, statistical, or machine learning methods and aim to convert raw monitoring data into indicators that reflect equipment health. For example, if X_i is a parameter that can be directly quantified to affect the health of the equipment, such as temperature, vibration level, or noise level, a linear function can be used to standardize it, expressed as:

$$f_i(X_i) = \frac{X_i - X_{i,\min}}{X_{i,\max} - X_{i,\min}} \tag{2}$$

Among them, $X_{i,\min}, X_{i,\max}$ represent the minimum and maximum values of the X_i parameter, respectively.

For aging parameters (such as equipment service life), an exponential function is needed to simulate the deterioration of equipment performance over time, which is expressed as:

$$f_i(X_i) = e^{-\lambda X_i} \tag{3}$$

In this formula, λ represents the decay coefficient; X_i represents time-related parameters, such as years of use.

II. D. 2) Equipment Failure Prediction

Researchers designed and deployed a dual-branch convolutional neural network model for predicting power equipment failures, with one branch processing visible light images and the other branch processing thermal imaging images. The features from these two branches are then merged for final fault prediction. The architecture of this model can be formalized as follows:

$$P = Predict\{Fusion[CNN_{visible}(V), CNN_{thermal}(T)]\} \tag{4}$$

In this context, V denotes the input visible light image; T denotes the input thermal imaging image; $CNN_{visible}$ denotes the convolutional neural network branch processing the visible light image; $CNN_{thermal}$ denotes the convolutional neural network branch processing the thermal imaging image; Fusion denotes the fusion function merging the feature vectors of the two different modalities; Predict denotes the function that converts the fused feature vectors into the final fault prediction; P denotes the network output, which is the predicted probability of a fault.

Specifically, the input layer of $CNN_{visible}$ accepts visible light images of a fixed size, followed by feature extraction using two convolutional layers, activation functions, and average pooling layers, and then advanced feature learning using a fully connected layer to output the feature representation of the visible light image. $CNN_{thermal}$ is processed similarly, outputting the feature representation of the thermal imaging image. The fusion layer fuses the feature representations of the visible light and thermal imaging images by element-wise addition, and further uses a fully connected layer to learn higher-order features of the fused features. Finally, a fully connected layer followed by a softmax activation function is used to output the probability of the fault.

III. Simulation verification analysis

III. A. System Health Assessment

This section uses the health status of gas turbine power generation modules as the data to be evaluated to verify the feasibility of the evaluation method described above.

Assuming that there are no external factors affecting the health status of the system, a data set of the health status of gas turbine power generation modules with a time interval of three days is randomly selected from the database. To obtain a representative value for the system's health status on a given day, a probability density estimation method is used to statistically analyze the health status measurement data set for that day, generating its statistical distribution diagram. The sample mean M is selected as the representative value for the system's health status on that day. This allows the trend in the health status of the gas turbine power generation module over a 50-day period with a 1-day step size to be determined.

First, the health data must be normalized. For the health indicators studied in this paper, if normalization is not performed, ZData will become a constant, making it impossible to display contour lines during the optimization process and preventing further operations. Next, the algorithm parameters for the network search must be set. Here, all parameters are first set to the default values of Lib SVM. After the initial search, cross-validation is performed using the 3-fold cross-validation method (3-CV) to refine the parameters for further precise search.

With the optimized parameters, the health assessment can be validated. The health data from the first 45 days is used as the training sample, and the health data from the last 5 days is used as the test sample. Finally, the results are denormalized to output the actual health values. The health assessment results are shown in Figure 4, and the training relative error is shown in Figure 5.

As can be seen from the training relative error, the evaluation method proposed in this paper achieves a training relative error of approximately 0–0.012 during the learning and training process based on the samples, indicating high training accuracy. The training data essentially converges with the trend of the actual data.

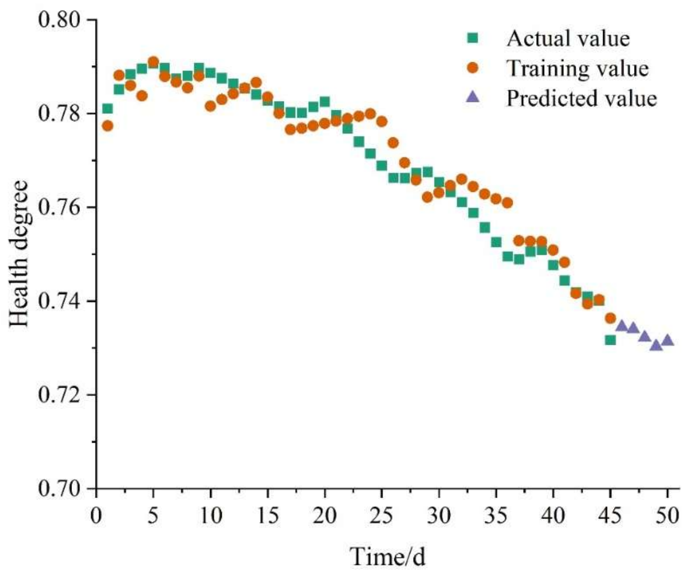

Figure 4: Health degree evaluation results

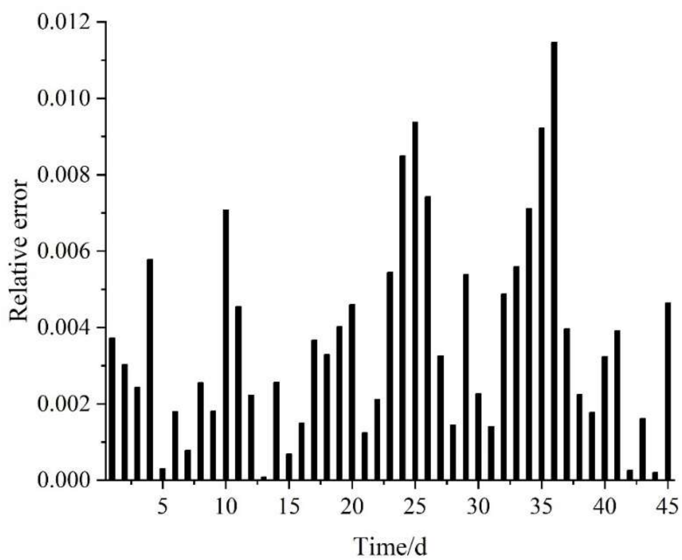

Figure 5: Health degree training relative error

III. B. Assessment accuracy

Ten groups were randomly selected from the test samples to test each model, and their test accuracy rates were calculated as shown in Table 1, where a, b, c, and d represent models based on voltage input, frequency input, motor speed input, and rectifier temperature input, respectively.

As shown in Table 1, the accuracy rates of the various models for health assessment of the 10 sets of test sample data are similar, all exceeding 98%, indicating that the selected feature parameters meet the requirements. Each feature parameter effectively reflects the system's health status, and the models have basically met the requirements for health assessment, enabling relatively accurate evaluation of the system's health status.

Table 1: The relationship between evaluation accuracy and input parameters (%)

Test number	a	b	c	d
1	98.55	98.17	98.35	99.47
2	98.10	98.32	98.85	98.95
3	98.72	99.14	99.24	99.76
4	98.75	98.67	98.35	99.57
5	99.26	98.57	99.17	98.75
6	98.50	98.35	99.69	98.55
7	98.65	99.26	99.54	98.17
8	98.74	99.35	98.79	98.74
9	99.69	98.74	98.67	98.95
10	99.35	98.37	99.24	99.07

To validate the effectiveness of the evaluation method based on the dual-branch convolutional neural network proposed in this paper, we also applied the backpropagation (BP) neural network, which belongs to artificial neural networks, and the deep belief network (DBN), which belongs to deep learning algorithms, to this health status evaluation study.

The parameters of the deep belief network were set as follows: the network consists of five layers, including three hidden layers, one input layer, and one output layer, with the number of nodes in each layer being 800, 600, 300, 1024 (32×32), and 5, respectively. Initially, the algorithm is unsupervised, so it is trained using unlabeled data and iterated 200 times to obtain the initial parameter values. Then, the trained network is combined with softmax to train labeled data, and the network parameters are adjusted using the backpropagation algorithm, thereby obtaining the parameters of the deep belief network.

The BP neural network parameters are set as follows: the network consists of five layers, including three hidden layers, one input layer, and one output layer. The number of neurons in the three hidden layers are 32, 16, and 8, respectively. The input is a vector containing four elements, and the output is a vector containing five elements (corresponding to the probabilities of the five health states). The initial values of the model network parameters are the same as those of the convolutional neural network model.

The training sample data is consistent with the convolutional neural network model. After the model training is completed, 15 groups are randomly selected from the test samples to train the model. Both the deep belief network and the convolutional neural network include four models, and the average of the evaluation accuracy of the four models is taken as the comparison result. The comparison results of the three algorithms are shown in Figure 6.

As shown in Figure 6, the evaluation accuracy of all algorithms exceeded 91% in 15 validations, with the other two algorithms exceeding 97%. This indicates that all three algorithms have good health assessment capabilities.

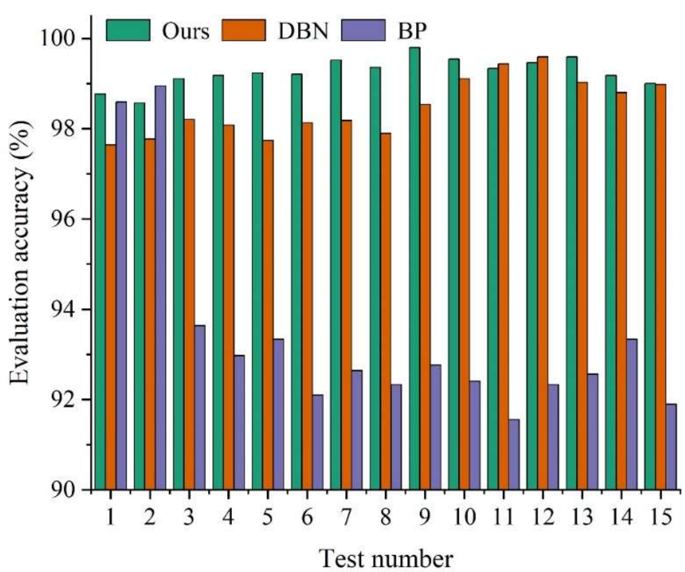

Figure 6: Evaluation performance

Further analysis of the average evaluation accuracy and evaluation time for the three algorithms reveals that the average evaluation time and evaluation accuracy for the aforementioned 15 experiments are as shown in Table 2. From Table 2, it can be analyzed that the average health status evaluation accuracy of the three algorithms all exceed 92%. Among them, the average accuracy of the BP neural network is at least 5.82% lower than the other two algorithms, and its evaluation time is also significantly longer than theirs. This indicates that the evaluation capability of shallow neural networks is far inferior to that of deep learning algorithms. The evaluation accuracy of the method proposed in this paper is comparable to that of the deep belief network, but the evaluation time of the method proposed in this paper is only 150.63 seconds, which is approximately 2.7% of the BP neural network and 4.6% of the deep belief network. This demonstrates that the health assessment method proposed in this paper exhibits superior performance in health assessment.

Table 2: Evaluation accuracy comparison

Algorithm	Mean evaluation accuracy (%)	Mean evaluation time (s)
Ours	99.39	150.63
DBN	98.36	3267.48
BP	92.54	5504.28

IV. Conclusion

This paper establishes the overall architecture of an intelligent power operation and maintenance system, refines the technical framework of the system through technologies such as multi-source heterogeneous databases, applies digital twin and artificial intelligence technologies to the operation and maintenance management of power systems, and conducts risk and health assessments of power systems. The relative error of the evaluation method in this paper is between 0 and 0.012, and the training accuracy is high. The average evaluation accuracy of the methods proposed in this paper is 99.39%, and the average evaluation time is 150.63 seconds, both of which outperform other health assessment models. In terms of overall performance and accuracy in health assessment, these methods are the optimal choice. Health assessment of power pipeline equipment holds significant reference value for the daily operation of power systems, and it can effectively enhance the reliability, safety, and efficiency of power systems through intelligent monitoring, assessment, and optimization. Artificial intelligence algorithms and digital twin models are continuously optimized and evolved to enhance the accuracy and efficiency of assessment and decision-making. Power system operation and maintenance based on artificial intelligence and digital twins represent an inevitable choice for the transformation and upgrading of the power industry, paving the way for a safer, more efficient, and sustainable power system.

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