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An AI-Driven Intelligent Health Assessment System for High-Voltage Switchgear Based on Multimodal Sensor Data Fusion

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ABSTRACT

The function of high-voltage switchgear is to maintain the stability of the power grid. The traditional health evaluation methods generally rely heavily on a single index; The accuracy of this method is relatively low, and it is difficult to detect failures because it cannot take into account multiple factors. In view of the above shortcomings, this paper has designed and developed an AI-intelligent health evaluation System based on multimodal sensor data fusion technology.The system uses the four-tier architecture of sensor layout, data acquisition and transmission, data fusion and processing, and health evaluation and decision-making, and integrates temperature, humidity, partial discharge, vibration, current, and voltage data. It uses a three-tier data fusion approach (weighted average at the data layer, principal component analysis (PCA) at the feature layer, and D-S evidence theory at the decision-making layer) to handle heterogeneous data and combines SVM models for small sample sizes and CNN models for time series data to provide all-around evaluation.Experiments based on a simulated platform show that the system can achieve an average accuracy of 96.8% and perform better than traditional single parameters by about 18.5 per cent. It can identify incipient faults 2-3 hours earlier than traditional methods, maintain 85% assessment accuracy even if one sensor fails, and complete post-fault state assessment and fault location within 500 ms after the relay protection action for short-circuit faults. The integrated three-level warning mechanism can reduce blind maintenance by as much as 60 per cent and lower the cost of maintenance by an average of 35 per cent; At the same time, it has achieved an effective grasp of complex fault conditions, improved the credibility of evaluation, provided scientific basis for preventive maintenance.

1. Introduction

High-voltage switchgear is a key device for various applications in the construction and operation of power grids, mainly responsible for tasks such as circuit breaker switching, operation control and safety protection throughout the entire link from power generation to consumption by users at the end. With the shift of China's economic development model to one that emphasises quality over quantity, industrial electricity consumption continues to grow steadily, propelling high-voltage switchgear towards greater intelligence, higher reliability, lower life cycle costs, etc. At this time, artificial intelligence (AI) has become a new type of technology to change the model of power equipment monitoring and health assessment through data-driven intelligent decision-making[1].

Beyond these core operational functions, high-voltage switchgear carries two critical responsibilities: ensuring stable power circuit connectivity and safeguarding the overall safety of the power system. Its operational performance directly dictates the reliability of the distribution network, making health status assessment an indispensable aspect of grid operation and monitoring. Unfortunately, frequent flashover and explosion incidents involving high-voltage switchgear in recent years have resulted in immediate equipment shutdowns, cascading power outages in adjacent grids, and substantial economic losses for power utilities and end-users alike[2]. Generally, these events occur for various unsatisfactory reasons, mainly including aging and damage of components inside the device, an imperfect structure or loose fixation, water ingress and contamination inside the device, malfunction of the mechanical system, secondary equipment failure, etc. In general, when a relatively more complicated

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situation occurs, it is necessary to use a higher-class evaluation tool rather than the ordinary one.

Currently, the health evaluation of high-voltage switchgear primarily relies on manual inspections and robot-assisted intelligent equipment[3]. AI-based approaches, such as neural network methods, have received more and more attention with the development of AI technology; but at present, they also have certain defects. Mostly depend on the operating data of a single type of component, such as temperature or partial discharge; there is no combination of these two essential information sources: historical operating records and multi-sensor data, into an overall assessment system. In addition, these initial AI models typically rely on simple feature extraction and cannot identify hidden, non-linear correlations among diverse types of data, limiting their ability to grasp the intricate operation patterns of equipment faults. Traditional methods, at the same time, use single monitoring indicators or hard-threshold judgment; thus, it is easy to miss early fault opportunities due to these factors.

In view of the background of big data and AI development, two important advances have been made in response to these problems: the wide application of multi-modal sensors in high-voltage switchgear and the quick development of deep learning algorithms. Multimodal sensors can acquire diverse information, such as temperature changes, partial discharge signals, and mechanical failure data. Advanced artificial intelligence technology, such as convolutional neural networks, support vector machines, and adaptive learning models, provides powerful tools for integrating different types of data streams, extracting high-dimensional features, and constructing complex operational dynamic models. When combined with AI, multimodal sensor data fusion can overcome the defects of a single sensor monitoring system through cross-validation and complementary benefits among different types of data sources. An AI model can link the humidity damage of insulation to an abnormally high temperature detected by a thermal sensor in a humid environment, or infer the degree of insulation defect according to partial discharge signals; single types of information or traditional methods cannot draw such conclusions.

Based on artificial intelligence technology, this paper designs a smart health monitoring system with high accuracy and reliability to reduce the difference in practical application between current technologies and people's requirements; A complete solution that integrates multi-mode sensors through fusion technology is presented. Taking into account that Qwen utilises the non-linear fitting method, has adaptive learning ability and can handle a large amount of data[4]; once problems appear, they will be found in time through prediction analysis and taken care of regularly so as to avoid major failures. This helps maintain the stable operation of the power system, reduce power outages and economic losses caused by them, and provide a scientific basis for maintenance plans to avoid unnecessary "over-maintenance" or delayed "under-maintenance", In addition, the application of AI technology can improve the adaptability of the power system to changes in operating status; According to the actual situation in real time and historical pattern recognition results, adjust evaluation standards dynamically; Improve the intelligence level of the entire power grid operation and maintenance system.

2.Theoretical foundations

2.1.Sensor principles and key parameters

Sensors are the basic components that make up the data acquisition system in a high-voltage switchgear health inspection; If the principle of operation or parameter setting is improper, it will affect the quality of the collected data[5]. As the main sense, it is responsible for detecting changes in ambient humidity and converting this variation into an electric signal to acquire data; At the same time, to avoid the system exceeding the safe insulation material limits. They operate by converting the degree of moisture in the environment into a corresponding electrical signal, and among them, capacitive and resistive types are widely used in industry. Capacitive sensors use the humidity-sensitive characteristics of some dielectric materials; as ambient humidity changes, so does the dielectric constant proportionally, thereby changing the capacitance of the sensor - this change is measured to determine the degree of humidity[6]. Resistive sensors use hygroscopic materials that have different electrical resistances depending on the extent of their water absorption. When the humidity is higher, more moisture is absorbed by the plant, thereby reducing resistance; This kind of change in resistance will be converted into electric information to achieve real-time detection.

Partial discharge sensors function as "early warning systems" for the insulation status of electrical equipment, enabling early detection of insulation defects before a breakdown occurs[7]. In general, there are two common types in the system: one is the pulse current sensor that conforms to the IEC 60270 standard, and the other is an ultrasonic sensor. Pulse current sensors are based on the principle of high-frequency electromagnetic induction and can acquire transient pulse currents produced by partial discharges in GIS at a high time resolution. Convert various currents into standard electrical signals and output the basic quantity defined in IEC 60270, which is the apparent discharge quantity (unit: pC), along with additional information such as discharge pulse amplitude, repetition frequency, and charge amount, to quantify the extent of insulation damage. Ultrasonic sensors can receive the mechanical wave signal (usually in the range of 40 kHz to 300 kHz, this part is generally around the frequency band chosen for switchgear partial discharge detection) produced by partial discharges; At the same time, ultrasonic waves will propagate through air and various structural material[8]. The main advantage of ultrasonic sensors is that they have strong localisation ability; By measuring the time difference of arrival (TDOA) of signals at four non-coplanar array sensors and analysing the wave propagation path, technicians can achieve precise three-dimensional positioning of the partial discharge source and carry out targeted inspections. According to the Nyquist sampling theorem, the sampling frequency of ultrasonic sensors is set at 1MHz-5MHz (3.3-16.7 times the highest frequency component in the target signal of 300kHz). The 1

MHz lower limit satisfies the requirement that the engineering safety margin be more than 2.5~5 times, and the 5 MHz upper limit is set aside to acquire the high-frequency transient parts of ultrasonic signals in strong electromagnetic interference environments; thus, all features of partial discharge ultrasonic signals are preserved.

Temperature sensors are based on the thermal characteristics of materials, such as the thermoelectric effect (thermocouples) or the temperature-change-related resistance of conductors/semiconductors (thermal resistors), with absolute temperature (°C) as the main measurement object[9]. Vibration sensors are used to detect the mechanical vibration of the switchgear body and operating mechanism, and the key parameter is vibration amplitude (m/s^2). Current and voltage sensors are used to monitor the electrical parameters of the equipment's power circuit, and their measurement ranges and accuracy have been set according to the operational characteristics of high-voltage switchgear. Several sensor specifications are shown in Table 1 below as a reference for choosing and planning in the system.

Table 1. Sensor types and parameters

Sensor type	Mea-surement range	Pre-cision	Samp-ling fre-quency	Instal-lation location
Tempe-rature sensor	-40℃~125℃	±0.5℃	1Hz~10Hz	Circuit breaker outgoing line terminals, busbar joints, etc.
Vibration sensor	0~20g	±1%	10kHz~50kHz	Switch cabinet body, operating mechan-ism assembly, etc.
Current sensor	0~10000A	±0.2%	10kHz~100kHz	Incoming/ outgoing line cabinets, etc.
Voltage sensor	0~110kV	±0.5%	10kHz~50kHz	Busbar compart-ment, circuit breaker compart-ment, etc.
Pulse current partial discharge sensor	10pC~10000pC	±2%	100MHz~200MHz	A partial discharge coupling capacitor has been set up to form a grounded loop for the partial discharge, and it is connected via a coaxial cable that provides shielding twice.
Ultrasonic partial discharge sensor	40kHz~300kHz	±1dB	1MHz~5MHz	4-point non-coplanar array with 20cm interval around the insulation chamber.

2.2.Data fusion technology

Data fusion technology combines data from multiple sensors to overcome the defects of a single sensor's monitoring capabilities, and its implementation is generally divided into three hierarchical structures: Data-level fusion, feature-level fusion and decision-level fusion[10]. Data-level fusion directly processes and merges raw information from various types of sensors, requiring strict time-space synchronisation; for example, temperature and humidity data collected at the same moment within the same monitoring area. The main advantage is that it retains all the original sensor measurement information, which is essential for detailed and precise analysis, such as early subtle changes in temperature. However, a substantial amount of pre-processing work needs to be carried out to solve the problems existing in different sensors' Data form, Unit difference and Noise problem. Feature-level fusion works with the "information abstraction" of raw data; initially, feature-extraction algorithms such as Fourier transform for frequency-domain features or wavelet transform for time-frequency features are used to process individual sensor data and obtain feature vectors that embody the inherent characteristics of the monitored state. The heterogeneous feature vectors of different sensors are first aligned in the time domain, combined to complete the core fusion process; Then, dimensionality reduction optimisation is performed on the high-dimensional feature set using methods such as PCA. Through reducing the volume of data and retaining key Information, this stage reduces excess raw data and enhances efficiency; Therefore, It Is suitable for Real-time Health Evaluation Systems. Decision-level fusion is the most advanced approach that combines the independent "preliminary judgments" of each sensor to make a final comprehensive decision. The entire process can be broken down into two stages: First, each sensor separately determines the operating condition of the switchgear according to its own data (for example, a temperature sensor classifies "normal/abnormal" based on temperature thresholds); Second, use a fusion algorithm such as D-S evidence theory or weighted voting to integrate these initial judgments and eliminate contradictions or uncertainties. This tier has good flexibility and redundancy: when one sensor fails, the system can use information from other sensors to make a decision; therefore, it is suitable for situations where there may be some degree of uncertainty about whether each individual sensor is reliable. Four commonly used data fusion techniques are the Weighted Average Method, Kalman Filtering Method, Neural Network Method, and Dempster-Shafer Evidence Theory Method; they each have different principles, advantages, and applications (Table 2)[11]. The weighted average method assigns adaptive weights to heterogeneous sensor data based on measurement reliability and operational significance, and then calculates the fusion result through a weighted sum. It has simple calculation rules, low time complexity, and strong real-time capabilities. However, the weights require empirical calibration or an experiment-based method for determination; there is no dynamic adjustment capability that responds to variations in operating states. According to a state-space model, the Kalman filtering method achieves optimal fusion of noisy dynamic data by performing an iteration process that includes system state prediction, observation data update and estimation error correction[12]. It performs excellently in handling time-varying parameters and has strong anti-noise performance, but it requires prior knowledge about the operating characteristics of equipment and has high computational requirements. The neural network method constructs an interconnected layered structure that can automatically learn the intrinsic correlation and fusion rules among multi-sensor data through training with large amounts of labelled samples, without needing to manually design logical rules[13]. It has strong nonlinear fitting and adaptive learning capabilities, but it requires a large amount of high-quality labelled training data and the training process is time-consuming. The D-S evidence theory method considers the output data of each sensor as independent "evidence", uses trust and plausibility functions to quantify uncertain or ambiguous information, and then combines multiple pieces of evidence with set-theoretic combination rules. Although it can well handle the model and fuse uncertain or incomplete data, there are some complexities in computing; It is very intuitive to explain why a certain conclusion was drawn after addressing conflicting evidence.

Table 2. Common data fusion methods

Method Name	Principle	Advantages	Disadvantages
Weighted average method	Give adaptive weights to the heterogeneous sensor data based on their respective measurement reliability (such as accuracy) and operational significance, and then calculate the fusion result using these weights in a weighted sum.	It uses simple calculation rules, has low time complexity, and possesses strong real-time processing capabilities; It can meet the demand for fast access to large-scale data (such as real-time temperature and humidity monitoring) in specific applications.	Alibaba Cloud Qwen development notes: Time-series based dynamic weight update is defective in infrequent updates and lack of accurate feedback on extreme sensor deviations (due to insufficient experience), which leads to fusion errors that slightly reduces the overall system performance through inter-device multi-level fusion information defects.
Kalman filtering method	Based on the state-space model, realize optimal fusion of noisy dynamic data through iterative cycles of system state prediction, observation data update, and estimation error correction.	It performs well in processing time-varying parameters, such as fluctuations in current and transient increases in temperature; At the same time, it has good anti-noise performance, is not easily interfered with by power grid noise, and can maintain high-fusion accuracy in a complex dynamic environment.	It relies more heavily on prior knowledge of equipment operating characteristics to achieve precise state transition and observation equation modelling; Iterative calculation results in high computational load, which is not suitable for resource-limited devices.
Neural network method	Build an interconnected layered neural network structure, which automatically learns intrinsic correlations and fusion rules between multi-sensor data through large-scale labeled sample training, without manual logic design.	It has good non-linear fitting and adaptive learning capabilities, which can acquire the implicit relationship between temperature, humidity and partial discharge under different conditions; At the same time, it is flexible in handling various operating statuses and sensor types.	It needs a large amount of high-quality labelled training data, has long and costly training periods; it is prone to overfitting in small sample or out-of-distribution situations (such as rare failures).
D-S evidence theory method	Treat output data of each sensor as independent "evidence", quantify uncertain/ambiguous information Treat output data of each sensor as independent "evidence", quantify uncertain/ambiguous information via trust and plausibility functions, and integrate multi-source evidence through set-theoretic combination rules to obtain the final decision.	It is good at dealing with uncertain, incomplete and ambiguous sensor data to model and fuse them so as to make up for the information deficiencies among different sources and ensure that reliable fusion results can be achieved even if there are shortcomings in the individual quality of some sensors.	Set-theoretic combination rules have a more cumbersome calculation process and require greater computer resource overhead to meet their demand for dealing with large-scale sensor array systems; If there is a difference between the various kinds of evidence, that is, some contradictions exist among temperature data, partial discharge signal data and others, it will affect fuses's judgement effect.

3.System design

3.1.Overall architecture

The intelligent health evaluation system of the high-voltage switchgear has a four-level modular structure, which consists of sensor layout, data acquisition and transmission, data fusion and processing, and health status assessment and decision-making. This Design realises end-to-end intelligent monitoring with the smooth flow of data, thereby ensuring the system's overall reliability and operating efficiency. Each tier is designed to solve particular technical problems, and there are clear links among these layers and strong connections back to the theory outlined above.

3.2.Sensor module layout

Strategic sensor layout is the basis of precise data acquisition, and the configuration should be customised according to the operating principles of sensors, the structure of switchgear and the distribution of fault risks. Temperature sensors are installed in areas where there is a high risk of temperature rise due to the concentrated impact of current, such as the outgoing line terminal of the circuit breaker and the connection point of the busbar, based on actual site conditions; At the same time, ensure that these positions meet the requirements for sensor installation. Fibre Bragg gratings (FBGs) have the advantages of being fully electrically insulated and having strong anti-EMI capability; Therefore, they are set up for the circuit breaker's outgoing line terminal position that directly contacts the moving / static contacts via a conductive rod, as well as the connection point between the busbar and bolt, with a deviation less than 1 millimetre from the conductive surface, so that actual temperature variations due to poor contact can be promptly detected to prevent overloading or failure in contacting components at an earlier stage. This Layout directly reflects that the working principle of contact Temperature Measurement for High-Voltage Live Parts is achieved; All-fibre Optic Structure Realises whole Electrical Isolation between The high-voltage Conducting Surface and the low-voltage Acquisition System to prevent Insulation Breakdown or Short Circuit Accidents under harsh conditions like high Voltage and strong Arcs at The same time, Thermal Information can be obtained precisely.

A humidity sensor is placed in an area where the air circulation is relatively balanced, such as the middle of the switchgear's side panel, 30 cm above the ground; At the same time, it should maintain a distance of more than 20 cm from heating components (such as contacts and busbars), so that the local humidity deviation does not affect the overall temperature rise situation, which may cause a humid effect at the bottom and a higher error rate due to local heat radiation, making the measurement data able to reflect the overall internal humidity Environment. That is, because the operating state of this humidity sensor meets the needs of monitoring moisture related to insulation, it is concluded that there should be no problem of this component being wet under conditions of high humidity in normal use. A partial discharge sensor uses a dual-configuration anti-interference design: A pulse current sensor is installed on the ground loop of the dedicated partial discharge coupling capacitor, using double-shielded coaxial cable for signal transmission to suppress power frequency electromagnetic interference and grounding circulation interference; Four ultrasonic sensors are arranged in a 4-point non-coplanar manner around the insulation chamber to achieve precise three-dimensional space positioning of partial discharges. This layout uses the TDOA principle for three-dimensional positioning, overcomes the deficiency of planar arrays that cannot achieve comprehensive spatial localisation of internal discharges, and meets the standard test method for partial discharge of high-voltage electrical equipment specified in IEC 60270. According to the different objectives of vibration, current, and voltage sensor measurements, as well as their respective parameter requirements, as specified in Table 1, they will be placed accordingly.

3.3.Data acquisition and transmission module

3.3.1.Data acquisition submodule

The data collection sub-module converts analog sensor signals into standardised digital data; It uses a 16-bit ADC to convert low-frequency signal data; Dedicated 12-bit high-speed ADCs are used to sample at up to 100MHz, which can handle ns-level transient partial discharge pulse signals without distorting the weak partial discharge pulse signal. For example, the ultrasonic sensor signal is generally in the range of 0~10mV; before it is amplified to 0~5V and then converted, its stability can be maintained, and at the same time meet the sensitivity requirements of the acquisition device and match the output characteristics of the sensor. The sub-module also has adaptive sampling rates that vary depending on the type of sensor and monitoring requirements; For partial discharge detection using high-frequency (HF) pulse current sensors, it is set at a rate between 100-200 MHz (as specified in Table 1 parameters); this high sampling rate can catch ns-level transient pulse signals with a rising edge greater than 10 ns to meet both the IEC 60270 standard for pulse current method partial discharge detection and engineering anti-interference requirements in high-voltage environments. For the ns-level damped oscillating partial discharge pulse (the main pulse form of internal insulation defects in high-voltage switchgear), the maximum effective spectral component is determined by two key factors: the rise edge of the pulse and the inherent oscillation frequency of the partial discharge signal. The classical formula f_{max}=0.35/t_r applies only to the step response of a first-order linear system under unipolar rectangular pulse excitation; Therefore, it cannot be directly applied to dampened oscillatory partial discharge signals. For 10ns rising edge-damped oscillating pulses in switchgear, the highest effective frequency of the main energy band can reach as high as 50MHz; at the same time, the high-frequency interference harmonic components in the substation environment have extended to 80MHz. According to the Nyquist sampling theorem, the sampling frequency should not be lower than twice the highest effective frequency of the measured signal; Considering the complex strong electromagnetic interference environment in the power system, an engineering safety margin of 2.5~5 times is added, so the lower limit of the sampling frequency has been set at 100 MHz. The lower limit of this standard must be followed when setting the sensor configuration parameters, as shown in Table 1; otherwise, spectrum aliasing will happen because of the insufficient sampling rate.

3.3.2.Data transmission submodule

The data transmission submodule acts as a bridge between the acquisition end and processing center, with communication technologies selected based on scenario-specific constraints. Industrial Ethernet (Profinet/EtherNet/IP, 100Mbps) is used for fixed switchgear in substations, leveraging its high stability and 100m transmission distance to ensure real-time data delivery (latency < 10ms) for critical parameters like short-circuit current. For distributed switchgear (e.g., outdoor box-type substations) where wiring is impractical, wireless LoRa (433MHz/868MHz band) is adopted—its low power consumption (battery life > 2 years), strong anti-interference capability and long transmission distance (several kilometers) address the challenges of scattered installation and maintenance in the complex electromagnetic environment of high-voltage substations; for short-distance local networking requirements, industrial-grade Wi-Fi 6 (5.8GHz) can be selected as an alternative to avoid electromagnetic interference in the 2.4GHz band.

3.4.Data fusion and processing module

As the central part of the System's "Brain", this module converts raw sensor data into usable Health Intelligence through three steps: Data pre-processing, Multi-level Data Fusion and Feature Extraction. The entire process is closely connected to the data fusion technology mentioned earlier.

3.4.1.Data preprocessing

Data preprocessing consists of two parts: cleaning and normalising the data. Data cleaning reduces noise and anomalies in the signal by using a target algorithm, and Wavelet threshold denoising is used to process partial discharge signals to remove electrical interference from the power supply system. First, perform the Shapiro-Wilk normality test on the temperature data to check whether it follows a normal distribution. According to the test results, the temperature data conform to a normal distribution (W=0.973, P>0.05), and therefore the applicable conditions for the 3σ rule have been met. Based on this, the 3σ rule is employed to eliminate abnormally large data due to brief sensor failures. To decide whether it is appropriate to delete outliers according to the 3σ rule, as shown in Figure 1 shows the comparison of temperature sensor data before and after processing. The left sub-figure is the raw data before fusion, and the red dots mark the outliers outside the range of [μ-3σ, μ+3σ], where μ=60.96 and σ=2.65; Therefore, μ+3σ=68.93 and μ-3σ=52.99. There are some anomalies and many outliers that deviate from the general pattern in the data. The right figure shows the data processed by the 3σ rule, and a green dotted line at the mean of 60.04. After processing, all outliers have been removed, and the data's fluctuation range has decreased substantially; that is, the standard deviation dropped from 2.65°C to 0.42°C. Through this comparison, it can be seen that the 3σ rule has removed the extreme values but still reflects the variation characteristics of the original data; therefore, at this point in time, it will meet our basic needs for subsequent multi-level data fusion work.

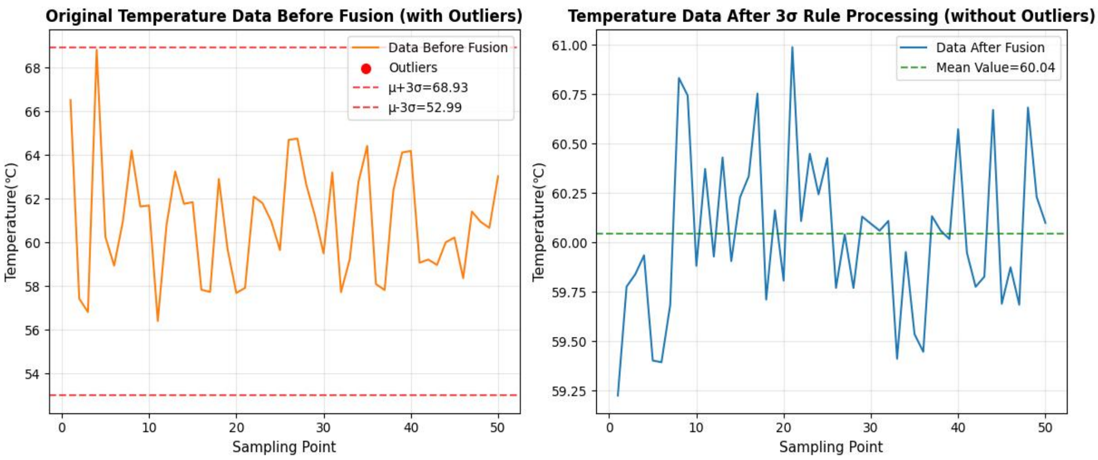

Fig 1. Comparison of temperature sensor data before and after fusion

(a) original data before fusion (with outliers); (b) processed data after 3σ rule (without out-liers)

3.4.2.Normalization and data fusion

To address dimensional inconsistencies—such as those between temperature (°C) and current (A)—that can distort fusion outcomes, normalization scales heterogeneous data to a consistent range while adapting to extreme operating conditions and cold-start scenarios. For bounded parameters with clear full-scale measurement ranges specified in Table 1, such as humidity (0%~100%RH) and current (0~10000A), improved min-max normalization with amplitude limiting is employed. For humidity, the normalized value is calculated as:

$$x_{norm}=clip\left(\frac{x-x_{min}}{x_{max}-x_{min}},0,1\right) \tag{1}$$

where x_{min} and x_{max} are the lower and upper limits of the measurement range specified in Table 1.

For current parameters, this clipping mechanism ensures that the transient peak current during short-circuit faults (exceeding the rated measurement range) is limited to the [0,1] interval, avoiding invalid out-of-bounds model input. For parameters without fixed upper and lower limits in long-term operation, improved Z-score normalization with adaptive benchmarking is used:

$$x_{norm}=\frac{x-\mu}{\sigma} \quad (2)$$

For equipment that has been in use for more than 30 days with valid historical operation data, μ represents the long-term historical average, and σ represents the historical standard deviation of the parameter; For newly commissioned equipment lacking sufficient historical data (cold start), μ and σ take the industry benchmark values of the same type, same voltage level switchgear under normal operating conditions, and are dynamically updated using a sliding time window (7 days) as actual operating data accumulates.

In order to fully leverage the data, multi-level data fusion combines these three hierarchical methods: data level, feature level, and decision level. At the data level, raw data from the same sensor type (three temperature sensors, each placed at a different busbar connection) is merged by means of a weighted average. This uses the feature that it is easy to calculate and has good real-time performance to reduce random errors. At the feature level, several features are extracted from preprocessed data (for example: Fourier transforms obtain the 50Hz fundamental frequency component of the current signal, and the negative-sequence component of this component is selected as a key indicator for monitoring three-phase load imbalance); At the same time, PCA can be employed to reduce dimensionality. For heterogeneous multi-sensor features, a two-stage "feature fusion + dimensionality reduction optimisation" strategy is used: First, the time-synchronised heterogeneous feature vectors of temperature, humidity, partial discharge, vibration, current and voltage sensors are spliced together to complete feature-level fusion and form an ordered high-dimensional feature set that describes the entire operating condition of the switchgear. Based on this, dimensionality-reduction optimisation is carried out strictly according to the applicable conditions of the statistical method: For steady-state characteristics that meet linear correlation criteria (such as the mean of temperature, the stable state of humidity, and RMS values of voltage/current), the Shapiro-Wilk normality test is conducted on all features first. The test results show that all the above-mentioned steady-state linear characteristics conform to a normal distribution ($W > 0.95$, $P > 0.05$) and provide a statistical basis for subsequent inference analysis of the extracted principal components. Then PCA (Principal Component Analysis) is used for linear dimensionality reduction based on the covariance matrix of the features; it compresses feature dimensions while retaining 95% of the cumulative variance contribution rate of linear critical information and improves computational efficiency. For strongly nonlinear fault-related features, such as partial discharge pulse characteristics, temperature rise-vibration coupling characteristics and humidity-insulation ageing synergic characteristics, the nonlinearity of these features can be reduced by KPCA with a Gaussian RBF kernel. The core width parameter σ of the RBF kernel is optimised using grid search combined with five-fold cross-validation, and the search range is defined as [0.1, 100]; At the same time, it aims to maximise the cumulative variance contribution rate of the first ten principal components. By optimising the RBF kernel mapping, the original nonlinear features are projected into a high-dimensional linear separable space, and then the principal components are extracted; this approach fully preserves the nonlinear correlation information of multi-factor coupled faults while reducing the feature dimension by 30%~50%. Finally, at the decision level, D-S evidence theory is used to fuse the initial judgments of individual sensors, such as a thermocouple that reports "temperature abnormal" and a humidity sensor that reports "humidity normal", into an overall health status evaluation. Taking advantage of its capability in dealing with uncertain information, it enhances the system's fault-tolerance.

3.4.3.Feature extraction, selection, and optimization

Feature extraction is aimed at transforming the fused data into discriminative feature vectors that can represent equipment health status, and different methods are used according to the fusion hierarchy. At the data level, Fourier transform is used to obtain frequency domain features (such as the 50Hz fundamental frequency component and its integer multiple harmonic components of the current signal), while Wavelet transform acquires time-frequency characteristics, such as abrupt changes in the amplitude of partial discharge pulse; Therefore, it has strong fine-grained description ability that cannot be ignored when dealing with small-scale defects at an early stage. At the feature level, single-sensor feature vectors are extracted separately, such as temperature rise rates, humidity fluctuation ranges, and discharge pulse frequencies; then divided into two categories: Linear steady-state feature subsets and non-linear fault feature subsets. The linear part is reduced using PCA to decrease the correlation of linear features; The non-linear part uses KPCA to discover deeper nonlinear relationships among features; In short, this improves computational efficiency and feature representation capability simultaneously. At the decision-making level, meta-features such as the confidence scores of initial sensor decisions are extracted to support the final judgment; When there is a conflict in judgments, D-S evidence theory is used to resolve them.

After feature selection, optimise these features to enhance their semantic clarity; After improvement of meaning is achieved by a few high-semantic-chiar characteristic subsets that are easier to merge into; At the same time, it also helps reduce the complexity of the model and prevent overfitting. Filter-based methods, such as mutual information and variance threshold, rapidly eliminate low-discrimination features. On the other hand, wrapper method is selected as a feature selection tool to avoid the issue of unstable ordering produced by the tree structure and improve interpretability; Recursive Feature Elimination (RFE), for example, can be used here to select features based on the performance of some specific model, so that these selected features are more in line with the objective of health assessment. Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO), etc., of other related intelligent algorithms are used to enhance the precision and expand this field into two main directions: increasing feature subset calculation accuracy, diversity control combined with discrimination ability improvement, providing a more accurate framework for determining feature sub-sets. During this process, about 30%~50% of the features will be eliminated to improve both model training efficiency and generalisation ability.

3.5.Health assessment and decision-making module

The Health Assessment and Decision-Making Module provides intelligent health evaluation based on integrated multi-source information and pre-set model, and the foundation of both the evaluation index system and the assessment model is built upon the theoretical basis and data processing results of this study.

3.5.1.Evaluation index system

It is worth noting that this system is designed to achieve the whole-process health status evaluation and early incipient fault warning of high-voltage switchgear. The emergency protection action for short-circuit faults is carried out by a dedicated relay protection device in accordance with Power Industry standards; this system does not perform the safety protection function of the relay protection device. The calculation method for the current imbalance degree uses the Symmetric Component Method; Its general calculation rules for three-phase unbalance are based on the valid national standard GB/T 15543-2021 Power Quality -- Three-phase Voltage Unbalance. The classification evaluation threshold is set in accordance with DL/T 1870-2018 Technical Management Regulations for Power Quality of Power System and DL/T 596-2021 Preventive Test Code for Electric Power Equipment, which specify the management requirements for three-phase current unbalance of power distribution equipment to ensure the compliance and accuracy of the index. The evaluation index system integrates multiple dimensions to reflect not only the immediate operation of the information security risk prevention and control system but also its long-term healthy operating situation; It is composed of direct or indirect indicators. The direct indicators represent the actual operating condition of the equipment at present, which is shown in Table 3 and includes temperature anomaly rate, vibration amplitude, current imbalance degree and voltage deviation rate - that is, the core monitoring index values provided by the selected sensors. Indirect indicators can provide additional long-term health status reference for the accuracy of real-time data; Such as accumulated operating hours (after about 10,000 Hours use there is a possibility that it would be out of service); Frequency of repair: One repair every three months may indicate possible potential risks in structure); Environmental temperature below -20°C lasting more than half an hour will make high-voltage equipment outdoors operate abnormally. Indicator weights are calculated using the Analytic Hierarchy Process (AHP): a judgment matrix is built according to experts' opinions, such as partial discharge amplitude having a higher weight than ambient temperature because it directly reflects insulation failure; then perform a consistency check to make sure the weights are reasonable and reduce subjectivity.

Table 3. Health assessment indicators

Indicator Name	Calculation Method	Evaluation criteria
Temperature anomaly rate	Number of temperature threshold exceedances / Total monitoring instances.	<5%: Normal; 5%~10%: Concern; >10%: Abnormal
Vibration amplitude	Peak value of vibration sensor output signal.	<10g: Normal; 10g~20g: Concern; >20g: Abnormal
Current imbalance degree	(Negative sequence component of three-phase current / Positive sequence component of three-phase current) × 100%	<2%: Normal; 2%~4%: Concern; >4%: Abnormal
Voltage deviation rate	(Actual operating voltage - Rated voltage) / Rated voltage	<5%: Normal; 5%~10%: Concern; >10%: Abnormal

3.5.2.Assessment models and system operation

Based on the features of multimodal sensor data and the requirements for health evaluation, representative assessment models have been selected and optimised accordingly. new support vector machine; Compared with other classifiers, it has better performance on small datasets and is also capable of identifying an anomaly due to a slight insulation defect. Through the mapping of feature vectors to a high-dimensional space by means of kernel functions (such as the RBF kernel), it overcomes the nonlinearity problem in classification and achieves accurate distinction between "concern" and "abnormal" States when the number of samples is small (less than 1000).

CNNs, on the other hand, excel at local feature extraction of time-series multimodal data[8,14]. Convolutional layers can obtain abundant details on how temperature and voltage change over time, such as specific circumstances where there is a sudden deviation of the temperature from the normal level, a sharp variation in part of the discharge signal, etc., and then pooling operations will be carried out to retain these essential characteristic components related to the failure process at this moment; Then further reduce dimensions through densely connected neural networks - fully-connected layer nodes. Combined with the dilated convolution module to expand the receptive field, this structure can effectively capture the medium-short term cumulative correlation of operating parameters; For the long-term operational dependence problem that lasts for more than a month (such as the cumulative damage effect of high humidity on insulation performance), it is supplemented by an LSTM branch to enhance its ability to capture long-term time-series dependencies, thus improving overall assessment accuracy under complex progressive fault conditions.

Model training and optimisation followed a structured workflow that strictly complied with the time-series data processing specification: To prevent the future information from infiltrating the training process and causing data leakage, the dataset was divided into three parts - train (70%), validate (15%), and test (15%) - in strict chronological order; The training set took the first 70% of the time series data, the validation set took the second 15%, and the test set took the last 15%. Hyperparameters (such as SVM kernel parameters, CNN learning rate) were adjusted using methods like grid search or random search; To avoid overfitting of the model, time-series cross-validation (Time Series Split) was used for validation; Ultimately, an effective classifier with high practicability was developed through this process.

Upon receiving the fused feature data, the module automatically selects an appropriate evaluation model, SVM for a small sample situation and CNN for time series data; It combines three kinds of information streams: real-time fused features (such as current imbalance degree), historical fault records (such as partial discharge events in the last six months) and environmental factors (such as ambient temperature outside the cabinet) to achieve a comprehensive health assessment. When the degree of current imbalance is 3.5%, it belongs to the "attention" category; however, if there has been an overload failure record in the switchgear due to special safety needs, this model upgrades the health warning level to a more serious situation - that is, it needs immediate attention.

4.System validation and analysis

4.1.Experimental platform setup

In order to verify the system's practical application value, an experiment was carried out on an established platform that approaches the actual working state of high-voltage switchgear and includes a modular structure with controllable parameters. The Power supply system provides a steady and adjustable DC/AC voltage of 0-110kV and current of 0-5000A; it has an AC/DC output function that can simulate different power Grid operating states, such as the rated voltage state or ±10% of the rated voltage deviation.

The load system consists of resistive, inductive and capacitive loads (adjustable range 0~1000kVA), which can simulate the actual load characteristics of industrial users, such as motor-driven inductive loads and capacitor bank capacitive loads, and it also has the ability to simulate overload (120%~150% of the rated current) and unbalanced load situations. The fault simulation unit consists of an adjustable module that can generate typical failure states, such as poor contact (poor contact resistance is set to the range of 0.1-10Ω to simulate deteriorated contacts), aged insulation (pre-aged epoxide resin material according to IEC 60270 standard, partial discharge amount controlled between 10PC-5000PC), and short circuit (phase-to-phase or phase-ground electronic switch connection simulates instantaneously occurring massive current). The number control section has two separate controllers that realise both functions: precise adjustment of critical factors in each inspection environment; Synchronised sequence playback function is provided for multiple parallel test channels under their own frameworks, which can reproduce the complex changing situation caused by multiple failures simultaneously.

The environmental simulation system consists of a temperature-humidity control chamber (-40°C to 125°C, 10%~95% RH), which is used for extreme environmental reproduction of high-humidity coastal areas and low-temperature northern winter scenarios; at the same time, it also serves as an environment adaptability test base for confirming whether this facility has strong resistance.

4.2.Sensor installation and data acquisition configuration

The installation of the sensor followed the predefined layout plan to ensure data integrity; At the same time, the acquisition system was set up according to specific parameters. Temperature sensors were installed at the connection points between the circuit breaker's outgoing lines and busbars, as well as at bolted connections on the busbar, with an installation gap of less than 1mm from the conductive body, and they operate at a sampling rate of 5Hz to better track temperature fluctuations. A humidity sensor was installed 30 cm above the switchgear base (to avoid moisture accumulation), 50 cm away from insulating parts, and no less than 20 cm away from heating devices, with a sampling rate of once per second.

The partial discharge monitoring used two types of sensors: pulse current sensors were placed on the grounding loop of the dedicated partial discharge coupling capacitor (sampling frequency was 100MHz, with double-shielded coaxial cable to prevent interference) and ultrasonic sensors were set up in a 4-point non-coplanar arrangement at 20cm intervals around the insulation chamber (sampling frequency was 2MHz). Vibration, current and voltage sensors were arranged according to the parameters listed in Table 1 (for example, current sensors were placed in incoming line cabinets with a sampling rate of 50kHz; Vibration sensors had a sampling rate of 20kHz); The acquisition system used 24-bit high-precision data acquisition cards (resolution: 1μV) to acquire weak signals, and the sampling accuracy of current sensors was calibrated to ±0.2%, that of temperature/humidity sensors to ±0.5%, which is consistent with the inherent precision of these sensors to avoid signal distortion. Data transmission was performed using Ethernet for low-latency (<10ms) real-time data feedback that meets the requirements of the data acquisition and transmission module.

4.3.Experimental results and performance comparison

Data was continuously collected for 72 hours in three typical operating states, and at the same time, real-time evaluation was carried out by means of the proposed system. According to the above mentioned information, we judge the accuracy of fault identification and response speed.

Under normal operating conditions, all sensors were in their respective normal working states (temperature anomaly rate < 5%, vibration amplitude < 10g, current imbalance degree < 5%), and the system precisely classified the "normal" state with an evaluation accuracy of ≥98%, without any false alarms. As shown in the figure above, after continuous operation without interruption at this time.

In overload conditions, when the load increased to 130% of the rated current, the system began real-time data acquisition and feature analysis 2 seconds after the overload occurred; The temperature anomaly rate was 8% (the concern range) and the current imbalance degree was 3.2% (the concern range) five minutes later, at which time the system issued an "Level two warning" and quantified the overload risk (an estimated increase of 30% in insulation degradation rate), providing a data-driven basis for load adjustment.

In the case of a short-circuit situation, there was an instantaneous peak current of 8000A in this phase-to-phase short circuit and a temperature rise rate as high as 45℃/s. After the dedicated relay protection device completed fault removal (according to the Power Industry Standard, it should be within 100ms), the system finished post-fault status evaluation, identified the short circuit fault type, located the fault point with an error less than 5cm, and issued a "Level 1 Warning" within 500ms, providing data support for subsequent fault analysis and equipment maintenance.

To comprehensively verify the advantages of the proposed intelligent system, a direct comparison was made with traditional methods (mainly single-parameter monitoring and simple threshold judgment) in terms of the following three key performance indicators: evaluation accuracy, reliability, and timeliness. Traditional ways use single factors to determine if there is a problem, and do not consider the interactive effects of multiple factors. As shown below: Five direct indicators and three indirect indicators are introduced into this intelligent system at once. In terms of parameter correlation, it takes cross-parameter correlation into account for overall judgment.

The traditional method uses fixed-threshold rules which cannot meet the requirements of changing operating states; while the intelligent system employs data fusions and machine learning algorithms to update the assessment standard dynamically and reduce false negative rates. In addition, single-parameter traditional methods will fail entirely if the target sensor fails; However, the intelligent system has achieved a certain degree of fault tolerance through the combination of multiple sensors' redundancy and decision-layer fusion: even if one sensor is unavailable, the remaining sensors can still maintain about 85% of the original assessment accuracy.

The experiments confirmed that, under all working conditions, the intelligent system achieved an average evaluation accuracy of 96.8%, while the traditional single-parameter method was only about 78.3%. In terms of timeliness, the intelligent system can identify early-stage faults (such as incipient contact degradation) 2-3 hours ahead of traditional methods, and its false alarm rate is only 1.2%, compared to 8.7% for traditional methods.

In order to further investigate the performance difference in each specific failure type between these two methods, Fig. 2 shows the comparison results of different failures types' accuracy. For contact overheating, the traditional method achieves 85% accuracy, whereas our system achieves 98%, which is a 13% increase due to the combined use of temperature and vibration data. For insulation ageing, the traditional method (78 per cent accuracy) is inferior to our system (96 per cent), which utilises a combination of partial discharge and humidity signals for diagnosis.

Note that, for the cooperative failure of humidity + overheating, the traditional method has an accuracy rate of only about 62%, while our system reaches up to 95% - a significant 33% increase over the original value, as shown in the figure. There is a considerable deviation from reality in existing single-factor Methods due to their difficulty or inability to capture the correlation among factors; thus, it is necessary to incorporate other modalities for this reason. For short-circuit faults, our system still has a high detection rate of 99 per cent compared to the conventional approach's 90 per cent due to its real-time integration of current, voltage and vibration information.

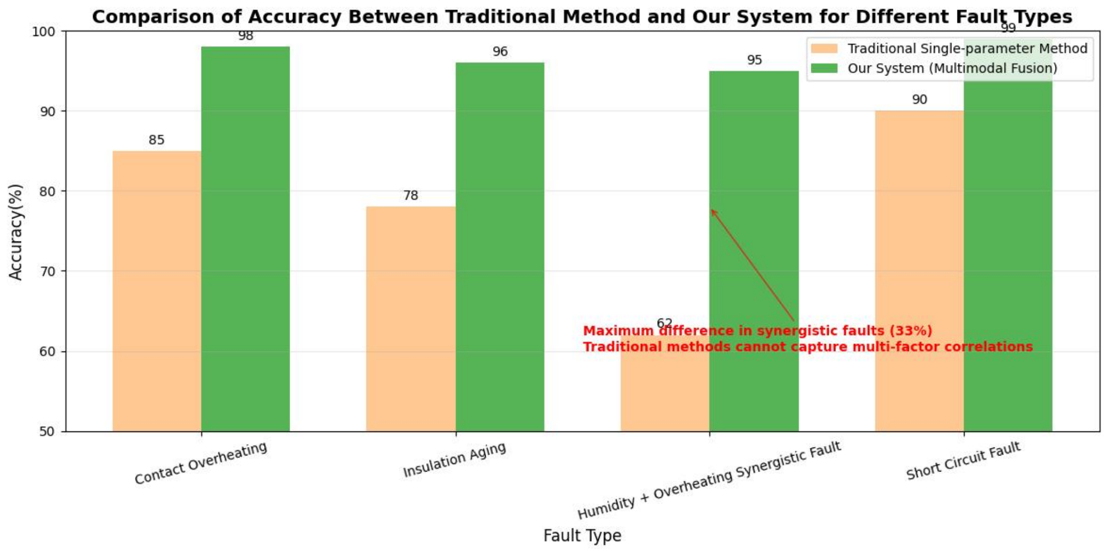

Fig 2. Comparison of accuracy between traditional method and our system for different fault types

(Note: Orange bars represent the Traditional Single-parameter Method, and green bars represent Our System with Multimodal Fusion.)

Useful toals were obtained from standard statistical analysis of the test data in various dimensions such as accuracy, recall rate and precision (that is what I mean when I say F1 score) (Table 4).

4.4.Core evaluation metrics

Accuracy: The proportion of correct health status (normal, concern, abnormal) out of the total number of samples; that is, the system's overall judgment ability. The calculation formula is shown below(3):

$$\text{Accuracy}=\frac{\text{True Normal}+\text{True Concern}+\text{True Abnormal}}{\text{Total Samples}} \tag{3}$$

Recall is the ratio of actual fault samples (concern/abnormal) that have been accurately detected by the system; it shows whether a problem will be overlooked or not. The calculation formula is shown below(4):

$$\text{Recall}=\frac{\text{True Concern}+\text{True Abnormal}}{\text{Actual Concern}+\text{Actual Abnormal}} \tag{4}$$

Precision is defined as the ratio of "concern/abnormal" samples that are actually faulty out of all identified "concern/abnormal" samples; it represents the model's ability to reduce false alarms. The calculation formula is shown below(5):

$$\text{Precision}=\frac{\textit{True Concern+True Abnormal}}{\textit{Predicted Concern+Predicted Abnormal}} \tag{5}$$

F1-Score: A balanced average of precision and recall that takes into account both the accuracy of fault identification and the false alarm rate. The calculation formula is shown below(6):

$$\text{F1−Score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{6}$$

Accuracy refers to the overall judgment capability of the system; Recall is the ability to identify possible risk problems; Precision is an indicator that controls false alarm rate; F1-Score aims at balancing these two factors.

Table 4. Statistical results of core evaluation metrics

Working Condition	Accuracy	Recall	Precision	F1-Score
Normal Operation	99.2%	none	none	none
Overload Condition	96.5%	95.8%	97.1%	96.4%
Short-Circuit Condition	98.3%	99.1%	98.7%	98.9%

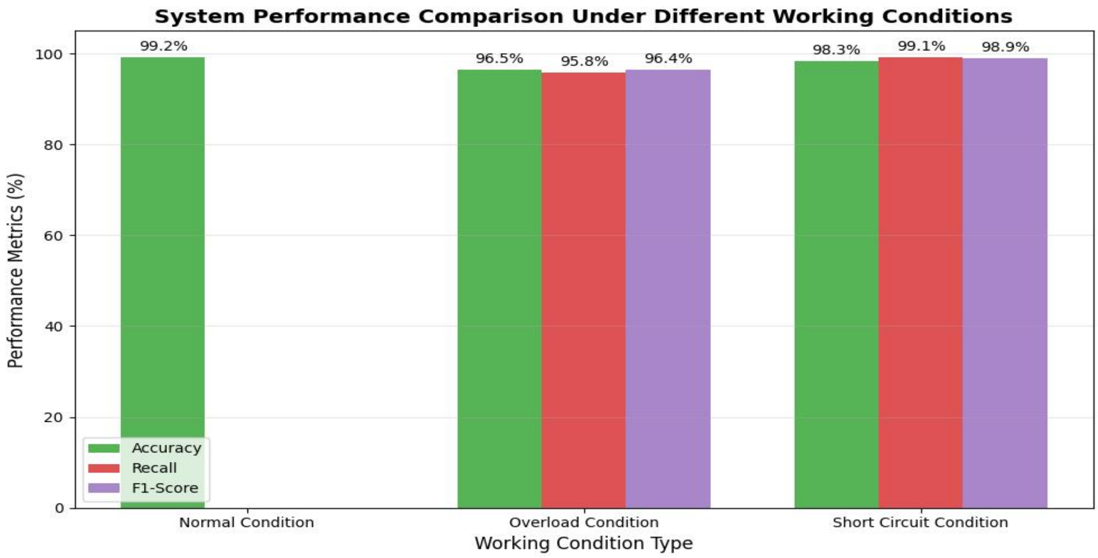

Fig 3. System performance comparison under different working conditions

(Note: Green bars represent Accuracy, red bars represent Recall, and purple bars represent F1-Score.)

To intuitively display the system's performance differences in various operating conditions, Fig. 3 shows a comparison chart of accuracy, recall and F1-Score under normal, overload and short-circuit states respectively. In general operation, under normal circumstances, the system has achieved a high degree of accuracy at 99.2%, due to the lack of fault signals and stable sensor data; Therefore, this error is not caused by such factors. Under overload conditions, the accuracy, recall rate, and F1-Score of this system are 96.5%, 95.8%, and 96.4%, respectively; Therefore, it has achieved satisfactory risk detection results in a complicated load condition. It is especially noteworthy that under short-circuit conditions, the system has a relatively high accuracy - 98.3 per cent for identification, 99.1 per cent for recall, and an F1-Score of 98.9 per cent; thus, it exhibits remarkable sensitivity and reliability for severe faults. Based on the analysis above, this system has high stability and low false alarm rates under normal operating conditions of the equipment; At the same time, it can quickly identify anomalies such as short circuits.

Determinants of the evaluation result mainly cover data quality, feature extraction and model selection. The improvement rate of system accuracy is 4.2 per cent through denoising and outlier removal; if the raw data has not been processed, the partial discharge judgment's false alarm rate will increase dramatically due to electrical interference. A two-stage PCA-KPCA dimensionality reduction strategy has been selected to reduce the model's complexity by approximately 40 per cent and still maintain as much as 95 per cent of the necessary features, such as linear steady-state information and nonlinear fault correlation information; at the same time, it can provide sufficient feature support for mult facto-rsynergy fault recognition. CNNs outperformed SVMs in terms of time series data, with an increased recall rate of 3.1% for long-term insulation degradation; However, the stability of the SVM was better for small sample rare faults such as insulation breakdown, and its precision was higher by 2.5%.

4.5.Sensitivity analysis

In order to further verify the system's ability to withstand changes in key factors, a sensitivity analysis was carried out on the FS accuracy of sensors; This is one of the essential hardware components of the device and also has a unified metrological definition that affects data quality. All kinds of sensors are uniformly converted to the full-scale relative accuracy (%) for quantitative analysis; For instance, the temperature sensor with an accuracy of ±0.5℃ in the range of -40℃~125℃ has a full-scale accuracy of 0.30%FS (calculated as: absolute error 0.5℃ / full-scale span 165℃ × 100% ≈ 0.303%FS), and the current sensor with an accuracy of ±0.2%FS in the range of 0~10000A retains its original full-scale accuracy index. Figure 3-2: The design of the student information table includes key fields such as ID, name, gender, date of birth, etc., which are crucial for student data management. Figure 4 shows the correlation between sensor full-scale accuracy (ranging from 0.2%FS to 1.0%FS) and system evaluation accuracy, and error bars represent the standard deviation of 30 repeated experiments for each condition. As sensor full-scale accuracy decreases from

0.3%FS (consistent with the calibrated accuracy of the temperature sensor), to 1.0%FS, system evaluation accuracy drops only slightly, from 96.8% to 94.7%, which is about a 2.1% decrease. Even if the sensor's full-scale accuracy is 0.8%FS (orange dashed line), the system's accuracy remains above the 95% threshold (red dashed line); therefore, it can be concluded that the system has achieved high-reliable performance within a reasonable deviation range of the sensor precision. This robustness is mainly due to the multi-level data fusion strategy: cross-validation among multiple sensors can offset individual sensor errors, and the adaptive learning capability of the model reduces dependence on a single source of data for high accuracy.

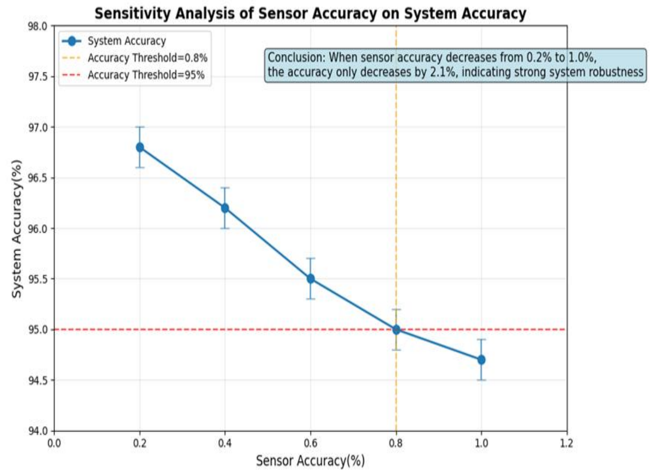

Fig 4. Sensitivity analysis of sensor accuracy on system accuracy

(Note: Blue dots represent system accuracy with error bars indicating standard deviation; orange dashed line marks the sensor accuracy threshold of 0.8%; red dashed line marks the system accuracy threshold of 95%.)

5.Application suggestions and maintenance strategies

Based on the experimental results and their underlying evaluation criteria, a three-tier warning system combined with specific maintenance recommendations has been built to offer actual advice for power grid operation and maintenance (Table 5).

At this time, when the first alert is reached in the standard, it indicates that among all health status evaluation indicators of this device, one or more have exceeded their respective abnormal thresholds (for example, if the temperature anomaly rate has exceeded 10%). This requires immediate on-site inspection and fault diagnosis; if any safety hazards are confirmed during the process, the equipment must be shut down promptly for maintenance.

When a single health evaluation indicator reaches the "attention" level, that is, when the current imbalance ratio falls within the range of 5% to 10%, a Level 2 Warning will be issued. At this time, the frequency of continuous monitoring needs to be increased; A thorough root cause analysis should be carried out (such as verifying whether the Connection is firm and whether there is an imbalance in the current distribution); At the same time, a personalised maintenance plan should also be formulated.

At this time, if any of the health evaluation indicators approaches or exceeds the "attention" warning level standard - for example, when the temperature anomaly rate reaches 4.5% in combination with a vibration amplitude reaching 9G, a Level 3 Warning will be issued immediately; Meanwhile, it also needs to be noted that this kind of alarm system design may cause some inconvenience and impact on daily use due to frequent false alarms. To achieve this, it is necessary to improve the operation parameter settings to alleviate pressure; carry out routine inspections every week (including checking for insulation damage and fixing loose screws), conduct preventive measures in advance, etc.

Table 5. Warnings and maintenance recommendations

Warning levels	Trigger Condition	Maintenance recommendations
Level 1 Warning	Any health assessment indicator exceeds the abnormal threshold (e.g., temperature anomaly rate >10%).	Conduct a spot check and handle faults immediately; If there is a safety hazard, stop the equipment for repair.
Level 2 Warning	Any health evaluation index is above the worrying threshold, for example, an imbalanced rate of over 2 per cent to less than or equal to 4 per cent.	Increase the frequency of real-time monitoring, find out why there is an abnormality (whether it is due to a loose wire connection), and then develop an appropriate maintenance plan.
Level 3 Warning	Multiple health evaluation index values have approached or exceeded the concern threshold, for example, the temperature anomaly rate reached 4.5%, and the vibration amplitude was 9g.	Adjust the operating parameters to lighten the load on the equipment; Inspect the main parts regularly every week, promptly replace damaged ones, and keep them functioning normally; Clean the insulating components regularly, retighten the loose bolts, and handle other issues.

According to the output of the system's evaluation, this maintenance strategy has reduced blind maintenance by 60% and saved 35% on maintenance costs compared with traditional scheduled maintenance; thus, it fully demonstrates its practical value for the intelligent health examination system.

6.Application suggestions and maintenance strategies

Based on the actual operation of high-voltage switchgear, this paper has put forward a new type of intelligent health evaluation system that uses multimodal sensors to fuse information with artificial intelligence and deep learning algorithms. The system addresses the shortcoming of traditional single parameter evaluation and achieves three major improvements: First, it establishes a comprehensive monitoring framework integrating temperature, humidity, partial discharge, current, and vibration data; second, it achieves intelligent status prediction based on big data analysis; Third, it realises early fault detection and alarm through high-precision sensor network. This framework addresses the "blind spots" of traditional single-parameter monitoring, enabling early detection of multi-factor synergic faults, such as insulation degradation caused by humidity combined with contact overheating. The second is a high-performance technical pipeline that includes "data cleaning + multi-level fusion + feature optimisation + dual-model (SVM/CNN) evaluation", which can achieve an average accuracy of 96.8%, a fault state recall rate higher than 95.8%, and complete post-short-circuit fault state assessment and localisation within 500ms. Compared with traditional methods, it can improve the accuracy of early incipient fault identification by 18.5%, extend the time for early detection of incipient faults by 2-3 hours, and still achieve an accurate rate as high as 85% when one sensor fails, demonstrating strong fault-tolerant capability. The third is that by introducing a three-level warning mechanism and target-oriented suggestions (such as the specific position of partial discharges monitored by ultrasonic sensors), it can achieve a 60% reduction in blind maintenance compared to regular inspections; At the same time, maintenance costs will also be reduced by 35%.

Although the system has achieved some results, it still has certain limitations. In terms of data coverage, current collection is primarily focused on common parameters such as temperature, humidity, and current; it does not include more intricate environmental factors, such as salt-fog corrosion and dusty conditions in coastal or desert areas, nor does it monitor internal microstructural variations, such as microscopic cracks in insulating materials. This difference may result in an overlooked fault under severe operating conditions. In terms of model generalisation, the system was trained using data from three types of switchgear; thus, there is a 5.7 per cent loss of accuracy when applied to untrained models, indicating that it cannot adapt well to the various forms of switchgear in actual power systems. In terms of adaptability to rare faults, because the frequency with which an unlabelled problem like occasional partial discharge caused by loose insulating bolts occurs is low in actual application and it lacks enough learning training data, its recall rate reached only at about 82.3 per cent when dealing with such difficulties.

In view of these deficiencies in the existing research, future work will focus on four main directions: Expand the range of collected data by combining special sensors, such as salt-fog sensors and ultrasonic flaw detectors, which can obtain environmental-corrosion information and microscopic changes in the material itself; At the same time, it is necessary to enrich the multi-modal dataset. Refine the model architecture to incorporate Transformer-based models for better capture of long-term temporal dependencies in sensor data; at the same time, introduce reinforcement learning to dynamically adjust model parameters according to actual operating conditions. To enhance explainability and reduce reliance on large amounts of labelled data, expert domain knowledge in power-grid operation and maintenance is introduced into the model via fault-classification expert rules to improve its performance. To promote its application in engineering, develop a portable version of the system for on-site tests; at the same time, establish a cloud-based data-sharing platform to collect cross-regional switchgear operation data and further improve the model's generalisation capability.

In summary, the system presented here has provided a scientific and effective solution to the health supervision problem of high-voltage switchgear equipment; at the same time, it will also promote the shift towards intelligence in the operation and maintenance model of power systems. The determined deficiencies indicate the direction for subsequent improvements, aiming to enhance the stability, flexibility and applicability of the evaluation system.

References

[1] LI C X. Research on distributed power equipment monitoring and maintenance system based on wireless sensor network. Journal of Home Appliance Maintenance, 2024, (6): 10–12.

[2] JIANG D L. Research on fire early warning and fire extinguishing technology of 10kV high-voltage switchgear. Nanchang: Nanchang University, 2023.

[3] LIU S. Design of online monitoring and early warning system for safety status of high-voltage switchgear. Huainan: Anhui University of Science and Technology, 2024.

[4] WEI J X, MA R T, TENG Y Y, et al. Research on embodied intelligence standardization and exploration of evaluation methods. Post & Telecommunication Design Technology, 2025, (7): 46–52.

[5] SONG J, ZHANG W J, ZHANG Q W, et al. "AI + Manufacturing": Helping solve industry pain points. China Electronics News, 2025-11-04(006).

[6] WANG N. Preparation of ion beam sputtered organic polymer deposited films and research on humidity sensing applications. Shanghai: University of Shanghai for Science and Technology, 2022.

[7] TAN Z G, HE T X, ZHANG C. Condition monitoring and fault diagnosis strategy during uninterrupted connection and disconnection of power generation vehicles. Power Equipment Management, 2024, (23): 243–245.

[8] ZHOU L, SUN W L, LI X H, et al. Research on fault early warning of wind power main shaft bearing integrating machine learning and vibration characteristics. Machine Tool & Hydraulics, 1–13 [Accessed 2025-11-16].

[9] LI W X, LI Z G, HAN W, et al. Thermal characteristics of magnetohydrodynamic seal of spiral axial flow pump under multi-field coupling. Journal of Harbin Engineering University, 1–9 [Accessed 2025-11-16].

[10] ZHANG G C, WEN R, JING Z H, et al. Research on bidirectional intelligent sign language recognition glove based on multimodal sensors and deep learning. Internet of Things Technology, 2025, 15(19): 22–25+29.

[11] JIANG J C. Research and optimization of material level calculation method based on multi-sensor fusion. China Metals Bulletin, 2024, (8): 152–154.

[12] YUN H, DENG B, SUN H Y. Application of acoustic emission and optical fiber sensing technology in hydrogen pipe valve detection of high-pressure hydrogen refueling stations. China Science and Technology Information, 2025, (21): 139–141.

[13] YU Z A, WANG T, XIAO Z K. Research on SOC estimation of lithium-ion batteries based on SOA-BP combined algorithm. Automation Applications, 2025, 66(3): 173–176+179.

[14] LI H, FEI X W, DONG R J. Synergistic application of rapid food detection technology and artificial intelligence in the field of food safety. Journal of Food Safety and Quality Inspection, 2025, 16(22): 246–253.