

Sensor-based Monitoring and Diagnosis of High-voltage Equipment in Modern Power Systems

Yanjie Zhang,^{1*} Lin Niu,¹ Shitao Wang,¹ Yong Yu,²
Jing Ding,³ Tao Fang,³ Weilai Wang,³ and Feng Jing⁴

¹Department of Electrical Engineering, Shandong Electric Power College, Jinan 250002, China

²State Grid Jibei Electric Power Co., Ltd., Tangshan Power Supply Company, Tangshan 063015, China

³State Grid Zhejiang Electric Power Co., Ltd., Hangzhou Power Supply Company, Hangzhou 310016, China

⁴State Grid Zhejiang Electric Power Co., Ltd., Hangzhou 310007, China

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The conventional risk assessment of power supply equipment relies on manual inspections or single-sensor alarms, which cannot capture multi-dimensional, time-varying equipment states. To solve this problem, we developed a multi-sensor data fusion method combining entropy-based initialization with particle swarm optimization (PSO) for dynamic sensor data weighting. The method comprises three layers: field sensing (infrared temperature, vibration, partial discharge, gas composition, and electrical quantity sensors), edge computing, and central platform layers. Using 4560 samples from a 220 kV substation collected over 24 months, PSO increased the partial discharge weight from 0.22 to 0.28 to prioritize insulation fault detection. The method shows a 96.8% accuracy, a 96.2% precision, an *F1-score* of 0.960, an area under the curve of 0.978, and a root mean square error of 0.072, outperforming the analytic hierarchy process, fuzzy evaluation, backpropagation neural network (an 88.2% accuracy), and Dempster–Shafer evidence theory. Online inference required only 0.15 ms per sample. Under simulated disturbances, the accuracy was determined to be 85.4% at a 10 dB signal-to-noise ratio, above 89% with a failed sensor, and 85.9% with 30% missing data. Despite the promising results, performance validation is required with multiple sites and various conditions, since the method was designed for a single substation, simulation-only robustness testing, overall risk-level rather than fault-type diagnosis, and static batch training. The results of this study can be used for the development of a self-adaptive, fault-tolerant framework for reliable risk assessment in modern power systems.

1. Introduction

A safe and reliable power supply is indispensable for sustaining industrial productivity, urban electricity distribution, and overall societal well-being.⁽¹⁾ Power equipment, which forms the central hub of modern power systems, encompasses machinery, hardware, and components

*Corresponding author: e-mail: sduzyj@163.com
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responsible for generating, transmitting, distributing, converting, and utilizing electrical and mechanical energies. However, with the continuous expansion of power networks, the increasing frequency of extreme weather events, and the progressive aging of equipment, the risk of failures in power supply systems has become increasingly significant.⁽²⁾

Between 2018 and 2025 in China, equipment failures accounted for 43.7% of total power outages, resulting in average annual economic losses exceeding USD 1.8 billion.^(3,4) These statistics underscore the need for accurate risk assessment methods that enable the early detection and timely warning of faults, ensuring the reliability of the power grid.

Conventional assessment methods of risk caused by equipment failure rely on periodic manual inspections and single-sensor monitoring. Such methods are constrained by limited information sources, poor timeliness, and strong subjectivity. In contrast, multi-sensor data fusion (MSDF), facilitated by advances in IoT and sensing technologies, enables equipment risk monitoring. By leveraging the complementary characteristics of heterogeneous data sources, MSDF enhances the accuracy and reliability of risk assessment.^(5,6) Nevertheless, the effective implementation of MSDF requires sophisticated algorithms capable of processing heterogeneous data streams and rationally allocating sensor weights.^(7,8)

The analytic hierarchy process (AHP), fuzzy comprehensive evaluation, and Dempster–Shafer (D–S) evidence theory are used for weight determination in MSDF. However, these methods rely heavily on expert judgment and typically assign fixed weights, which limits their adaptability to the time-varying operational states of equipment.^(9–11) To address the limitations, particle swarm optimization (PSO), a metaheuristic algorithm inspired by swarm intelligence, has been widely applied for sensor data weight allocation. MSDF integrated with PSO enables the adaptive and dynamic adjustment of sensor weights, improving both the accuracy and adaptability of risk assessment methods.^(12,13) The risk of power equipment must be assessed in thermodynamics, mechanics, electrical phenomena, and chemical processes. Therefore, a single sensor is insufficient to capture the full spectrum of operating conditions. Consequently, multiple sensors are required for comprehensive monitoring.^(14,15)

On the basis of the previous research results, we developed a multi-sensor fusion risk assessment model for power equipment by integrating entropy-based initialization with dynamic weight optimization using PSO. The developed method overcomes the limitations of traditional fixed-weight methods and enables the adaptive adjustment of sensor contributions in response to varying operational conditions. The method also captures the multifactorial nature of equipment risk, thereby overcoming the limitations of delayed fault detection and insufficient warning mechanisms. By leveraging heterogeneous sensor data and adaptive optimization, the system provides a reliable and timely framework for risk monitoring.

2. Methodology

2.1 System architecture

The architecture of the proposed risk assessment system comprises three layers (Fig. 1). Each layer is responsible for distinct functions, enabling seamless integration from raw sensor measurements to risk evaluation and fault warning.

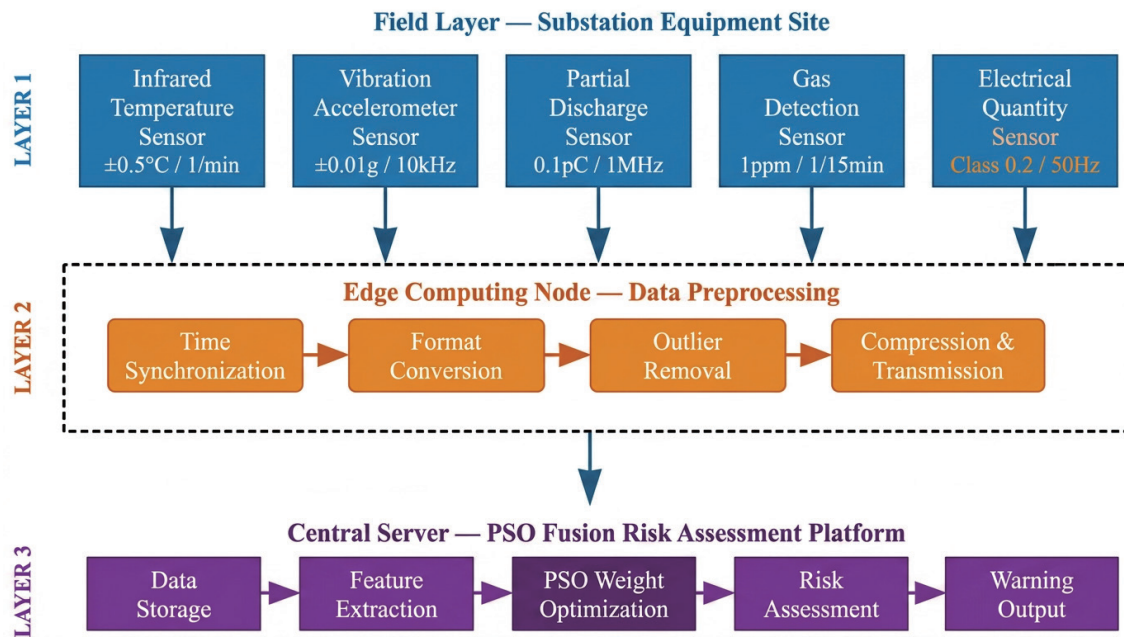


Fig. 1. (Color online) Data collection and transmission in risk assessment systems.

- Field layer

At the equipment site, sensors in five categories are deployed to capture multidimensional operational parameters, including infrared temperature sensors for thermal monitoring, vibration accelerometers for mechanical condition assessment, partial discharge sensors for insulation integrity evaluation, gas detection sensors for monitoring chemical by-products involving SF_6 and H_2 , and electrical quantity sensors for voltage, current, and power measurements. Together, these sensors provide a comprehensive dataset reflecting the thermodynamic, mechanical, electrical, and chemical states of the equipment.

- Edge computing node layer

Sensor data are transmitted to edge computing nodes, where preliminary preprocessing, involving time synchronization, format conversion, outlier removal, and data compression, is performed. By standardizing heterogeneous data streams and reducing transmission overhead, the edge computing node layer ensures that only high-quality, structured information is forwarded to the central server. This design reduces latency and enhances the efficiency of subsequent analysis.

- Central server

The central server is the core of the risk assessment system. It integrates preprocessed data into a unified database, performs feature extraction, and applies PSO for dynamic sensor weight optimization. The PSO fusion algorithm enables the adaptive optimization of multi-sensor contributions and improves the accuracy and robustness of risk assessment. Finally, the system generates diagnostic outputs and early warning signals, which can be used to support preventive maintenance and enhance grid reliability.

The layered architecture of the system ensures that raw sensor data are transformed into actionable insights. By combining edge-level preprocessing with centralized PSO-based fusion,

the system ensures efficiency and adaptability in monitoring the operational health of power equipment.

2.2 Data collection and preprocessing

Data were collected on a 220 kV substation in East China, equipped with four main transformers, a geographic information system switchgear, and a multi-sensor monitoring system. Operational data from January 2023 to December 2024 were collected, resulting in a dataset of 4560 samples. The dataset included 50.1% normal samples and 8.9% critical samples and was split into training, validation, and test sets (Table 1).

In the substation, five categories of sensors are deployed across key components of power equipment to enable holistic state perception (Table 2). All sensors transmit collected

Table 1
Experimental dataset.

Statistical item	Value
Total number of samples	4560
Number of normal samples (Level I)	2284 (50.1%)
Number of Caution samples (Level II)	1152 (25.3%)
Number of Abnormal samples (Level III)	718 (15.7%)
Number of Critical samples (Level IV)	406 (8.9%)
Training/validation/test split	70% / 15% / 15%
Feature dimensionality	28
Data labeling method	Multi-expert consensus + historical fault verification

Table 2
Sensors used in power supply system.

Sensor	Parameter	Installation location	Sampling frequency	Data accuracy	Communication protocol
Infrared temperature sensor	Surface temperature/ thermal distribution	Transformer body, switchgear cabinets	1 sample/min	±0.5 °C	Message queuing telemetry transport
Vibration accelerometer	Vibration amplitude/ spectrum	Transformer core, bearings	10 kHz	±0.01 g	International Electrotechnical Commission (IEC) 61850
Partial discharge sensor	Discharge magnitude/ pulse frequency	GIS busbars, cable terminations	1 MHz	0.1 picocoulomb	Modbus transmission control protocol
Sensor	Frequency	Terminations			Control protocol
Gas detection sensor	SF ₆ /H ₂ /CO/ C ₂ H ₂	Main transformer oil conservator, gas-insulated switchgear compartments	1 sample/15 min	1 ppm	4–20 mA
Electrical quantity sensor	Voltage/ current/ power	Secondary side of potential transformers/ current transformers	50 samples/s	Class 0.2	IEC 61968

measurements to edge computing nodes through fieldbus or wireless networks. After preprocessing, the data are forwarded to the central server for integration from the edge computing nodes. For thermal monitoring, the high-precision MI3 Series infrared sensor from Fluke Process Instruments (USA) is used. Structural diagnostics are handled by the rugged Model 603C01 vibration accelerometer from PCB Piezotronics (USA), whereas insulation integrity is monitored using the high-frequency ultra-high-frequency (UHF) partial discharge sensor from OMICRON electronics (Austria). For chemical and gas analyses, the Optimus DGA series from Vaisala (Finland) provides high-accuracy ppm gas detection. Finally, electrical parameters are captured on the secondary transformer side using the revenue-grade Acuvim II Series power meter from Accuenergy (Canada).

Owing to substantial differences in physical dimensions, numerical ranges, and sampling frequencies of different sensors, the direct fusion of raw data introduces scale bias. To address this, a multi-step preprocessing is conducted as follows.⁽¹⁶⁾

2.2.1 Time synchronization

GPS timing signals serve as the reference. Linear interpolation is performed to align sensor data of varying sampling frequencies to a unified time base of one sample per minute.

$$x_i(t_k) = x_i(t_m) + \frac{x_i(t_{m+1}) - x_i(t_m)}{t_{m+1} - t_m}(t_k - t_m) \quad (1)$$

Here, $x_i(t_k)$ is the interpolated data of the i -th sensor at time t_k , $t_m \leq t_k \leq t_{m+1}$.

2.2.2 Outlier detection and handling

An improved 3σ criterion combined with temporal continuity testing is applied as follows.

$$\text{Outlier}_{i,k} = \begin{cases} 1, & |x_i(t_k) - \mu_i| > 3\sigma_i \text{ and } |x_i(t_k) - x_i(t_{k-1})| > \delta_i \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Here, μ_i and σ_i are the sliding window mean and standard deviation, respectively, and δ_i is the continuity threshold.

2.2.3 Data normalization

The min–max normalization method is used to normalize data to the interval.^(0,1)

$$\hat{x}_i = \frac{x_i - x_i^{\min}}{x_i^{\max} - x_i^{\min}} \quad (3)$$

Here, $x_i^{\max}$ and $x_i^{\min}$ are the maximum and minimum values, respectively.

2.2.4 Feature extraction

For high-frequency signals from vibration and partial discharge sensors, time-domain and frequency-domain features are extracted, including mean, variance, kurtosis (K_i), skewness (S_i), dominant frequency components, and band energy ratios.

$$K_i = \frac{E[(x_i - \mu_i)^4]}{\sigma_i^4}, S_i = \frac{E[(x_i - \mu_i)^3]}{\sigma_i^3} \quad (4)$$

Here, x_i is the data value from the i -th sensor, μ_i is the average of the sensor data, and σ_i is the standard deviation of the sensor data. For vibration or partial discharge signals, kurtosis is used to detect abnormal spikes or impulsive events that indicate faults, and skewness represents directional bias in signals. For example, persistent positive skew in temperature or current data may indicate gradual overheating or load imbalance. In risk assessment, these features are used to improve fault detection sensitivity, especially for early-stage anomalies in equipment.

Table 2 presents the results of the data quality assessment for each sensor after preprocessing. Raw data volume presents the total number of measurements generated daily by each sensor, highlighting differences in sampling frequency. For example, electrical quantity sensors produce millions of entries per day, while gas detection sensors generate fewer than one hundred. Outlier ratio indicates the proportion of abnormal or spurious values detected. Higher ratios, such as in partial discharge sensors, suggest greater signal variability and sensitivity to transient events. Missing rate represents the percentage of data points lost or not recorded. Low values across all sensors confirm stable acquisition performance. Time alignment error is calculated to quantify synchronization accuracy after preprocessing. Errors remain within acceptable limits (≤ 10 ms), ensuring reliable temporal alignment across heterogeneous data streams. Effective data rate represents the proportion of usable data after preprocessing. Values above 97% for all sensors demonstrate that the preprocessing pipeline successfully preserves data integrity while filtering noise and anomalies.

Table 3 shows that despite differences in sampling frequency and data characteristics, high-quality, synchronized datasets across all sensor types are achieved through data preprocessing. This ensures that subsequent fusion and risk assessment processes are based on reliable and consistent information.

2.3 Risk assessment index

Operational risks in power equipment are caused by a combination of equipment degradation, external environmental conditions, electrical operating stresses, and the accumulation of historical faults. Each factor contributes differently to equipment failure, so their combined effects must be determined to assess the overall risk of the power supply system.

The statistics of the National Energy Administration and regional grid operators in China provide detailed data on the distribution of fault causes in transmission and distribution

Table 3
Data quality assessment results for various sensors.

Sensor	Data volume (samples/day)	Outlier ratio (%)	Missing rate (%)	Time alignment error (ms)	Effective data rate (%)
Infrared temperature sensor	1440	0.83	0.21	≤ 5	98.96
Vibration accelerometer	864000	1.24	0.35	≤ 2	98.41
Partial discharge sensor	86400	2.16	0.48	≤ 1	97.36
Gas detection Sensor	96	0.52	0.63	≤ 10	98.85
Electrical quantity sensor	4320000	0.31	0.12	≤ 1	99.57

equipment.⁽¹⁷⁾ The results are consistent with the results shown in Ref. (18), in which large-scale transmission line failures were analyzed to identify insulation aging, mechanical wear, and electrical overload as the most significant risk factors (Fig. 2).

Insulation aging is the leading contributor, accounting for 28.6% of failures. This indicates the gradual deterioration of dielectric materials under long-term thermal and electrical stresses, a phenomenon widely reported in sensor-based monitoring studies.⁽⁷⁾ Mechanical wear is the second most significant factor, responsible for 19.8% of failures, found in moving components such as bearings and transformer cores. Electrical overloads contribute 19.3%, linked to sustained overcurrent conditions or poor load management, which aligns with reports on overload detection in power equipment.⁽⁴⁾ Environmental effects, including temperature extremes, humidity, and pollution, account for 14.7%. Human-related issues such as maintenance errors (9.4%) and installation defects (8.2%) also play a notable role.

This distribution highlights the multifactorial nature of equipment risk. Failures cannot be attributed to a single cause but rather to the interplay of physical aging, mechanical stress, electrical loading, environmental exposure, and human factors. Consequently, a comprehensive risk assessment system must integrate indicators across all these domains to capture the full spectrum of potential vulnerabilities.

On the basis of the fault cause distribution, we developed a risk assessment index system in the dimensions of (1) equipment status, including thermal, mechanical, insulation, chemical, and service life indicators, (2) environmental factors, including ambient temperature, humidity, pollution level, altitude, and meteorological stress (thunderstorm frequency), (3) electrical characteristics, including load ratio, voltage deviation, harmonic distortion, power factor, and short-circuit current multiples, and (4) historical faults, including past failure frequency, mean time between failures, maintenance intervals, and cumulative overload duration.

As a result, we defined four first-level indicators and 23 second-level indicators (Table 4). Each indicator was considered positive or negative, depending on whether higher values correspond to increased or reduced risk. Data were standardized, ranging from sensor measurements to maintenance records and meteorological databases. This approach was used to ensure that the risk assessment system is holistic by capturing real-time operational conditions

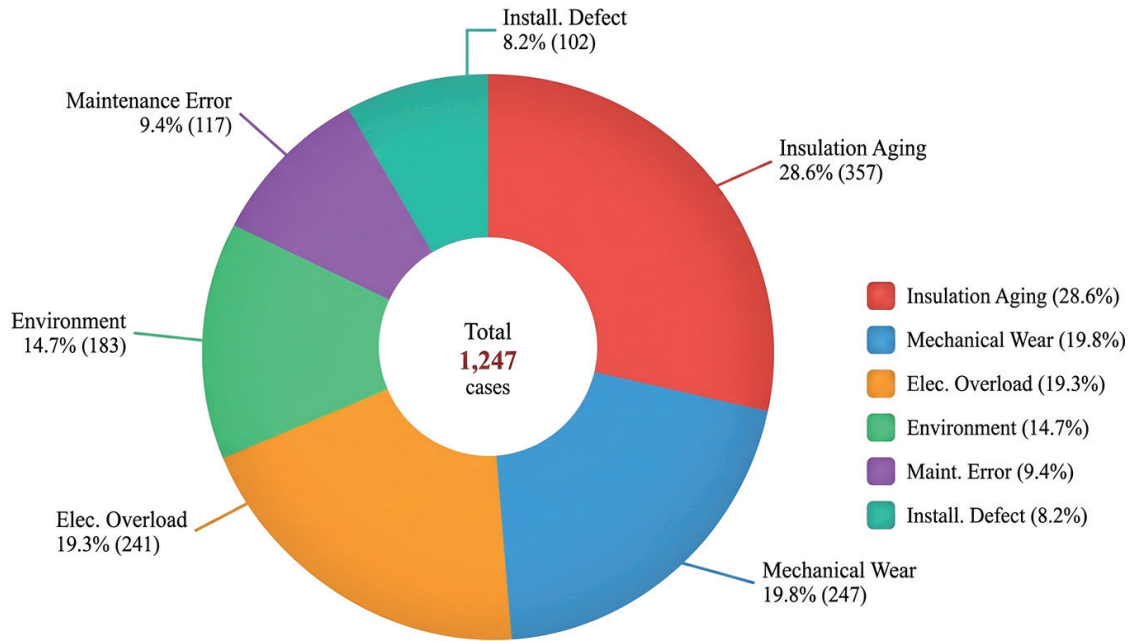


Fig. 2. (Color online) Distribution of fault causes in power equipment.

and long-term historical trends. By combining sensor data with contextual information, subsequent fusion and optimization were conducted.^(12,13)

To reduce reliance on subjective expert judgment, an information entropy method was employed to determine the initial indicator weights, assuming that indicators with greater variability across samples contain useful information and must be assigned higher weights.⁽¹⁸⁾ First, a decision matrix was constructed, where each row represents an evaluation sample, and each column corresponds to a normalized indicator value. Then, the information entropy of each indicator was calculated as

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}, \quad p_{ij} = \frac{\hat{x}_{ij}}{\sum_{i=1}^n \hat{x}_{ij}}. \quad (5)$$

Here, E_j is the entropy of indicator j , which measures the degree of uncertainty or dispersion in its values, n is the number of evaluation samples, $\hat{x}_{ij}$ is the normalized value of the j -th indicator for the i -th sample, and p_{ij} is the proportion of the normalized value of sample i relative to the total for indicator j . The initial weights were determined as

$$w_j^0 = \frac{1 - E_j}{\sum_{j=1}^m (1 - E_j)}, \quad j = 1, 2, \dots, m. \quad (6)$$

Here, m is the total number of indicators and w_j^0 is the initial weight assigned to indicator j .

The information entropy of each indicator was calculated, reflecting the degree of uncertainty or dispersion in its values. Indicators with greater variability contribute more information and

Table 4
Risk assessment index system for power equipment.

First-level indicator	Second-level indicator	Code	Unit	Positive/negative	Data source
Equipment status	Transformer body temperature rise	A1	°C	Negative	Temperature sensor
	Core vibration intensity	A2	mm/s	Negative	Vibration sensor
	Partial discharge magnitude	A3	pC	Negative	Partial discharge (PD) sensor
	Insulation resistance	A4	MΩ	Positive	Electrical sensor
	Total dissolved gas in oil	A5	ppm	Negative	Gas sensor
	Dielectric loss factor	A6	%	Negative	Electrical sensor
	Equipment service life	A7	years	Negative	Asset records
Environmental factor	Ambient temperature	B1	°C	Negative	Temperature sensor
	Relative humidity	B2	%	Negative	Environmental sensor
	Pollution level	B3	level	Negative	Periodic inspection
	Altitude	B4	m	Negative	Geographical information system
	Thunderstorm days per year	B5	day/year	Negative	Meteorological data
Electrical characteristics	Load ratio	C1	%	Negative	Electrical sensor
	Three-phase unbalance degree	C2	%	Negative	Electrical sensor
	Harmonic distortion rate	C3	%	Negative	Electrical sensor
	Voltage deviation	C4	%	Negative	Electrical sensor
	Short-circuit current multiple	C5	×	Negative	Calculated value
	Power factor	C6	—	Positive	Electrical sensor
Historical faults	Number of faults in past 3 years	D1	count	Negative	Operation and maintenance records
	Mean time between failures	D2	months	Positive	Operation and maintenance records
	Time since last maintenance	D3	months	Positive	Operation and maintenance records
	Historical maximum temperature rise	D4	°C	Negative	Historical records
	Cumulative overload duration	D5	h	Negative	Operation and maintenance records

therefore receive higher weights. Finally, initial weights were assigned using entropy-based formulas, ensuring that the weighting scheme is data-driven rather than purely expert-based. By this procedure, a rigorous starting point for weight allocation was identified, later refined through dynamic optimization using PSO.

2.4 PSO algorithm

Entropy provides an objective starting point for indicator weights, but is static and might not reflect the changing importance of different sensors under real operating conditions. To overcome this limitation, we applied PSO as a dynamic optimization method. The PSO algorithm simulates the collective intelligence of bird foraging behavior. Each particle represents a possible set of sensor weights, and the particles move through the search space by adjusting their positions based on both their own best experience and the best solution found by the group. This collaborative search allows the rapid localization of the global optimal solution.

2.4.1 Parameter setting

In a population containing N_p particles and a search space of dimension D , the position of the i -th particle is represented as $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, and its velocity is $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. Then, the velocity update equation is

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 (p_i^{best} - x_i^{(t)}) + c_2 r_2 (g^{best} - x_i^{(t)}), \quad (7)$$

where ω is the inertia weight, controlling the balance between exploration and exploitation, c_1 is the individual learning factor, guiding particles toward their own best-known position, c_2 is the social learning factor, guiding particles toward the global best position, r_1, r_2 are random numbers between 0 and 1, ensuring stochastic behavior, p_i^{best} is the best position found by particle i , and g^{best} is the best position found by the entire swarm. The position update equation is

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}. \quad (8)$$

Here, $x_i^{(t)}$ is the current set of fusion weights assigned to the different sensors, $v_i^{(t+1)}$ is the updated velocity of particle i at iteration $t + 1$, and t is the iteration step, showing the progression of the optimization process. This means that each particle moves to a new position on the basis of its updated velocity.

2.4.2 Adaptive inertia weight

To ensure global exploration and local refinement, a nonlinear decreasing inertia weight is used.

$$\omega(t) = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{T_{max}^2} \cdot t^2 \quad (9)$$

Here, $\omega_{max} = 0.9$, $\omega_{min} = 0.4$, and T_{max} is the maximum number of iterations. This strategy allows wide exploration at the beginning and fine-tuned convergence later.

2.4.3 Fusion weight vector

The multi-sensor fusion weight vector is defined as

$$w = (w_1, w_2, \dots, w_m), \quad (10)$$

which is subject to the normalization constraint.

$$\sum_{j=1}^m w_j = 1, w_j \geq 0 \quad (11)$$

This ensures that all weights are non-negative and sum to one, so each sensor contributes proportionally.

2.4.4 Fitness function

The fitness function is used to evaluate how well a set of weights performs. It combines three criteria.

$$f(w) = \alpha \cdot Acc(w) + \beta \cdot (1 - RMSE(w)) + \gamma \cdot AUC(w) \quad (12)$$

Here, $Acc(w)$ is the classification accuracy, $RMSE(w)$ is the root mean square error between predicted and actual risk values, $AUC(w)$ is the area under the ROC curve, measuring diagnostic reliability, and α, β, γ are trade-off coefficients (0.4, 0.3, 0.3), ensuring that the three criteria are balanced. To evaluate the sensitivity of the optimization performance to variations in trade-off coefficients (α, β, γ), a sensitivity analysis of the parameters was conducted in five coefficient configurations satisfying $\alpha + \beta + \gamma = 1.0$.⁽¹⁹⁾ The diagnostic performance and optimization stability for each parameter are shown in Table 5.

By prioritizing accuracy ($\alpha = 0.6$), prediction error ($RMSE = 0.088$) increased, whereas heavily weighting $RMSE$ ($\beta = 0.6$) indicates marginal risk boundary classifications, reducing the overall accuracy (94.5%). The balanced configuration ($\alpha = 0.4, \beta = 0.3, \gamma = 0.3$) enabled the optimal trade-off, leading to the highest $F1$ -score (0.960) and the lowest optimization variance (± 0.005), ensuring numerical robustness.

2.4.5 Weight constraint

If particle positions do not meet the normalization constraint, they are corrected using a projection method to ensure that all weights remain valid and properly normalized.

Table 5
Sensitivity analysis results of PSO fitness function coefficients.

Configuration	Set 1 (accuracy-focused)	Set 2 (RMSE-focused)	Set 3 (AUC-focused)	Set 4 (balanced-selected)	Set 5 (equal weights)
α (accuracy)	0.6	0.2	0.2	0.4	0.333
β ($1 - RMSE$)	0.2	0.6	0.2	0.3	0.333
γ (AUC)	0.2	0.2	0.6	0.3	0.333
Accuracy (%)	96.2	94.5	95.1	96.8	96.1
<i>F1-score</i>	0.952	0.938	0.944	0.96	0.954
AUC	0.961	0.954	0.982	0.978	0.971
<i>RMSE</i>	0.088	0.065	0.081	0.072	0.075
Optimization stability (standard deviation)	± 0.014	± 0.011	± 0.012	± 0.005	± 0.008

$$w_j^* = \frac{\max(w_j, 0)}{\sum_{k=1}^m \max(w_k, 0)}, j = 1, 2, \dots, m \quad (13)$$

In terms of computational complexity, to iterate the PSO weight optimization, $O(N_p \cdot D)$ operations must be conducted, where $N_p = 50$ is the swarm population size and $D = 28$ is the indicator dimension. Since weights are optimized periodically at the central server level (or upon detecting state transitions at edge computing nodes) rather than on every high-frequency data point, the computational burden on the real-time sensor network becomes minimal. When the optimal fusion weight vector w^* is derived, online risk score computation for incoming preprocessed data requires only vector dot-product evaluations with time complexity $O(D)$ per sample, ensuring low latency for real-time monitoring.

The final results of PSO weight optimization are shown in Fig. 3. The comparison result of the weights shows how PSO adjusts sensor weights. PD sensors gained the most weight, increasing from 0.22 to 0.28. This adjustment highlights their strong diagnostic value in detecting insulation faults, which are the leading cause of equipment failures. The weights of infrared temperature, vibration, gas detection, and electrical quantity sensors changed from 0.18, 0.15, 0.20, and 0.25 to 0.21, 0.13, 0.17, and 0.21, respectively. These reductions do not mean that these sensors are unimportant; rather, PSO indicates that their relative contribution to accurate risk prediction is lower than those of partial discharge and temperature monitoring.

Regarding the adaptive nature of PSO, instead of relying solely on static entropy-based weights, PSO redistributes importance among sensors on the basis of historical fault data and diagnostic performance. Sensors closely linked to insulation and thermal faults were identified. The result was used for accurate risk assessment.

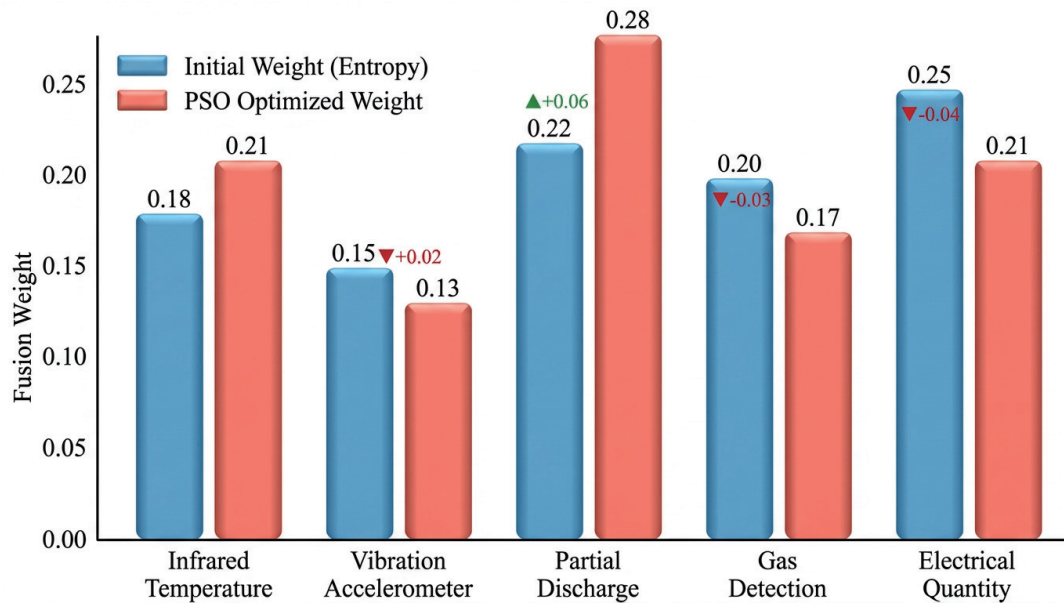


Fig. 3. (Color online) Comparison of fusion weights of various sensors before and after PSO.

2.5 Risk assessment model

Once the optimized sensor weights were obtained, they were applied to calculate a risk score for equipment. This score reflects the combined effect of all indicators and provides a single value between 0 and 1, which can then be mapped to risk levels.

To translate raw indicator values into risk contributions, membership functions were used. These functions determined how strongly each indicator reflects risk, depending on whether it is a negative or positive indicator. Negative indicators are those where higher values mean higher risk. Examples of negative indicators in this study included transformer temperature rise, vibration intensity, and partial discharge magnitude. For the indicators, an increasing membership function was applied. That is, when the indicator value is below a safe threshold (a_j), the risk contribution is zero. As the value increases toward a critical threshold (b_j), the risk contribution rises linearly. Once the value exceeds b_j , the risk contribution is set to one, indicating maximum risk. Positive indicators are those where higher values mean lower risk. Examples include insulation resistance and power factor. For these, a decreasing membership function is applied. When the indicator value is below a minimum acceptable threshold (c_j), the risk contribution is one (high risk). As the value increases toward a safe threshold (d_j), the risk contribution decreases linearly. Once the value exceeds d_j , the risk contribution becomes zero, indicating no risk. The threshold parameters a_j , b_j , c_j , and d_j were determined by historical data analysis and expert knowledge to define the boundaries between safe, cautionary, and dangerous conditions for each indicator.

After each indicator was converted into a risk score, its contribution to the risk was combined using the optimized sensor weights. Indicators with higher importance have a stronger effect on the final risk score. The overall risk score for equipment is calculated as

$$R = \sum_{j=1}^m w_j^* \cdot \varphi_j(I_j), \quad (14)$$

where R is the risk score of equipment, m is the total number of indicators, w_j^* is the optimized weight of the j -th indicator (ensuring that all weights sum to 1), $\varphi_j(I_j)$ is the membership function value of the j -th indicator, representing its risk contribution, and I_j is the normalized value of the indicator. This calculation ensures that each indicator contributes proportionally to the final risk score, depending on both its measured value and its optimized weight.

To refine the result, risk scores were aggregated at the dimension level (equipment status, environmental factors, electrical characteristics, and historical faults). Each dimension has its weight (W_A , W_B , W_C , and W_D), and the total risk score is calculated as

$$R_{total} = W_A R_A + W_B R_B + W_C R_C + W_D R_D, \quad (15)$$

where R_A , R_B , R_C , and R_D are the risk scores for each dimension. In this study, the final optimized weights were as follows: 0.38 for equipment status, 0.17 for environmental factors, 0.28 for electrical characteristics, and 0.17 for historical faults. This shows that equipment status and electrical characteristics are the most influential dimensions in determining overall risk, while environmental and historical factors play supporting roles.

2.6 Cost–benefit analysis

To evaluate the applicability and financial viability of the PSO fusion method, a cost–benefit model was used. System deployment expenditures were modeled to project operational savings on the basis of condition-based maintenance and risk mitigation. The model included capital and operational investments for sensor deployment and computational infrastructure. Capital expenditures (CapEx) include the procurement and installation costs of multi-modal monitoring hardware, specifically UHF PD sensors, infrared thermography, vibration sensors, dissolved gas sensors, and edge-computing units. Operational expenditures (OpEx) include operational costs, including routine sensor calibration, communication network bandwidth, ongoing software updates, and periodic physical maintenance of hardware.

The economic benefit of early fault detection was modeled by using the weights of sensor data from historical fault data. Because UHF PD sensor data are used as a precursor to dielectric breakdown during early micro-void ionization and electrical treeing stages, increases in the weights of PD sensor data are related to early defect identification. The avoided risk cost (ΔC_{risk}) is formulated as

$$\Delta C_{risk} = \sum_k P_k \cdot L_k \cdot \eta_{detect}. \quad (16)$$

Here, P_k represents the historical occurrence probability of failure mode k (insulation aging), L_k represents the financial loss incurred by failure mode k , incorporating unsupplied energy penalties, busbar repair, and capital component replacement costs, and η_{detect} is the early detection efficiency coefficient of the multi-sensor fusion model. The model converts real-time multi-sensor data into dynamic risk scores ($R_{total} \in [0,1]$ across Levels I–IV). To model the changes from fixed time-based periodic overhauls to dynamic condition-based maintenance (CBM), the reduction in routine maintenance expenditure (ΔC_{maint}) is calculated as

$$\Delta C_{maint} = C_{scheduled} - C_{CBM}(R_{total}). \quad (17)$$

Here, $C_{scheduled}$ is the baseline cost of fixed-interval preventive overhauls and $C_{CBM}(R_{total})$ represents the optimized maintenance cost dynamically scheduled according to evaluated risk levels. This formulation quantifies savings from eliminating redundant teardowns and reducing unnecessary labor hours during low-risk states. The overall economic performance of the method is evaluated using net present value (NPV) and payback period ($T_{payback}$) equations.

$$NPV = \sum_{t=1}^N \frac{\Delta C_{risk,t} + \Delta C_{maint,t} - OpEx_t}{(1+r)^t} - CapEx \quad (18)$$

Here, r denotes the discount rate, t denotes the operational year, N is the evaluation horizon, and $T_{payback}$ is determined as the time threshold at which cumulative net operational savings ($\Delta C_{risk} + \Delta C_{maint} - OpEx$) fully offset initial CapEx.⁽²⁰⁾

3. Results

3.1 Risk classification and performance evaluation

According to the risk assessment value $R_{total} \in [0,1]$, the operational risks of power equipment were divided into four levels, with corresponding warning response strategies. The classification ranged from Level I (normal), where equipment operates within safe limits, to Level IV (critical), where imminent failure requires urgent intervention. Each level is associated with a color-coded alert, inspection frequency, and response strategy, ensuring that the risk assessment results are not only quantitative but also actionable for operators (Table 6).

3.2 Comparison with conventional risk assessment methods

To verify the effectiveness of the developed system, its performance was compared with those of AHP, fuzzy evaluation, backpropagation neural networks (BPNNs), and D–S evidence theory. AHP is a classical decision-making tool that relies on expert judgment and structured pairwise comparisons. It is often used in engineering risk analysis for its simplicity and

Table 6
Risk levels and warning response strategy.

Risk level	Risk score range	Alert color	Status description	Response interval	Response strategy
I (normal)	[0, 0.25]	Green	Equipment operating normally; all indicators within acceptable limits	Routine inspection (monthly)	Perform scheduled maintenance and routine logging
II (caution)	[0.25, 0.50]	Yellow	One or more indicators deviate from normal; requires close attention	Enhanced inspection (weekly)	Conduct continuous monitoring and develop a maintenance plan
III (abnormal)	[0.50, 0.75]	Orange	Multiple indicators abnormal; evident risk exists	Emergency response (daily)	Immediate investigation; perform outage-based maintenance as appropriate
IV (critical)	[0.75, 1.00]	Red	Equipment in critical condition; failure imminent	Immediate response (hourly)	Urgent de-energization and emergency repair

transparency. Fuzzy evaluation handles uncertainty and imprecision in sensor data for complex systems where crisp thresholds are difficult to define. BPNN is a machine learning approach capable of modeling nonlinear relationships between indicators and risk outcomes, widely applied in fault diagnosis. D–S evidence theory is a probabilistic reasoning framework that combines evidence from multiple sources, making it useful for sensor fusion when data are incomplete or conflicting.

The PSO fusion method in this study showed the highest performance for all metrics, with an overall accuracy of 96.8%, a precision of 96.2%, a recall of 95.9%, and an *F1-score* of 0.96. The area under the curve (AUC) reached 0.978, and the *RMSE* was 0.072, indicating consistency between predicted and actual risk states. In computational execution, although the initial offline weight optimization using Entropy-PSO requires 14.3 s (80 iterations) on the central platform (Intel Xeon Gold 6248R CPU @ 3.0 GHz, 64 gigabytes of random access memory), it is significantly faster than BPNN (28.6 s). The online inference latency per sample is only 0.15 ms, which is lower than those of BPNN (1.85 ms) and D–S evidence theory (0.45 ms) (Table 7), satisfying the sub-second response requirement for emergency warnings shown in Table 5. The memory footprint during dynamic execution remained below 42 MB, supporting its deployment on standard industrial servers and edge computing architectures.

Classification accuracy across risk levels was compared as shown in Fig. 4. The PSO fusion method consistently outperformed other methods, achieving accuracies of 98.2% (Level I), 96.4% (Level II), 95.1% (Level III), and 97.8% (Level IV). This indicates that the method is robust under normal and abnormal operating conditions, and particularly effective in distinguishing critical states where accurate diagnosis is most important.

The confusion matrix was drawn to compare classification performance (Fig. 5). Correct predictions dominate the diagonal, with accuracies of 98.3% (Level I), 93.9% (Level II), 92.6% (Level III), and 96.0% (Level IV). Misclassifications were observed between adjacent levels

Table 7
Performance comparison of different methods.

Metric	AHP	Fuzzy evaluation	BPNN	D–S evidence theory	Entropy-PSO method (this study)
Accuracy (%)	81.4	83.7	88.2	85.6	96.8
Precision (%)	79.6	82.1	87.4	84.2	96.2
Recall (%)	78.3	81.5	86.9	83.8	95.9
<i>F1-score</i>	0.789	0.818	0.871	0.84	0.96
AUC	0.836	0.861	0.903	0.878	0.978
<i>RMSE</i>	0.183	0.162	0.134	0.149	0.072
Offline training/ optimization time (s)	0.12	0.18	28.6	1.43	14.3
Online inference latency per sample (ms)	0.08	0.12	1.85	0.45	0.15

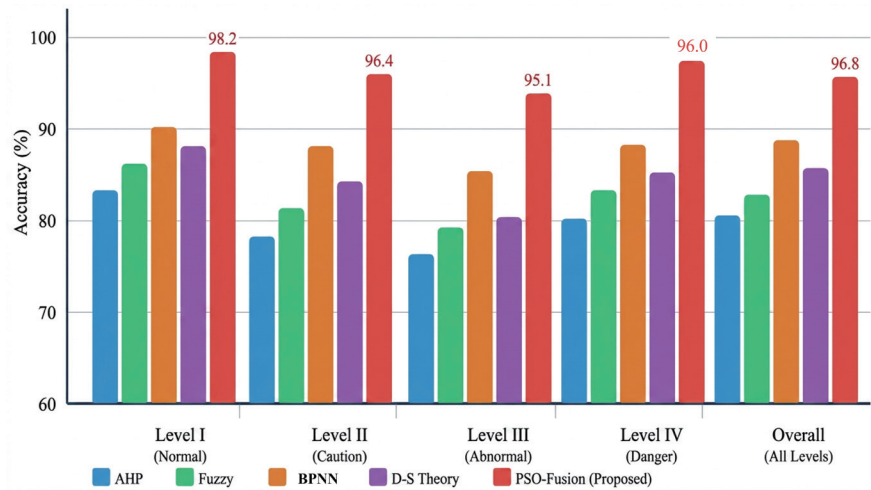


Fig. 4. (Color online) Classification accuracy per risk level for each method.

	Level I	Level II	Level III	Level IV
Level I	340 98.3%	5 1.4%	1 0.3%	0 0.0%
Level II	4 2.2%	169 93.9%	7 3.9%	0 0.0%
Level III	0 0.0%	4 3.7%	100 92.6%	4 3.7%
Level IV	0 0.0%	0 0.0%	2 4.0%	48 96.0%

Fig. 5. (Color online) Confusion matrix of PSO results in this study.

(e.g., Level II $\leftrightarrow$ Level III), which is acceptable in engineering practice since these states represent gradual transitions in equipment health. Importantly, there are no severe misjudgments across two or more levels, ensuring that safety-critical decisions are not compromised.

3.3 Optimization characteristics of PSO fusion method

The convergence behavior of PSO is shown in Fig. 6, which shows fitness curves under different population sizes. Larger populations ($N_p = 50$) converge faster and achieve higher fitness values, reaching stability after about 80 iterations. Smaller populations converge more slowly to lower fitness levels, confirming that population size is a key factor in optimization efficiency.

Robustness was tested under three disturbance scenarios: Gaussian noise, sensor failure, and random data missingness. These three disturbance scenarios were selected because they represent the most common and realistic challenges faced in multi-sensor monitoring systems for power equipment. In Gaussian noise, sensor signals are affected by electrical interference or environmental fluctuations, which manifest as random noise. Testing under different signal-to-noise ratios verifies whether the model can still extract meaningful information when data quality is degraded. In substations, individual sensors fail owing to hardware malfunction or communication loss. Evaluating performance when a sensor goes offline indicates whether the system can adaptively redistribute weights and maintain reliable risk assessment. Data missingness was selected since datasets frequently suffer from incomplete records due to transmission errors or logging gaps. Simulating random data loss tests the resilience of the model to missing information, ensuring robustness in practical deployment.

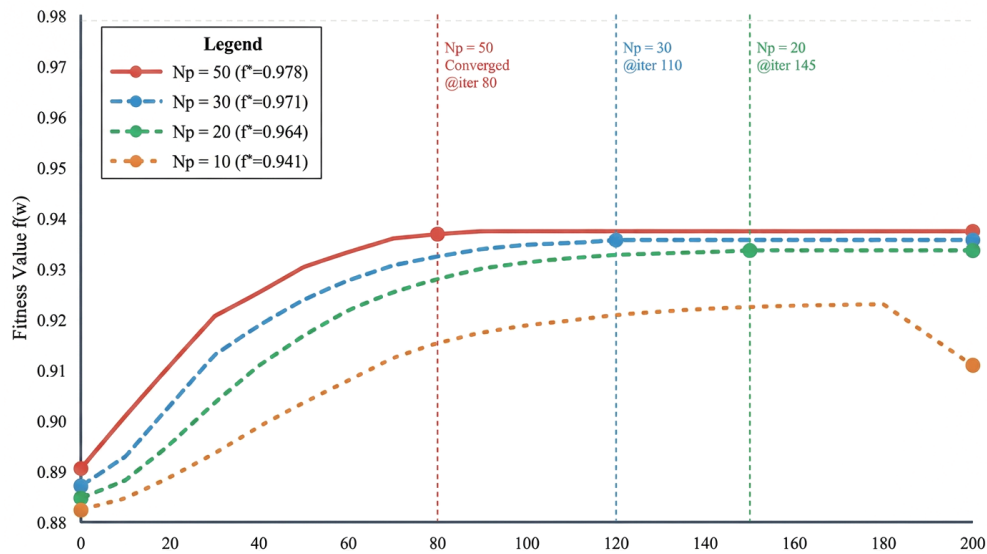


Fig. 6. (Color online) Convergence curve of PSO algorithm under different population sizes.

3.4 Robustness analysis

PSO consistently outperformed other methods. Even under strong noise interference (signal-to-noise ratio = 10 dB), accuracy remained at 85.4%, higher than those obtained by some methods without noise. When sensors failed, PSO adaptively redistributed weights to compensate, maintaining accuracy above 89.3%. Under data missing rates up to 30%, PSO showed 85.9%, presenting resilience to incomplete information (Table 8).

To evaluate the computational efficiency and convergence characteristics of the PSO algorithm, an experiment was conducted to compare the PSO fusion method with other metaheuristic optimization algorithms in identical conditions ($N_p = 50$, $T_{max} = 200$, and $D = 28$), including genetic algorithm (GA), grey wolf optimizer (GWO), and differential evolution (DE).⁽²¹⁾ The results are shown in Table 9. The PSO fusion method showed the highest convergence rate (80 iterations), the lowest total optimization execution time (14.3 s), and the highest diagnostic accuracy (96.8%). Because all optimization algorithms yield a fixed optimal weight vector w^* for execution, their online inference latencies remain identical (0.15 ms/sample). This result indicates that PSO balances best between convergence speed, computational overhead, and optimization effectiveness.

To enhance the transparency and interpretability of the PSO fusion method, the changes in optimized weights were compared in four fault scenarios: normal baseline, insulation degradation, thermal overheating, and mechanical/structural wear.⁽¹⁹⁾ The optimized weights of different sensors in each scenario are presented in Table 10. The PSO algorithm redistributed data weights on the basis of physical fault signatures. Weights of the partial discharge data increased from 0.22 to 0.38, showing increases in the weights of gas data (0.25) to show dissolved gas accumulation. The weights of infrared temperature data increased from 0.18 to 0.34, enabling the determination of thermal distribution. The weights of vibration data increased from 0.15 to 0.35, presenting structural looseness and core anomaly harmonics. This result shows the method's adaptability, enabling the avoidance of rigid static weighting and autonomous sensitivity monitoring of the dominant risk drivers in real time.

Table 8
Accuracies of different methods under different disturbance scenarios.

Disturbance scenario	Perturbation severity	AHP	Fuzzy evaluation	BPNN	D-S	PSO
Gaussian noise	Signal-to-noise ratio (SNR) = 30 dB	80.1	82.6	86.4	84.3	95.2
	SNR = 20 dB	77.3	79.8	82.1	80.6	92.7
	SNR = 10 dB	70.2	72.4	74.8	73.1	85.4
Sensor failure	Temperature sensor offline	74.6	77.2	81.3	78.9	91.6
	PD sensor offline	72.1	75.8	79.6	76.4	89.3
Data missingness	Missing rate = 10%	79.4	81.7	84.9	82.6	94.1
	Missing rate = 20%	75.8	78.3	80.2	78.9	90.5
	Missing rate = 30%	69.3	72.1	75.4	73.8	85.9

Table 9
Performance and runtime comparison among metaheuristic optimization algorithms for sensor weight determination.

Optimization algorithm	Convergence iteration	Optimization time (s)	Online inference latency (ms)	<i>F1-score</i>	Accuracy (%)
GA	124	22.8	0.15	0.932	93.8
GWO	95	16.5	0.15	0.948	95.1
DE	108	18.2	0.15	0.941	94.6
PSO (this study)	80	14.3	0.15	0.96	96.8

Table 10
Changes in sensor data weights in different fault scenarios.

Fault scenario	Normal state (baseline)	Insulation degradation	Thermal overheating	Mechanical/core wear
Primary diagnosis	Balanced operational state	PD activity and SF ₆ /DGA	Transformer body rise and overload	Vibration amplitude and harmonics
Weight of infrared temperature data (w_1)	0.18	0.14	0.34	0.12
Vibration accelerator data weight (w_2)	0.15	0.1	0.1	0.35
Partial discharge data weight (w_3)	0.22	0.38	0.16	0.15
Gas detection data weight (w_4)	0.2	0.25	0.18	0.12
Electrical quantity sensor weight (w_5)	0.25	0.13	0.22	0.26

4. Discussion

4.1 Weight changes

The PSO fusion method can be effectively applied to the sensor-data-based risk assessment of power supply systems to ensure high accuracy and resilience. By dynamically redistributing sensor importance, PSO ensures reliable performance even under noise interference, sensor failures, and missing data. This dual capability directly supports the development of fault-tolerant sensor networks in power systems, where data imperfections are inevitable.

The changes in weights optimized by the PSO algorithm indicate the progression of equipment degradation. In particular, the increases in the weights of PD sensor data (from 0.22 to 0.28) are attributed to the nature of insulation failure. Insulation aging, identified as the primary cause of equipment failure in 28.6% of historical cases (Fig. 2), is initiated by micro-void ionization and localized electrical treeing before macro-thermal anomalies or chemical oil degradation starts. Because PD data can be used as the high-frequency precursor to dielectric breakdown, higher PD data weights indicate the enhancement of the diagnostic sensitivity of early-stage degradation. In contrast, the PSO fusion method rebalances infrared and vibration weights, aligning algorithmic attention with the dominant physical risk driver.

Adaptive data fusion methods have been widely used to improve reliability in multi-sensor environments, particularly under uncertainty and incomplete information. By integrating entropy-based initialization with PSO, the developed method balances accuracy, robustness, and computational efficiency. This balance is essential for engineering applications, where both diagnostic precision and computational timeliness are required. The developed method enables substations to conduct PSO fusion monitoring for early fault detection and risk classification with higher confidence. This reduces vulnerability to sensor degradation or communication errors and supports proactive maintenance strategies. Embedding optimization algorithms such as PSO into monitoring systems enhances resilience and contributes to the design of intelligent sensor infrastructures in modern power supply systems.

To evaluate how the PSO fusion method is applied to different equipment types at diverse voltage levels and conditions, the entropy-PSO mechanism must be used. Equipment operating in extreme conditions, such as high-humidity areas or arid environments, shows fluctuating baseline signal distributions and failure probabilities. Because initial weights are calculated from localized feature variances in the entropy-based weight initialization, the PSO algorithm optimizes weights according to regional fault characteristics. The method is adapted to changing environments without requiring rigid manual recalibration. However, domain shift issues occur in deployments owing to background noise and equipment parameters. Therefore, deep transfer learning techniques must be used for adaptation to different domains,⁽²¹⁾ to address distribution discrepancies among different target substations with limited labeled data and ensure robust cross-site generalization.

For effective sensor deployment, PSO must be integrated into multi-sensor data fusion to enhance fault tolerance, resilience to noise, and adaptability to sensor failures or missing data. Advances in sensor technology for improved accuracy, IoT connectivity, and real-time monitoring enhance the effectiveness of PSO-based fusion models for the development of intelligent, self-adaptive monitoring infrastructures that can significantly reduce outage risks and economic losses in modern power systems.

4.2 Implications for predictive maintenance and cost–benefit analysis

Other than risk classification, the PSO fusion method can be used for the formulation of operational guidance for condition-based maintenance. By converting real-time sensor data into risk scores as follows, risk-driven intervention is achieved beyond rigid time-based periodic maintenance.

- Level I ($R_{total} \leq 0.25$): Baseline operation with routine monthly inspections
- Level II ($0.25 \leq R_{total} \leq 0.50$): Early degradation detected. Maintenance windows are scheduled within 7–14 days during planned off-peak hours.
- Level III ($0.50 \leq R_{total} \leq 0.75$): Significant risk. Diagnostic targeted inspections are scheduled within 24–48 h.
- Level IV ($R_{total} > 0.75$): Critical risk. Immediate load redirection and emergency de-energization within hours are required to prevent catastrophic explosion or flashover.

To quantify the relevance in application, an economic cost-benefit was estimated using operational data from 220 kV substations. The PSO fusion method can yield the following economic benefits:⁽²²⁾ The early detection of insulation defects is estimated to reduce catastrophic transformer failures by 65–75%, avoiding severe financial penalties associated with unsupplied power and secondary busbar damage. Transitioning from fixed-interval overhauls to targeted CBM reduces unnecessary teardown inspections by up to 35%, component service life can be extended and labor costs can be reduced. By considering *CapEx* for sensor deployment and edge-computing infrastructure, an estimated payback period of 1.4 years was obtained, indicating economic viability for industrial power networks.

4.3 Limitations

To assess the applicability of the PSO fusion method to different equipment types, voltage levels, and operating conditions, further validation across diverse power-system environments is required. Although the entropy-PSO weighting mechanism is designed to adaptively adjust sensor importance according to changing operating states, its performance for different equipment configurations, climatic conditions, and loading profiles has not been investigated. In such scenarios, variations in sensor distributions and fault characteristics introduce domain-shift effects that affect model performance. Future studies may therefore explore transfer learning and domain adaptation techniques to improve cross-site generalization and facilitate deployment in heterogeneous power-system environments.⁽²³⁾

Several limitations must also be addressed. First, the proposed method was developed and validated using the data collected from a single 220 kV substation. Therefore, its generalizability for different voltage classes, asset compositions, and operating conditions must be further verified through large-scale multi-site investigations. Second, the robustness evaluation was conducted in simulated scenarios, including Gaussian noise, sensor failures, and missing data. Although the resilience of the method is verified, it must be considered that real-world power systems are subject to multiple interacting disturbances. Although the PSO algorithm showed convergence behavior and computational efficiency, the optimization overhead must be assessed when deployed in large-scale monitoring networks involving numerous substations and high-dimensional sensor datasets.

Another limitation is related to the scope of the risk assessment framework. The current method is designed to estimate overall equipment risk and categorize operating conditions into four actionable risk levels (Levels I–IV). Although the method can be used for condition monitoring and early warning, it must be extended to identify specific fault mechanisms, such as thermal overheating, mechanical looseness, insulation deterioration, and/or internal electrical arcing. In asset management systems, fault-type identification is required to support targeted maintenance planning, enhance diagnostic interpretability, and reduce troubleshooting time. However, such functionality requires addressing the lack of sufficiently detailed multi-class fault labels in the historical dataset. Through the collection and annotation of fault data from multiple substations, the developed method can be improved for preventive fault diagnosis.

Such limitations necessitate further research. It is necessary to expand the dataset to include multiple substations, voltage classes, and equipment categories to enhance model robustness and cross-domain applicability.⁽²⁴⁾ Hybrid optimization strategies must be constructed by combining PSO with metaheuristic or learning-based methods to enhance convergence performance and adaptation capability. Through the incorporation of edge-computing and industrial IoT architectures, distributed real-time implementation is achieved to reduce communication latency and computational burden. The PSO fusion method can be improved by using a dataset that contains fine-grained fault records, enabling the evaluation of fault severity and root-cause identification.

5. Conclusion

We developed a multi-sensor data fusion method for the risk assessment of high-voltage power equipment. The method combines entropy-based weight initialization with PSO to integrate heterogeneous sensor measurements and evaluate equipment operating conditions. In the method, a three-layer monitoring architecture is adopted to collect, process, and analyze data from multiple sensor types. By optimizing the contribution of individual sensor measurements to the overall risk assessment, the limitations of conventional approaches can be addressed, which rely on fixed weighting methods or have difficulty integrating heterogeneous monitoring data. The model classifies equipment conditions into four risk levels and provides a basis for identifying abnormal operating conditions and supporting maintenance decisions.

The method's effectiveness was evaluated using 4560 samples collected for 24 months from a 220 kV substation. The method showed an accuracy of 96.8%, an *F1-score* of 0.960, an AUC of 0.978, and an *RMSE* of 0.072. It outperformed the four conventional methods in the evaluated classification and risk-assessment tasks. The results present the contribution of PSO-based weight optimization to the data fusion process. In the disturbance tests, the proposed method maintained higher classification performance than the conventional methods under noise, sensor-failure, and missing-data conditions. The online inference latency was 0.15 ms per sample, indicating that the model can process individual samples rapidly under the evaluated experimental conditions. These results proved the effectiveness of the method for integrating multi-source sensor information and assessing equipment risk.

The method can be used for the condition-based maintenance of high-voltage power systems. By using sensor data in a unified risk assessment, maintenance personnel can identify equipment requiring inspection and prioritize maintenance activities according to estimated risk, using the developed method. However, the economic benefits and long-term operational effectiveness require further validation through multi-site field studies and extended deployment. It is also necessary to examine the method's generalizability across substations, equipment types, and operating environments, as well as its performance for new fault patterns. Through such validation, the developed method can be deployed in large-scale power-system monitoring and maintenance.

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