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Article

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Research on Multi-Information Sensing and Graded Warning Technology for Fires in Electromechanical Chambers

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Abstract: This study presents a comprehensive framework for intelligent fire prevention and control in underground coal mine electromechanical chambers. Addressing the limitations of traditional fire monitoring systems—such as narrow coverage, information silos, and delayed response—this research proposes a full-dimensional information perception and linked control system. The system integrates multi-parameter sensors, deep learning-based flame detection, and optimized sensor layout strategies to achieve real-time monitoring, early warning, and collaborative control. A multi-parameter sensor was developed for synchronous detection of temperature, smoke, and hazardous gases (CO, SO₂, HCl), with enhanced portability and battery life. Flame detection was improved using an optimized YOLOv5 algorithm incorporating attention mechanisms and multi-scale detection layers, enabling accurate recognition of small-scale flames in complex underground environments. Sensor layout optimization was achieved through 3D spatial modeling and multi-objective intelligent algorithms, significantly improving monitoring coverage and reducing redundancy. Furthermore, a hybrid fire risk assessment model combining Fuzzy Neural Networks (FNN) and Grey Relational Analysis (GRA) was established, and a graded early warning mechanism based on the EPI model was developed. The results demonstrate that the proposed system enhances fire perception accuracy, response speed, and decision-making reliability, providing a robust technical foundation for intelligent fire safety management in underground mines.

Keywords: Self-ignition, Underground fire; Fire detection and recognition; Multi-parameter sensor; YOLOv5; Fuzzy neural network; Advanced monitoring

1. Introduction

Electromechanical chambers in underground coal mines serve as critical hubs housing essential equipment such as substations, pumping stations, and belt conveyor drives. Their safe operation is fundamental to mine production and personnel safety. With the continuous expansion of mining operations and the increasing adoption of intelligent equipment, the number and power of electrical installations continue to rise, thereby escalating the fire risk and complexity within electromechanical chambers (Deng et al. 2024; Sun et al. 2019). These chambers are characterized by dense electrical apparatus, intricate cabling, and the presence of combustible materials within a confined, poorly ventilated space. Once a fire ignites, it propagates rapidly, generating high temperatures and toxic smoke that can quickly incapacitate escape routes and trigger secondary disasters like gas or coal dust explosions (Wang et al. 2022; Chen et al. 2021). Notably, the incipient stage of an electrical fault often manifests only as localized abnormal temperature rise or trace amounts of pyrolytic gases. This "extremely early" period, from the initial anomaly to the appearance of open flames, represents a critical window for fire suppression (Bai et al. 2022). Therefore, developing multi-information sensing and graded warning technologies tailored to the electromechanical chamber environment to achieve "proactive detection, early warning, and timely localization" of fire hazards is of paramount theoretical and engineering significance for enhancing mine disaster prevention capabilities and safeguarding miner lives.

Traditional fire monitoring methods in electromechanical chambers rely predominantly on single-parameter sensors with fixed threshold alarms, supplemented by periodic manual inspections (Liu et al. 2024). Studies have

shown that while existing mine fire monitoring systems can acquire individual fire-related parameters like temperature, smoke, and CO, they suffer from significant limitations (Chen 2022). Single sensors are prone to interference from harsh underground conditions such as high humidity and dust, leading to decreased measurement accuracy and frequent false alarms (Ma et al. 2020). Furthermore, single-indicator monitoring cannot fully capture the multi-physics changes during fire development; by the time a single indicator crosses a threshold, the fire has often already entered a rapid development phase, resulting in delayed warnings (Wang et al. 2015). Traditional systems also lack deep correlation analysis of multi-source monitoring data, making early identification and precise localization of fire risks difficult (Li et al. 2022; Zheng et al. 2020). These deficiencies render conventional approaches inadequate for meeting the "proactive detection, early warning, and timely localization" requirements of modern intelligent mines (Zhong et al. 2021).

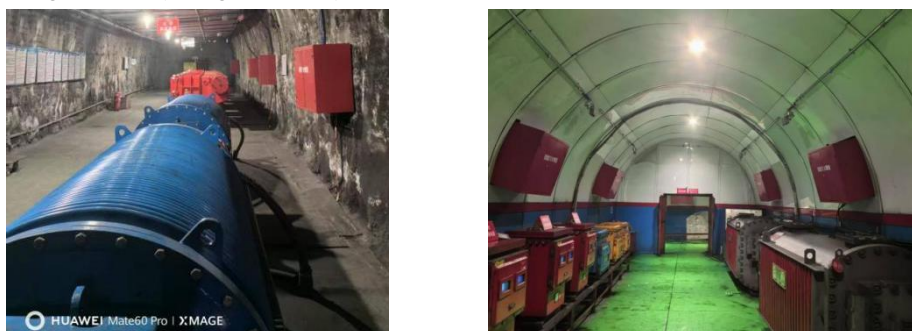


Figure 1 Field Photograph of Electromechanical Chamber

In recent years, the rapid advancement of the Internet of Things (IoT), big data, and artificial intelligence has opened new avenues for mine fire prevention through multi-information fusion and intelligent warning technologies (Zheng et al. 2020). Researchers have proposed source- and zone-specific monitoring strategies that categorize indicators into dynamic (e.g., CO concentration, temperature change), static (e.g., equipment attributes), and correlative (e.g., air leakage rate) types (Zhong et al. 2021; Yue et al. 2020). For coal spontaneous combustion warning, multi-indicator graded warning models have been established using CO, O₂, C₂H₄, and C₂H₆ as primary indicators to define multiple warning levels (Yue et al. 2020). For exogenous fire warning, multi-sensor data fusion methods based on fuzzy sets and D–S evidence theory have been developed, effectively integrating temperature, smoke, and CO information to significantly improve warning accuracy (Duan et al. 2017; Han et al. 2022).

Regarding temperature monitoring technology, distributed optical fiber sensing based on Raman scattering and optical time-domain reflectometry enables continuous temperature monitoring along cables and equipment with meter-level spatial resolution, allowing early detection of abnormal heating caused by cable overload or insulation degradation (Cheng 2019; Zhang et al. 2023). This technology has been successfully applied to belt conveyor fire monitoring and coal spontaneous combustion detection in goafs, demonstrating reliability in harsh underground environments (Cheng 2019; Zhang et al. 2023).

Image-based fire recognition using deep learning has achieved significant progress in recent years. Various improved YOLO series algorithms have been proposed for fire and smoke detection, including YOLOv3 embedded with DenseNet and dilated convolution modules (Zhang and Wei 2020), YOLOv5 combined with K-means improved dark channel defogging for mine fire video recognition (Wang et al. 2021), edge-deployed lightweight YOLOv5 for real-time fire source detection (Zhao et al. 2022), YOLOv7 optimized for infrared smoldering fire detection (Tang et al. 2024), and feature engineering-enhanced S-FCN methods (Li et al. 2024). More recent advances include YOLOv9 with programmable gradient information learning (Wang et al. 2024), cross-scale YOLOv10 integrating efficient attention mechanisms (Gao et al. 2025), entropy-enhanced image processing with improved YOLOv8 for smoke recognition (Li and Liu 2025), and enhanced YOLOv8n methods validated under complex interference conditions (Zhao et al. 2025).

In the areas of multi-sensor fusion and graded warning, hybrid Bayesian network models have been proposed for risk analysis of overload-induced early cable fires, highlighting the need for real-time fusion mechanisms for heterogeneous multi-source data (Chen et al. 2021). Machine learning approaches such as random forest have been employed to predict coal spontaneous combustion, though closed-loop prevention and control integrating warning systems with fire extinguishing facilities remain underdeveloped (Deng et al. 2018). The need for optimized sensor placement strategies in chambers with dense equipment and strong electromagnetic interference has been emphasized (He et al. 2022), and the influence of confined space geometry and ventilation patterns on fire evolution requires the development of tailored fire models (Wang et al. 2023).

Despite the significant progress made in multi-information sensing and intelligent warning technologies, challenges remain in their application within the specific context of electromechanical chambers. Most existing research focuses on single technical approaches, lacking a systematic monitoring indicator system tailored to the chamber environment. The depth of multi-source information fusion is insufficient, making dynamic inference of fire evolution difficult. Graded warning mechanisms and linkage with fire extinguishing facilities have not yet formed a closed loop. To address these gaps, this paper focuses on the research of multi-information sensing and graded warning technology for fires in electromechanical chambers. A comprehensive monitoring indicator system suitable for chamber environments is first established. Then, a multi-source information fusion model based on D–S evidence theory and joint logical reasoning is designed to enhance early detection reliability. A graded warning mechanism based on dynamic risk entropy calculation is proposed to provide progressive alert levels corresponding to fire development stages. Finally, the proposed system is implemented and validated in a coal mine, demonstrating its effectiveness in improving warning accuracy and enabling coordinated firefighting actions. The outcomes of this study are expected to provide theoretical support and technical guidance for intelligent fire prevention in underground mines.

2. Overall Planning and Design for Fire Safety in Electromechanical Chambers

2.1 System Architecture

To achieve an integrated closed-loop management of fire perception, early warning, prevention, and control within electromechanical chambers, and to address the limitations of single-point sensing—such as narrow coverage, information silos, and delayed response—this study proposes a holistic architectural design. By deeply integrating diverse fire information sensing resources, a Full-Dimensional Information Perception System is constructed. This system is characterized by six core capabilities: comprehensive perception, real-time interconnection, analytical decision-making, autonomous learning, dynamic prediction, and collaborative control. The functional positioning and cooperative logic of each system layer are clearly defined, as illustrated in Figure 2.

(1) Perception Layer

Serving as the core source of system data acquisition, the perception layer manages the unified integration and standardized operation of various fire-related sensors, covering multi-dimensional devices for temperature, smoke, gas, flame, and equipment operational parameters. By leveraging low-power self-organizing network technologies such as ZigBee and LoRa, along with edge computing resources, this layer achieves data fusion, real-time preprocessing, and intelligent edge analysis at the source. This significantly enhances the timeliness and accuracy of sensing, providing high-quality raw data support for subsequent early warning and prevention.

(2) Network Layer

Relying on the existing wired/wireless private networks within coal mines, this layer constructs a stable, reliable, and high-bandwidth bidirectional transmission network tailored to the communication requirements of underground environments. It focuses on resolving data transmission bottlenecks, ensuring the efficient transfer of fire information, equipment status data from the perception layer, and commands from upper layers. This guarantees real-time interconnection between sensing, platform, and application ends, supporting both routine operations and

emergency response within the coal mine fire prevention system.

(3) Platform Layer

Functioning as the data hub and decision-making core, this layer enables unified access, status monitoring, and remote management of underground sensing terminals and prevention devices. On one hand, it advances the construction of a unified data center for intelligent fire prevention, facilitating the aggregation, cleaning, storage, analysis, and mining of multi-source data to build a standardized data resource system. On the other hand, it expands standardized interoperability interfaces with existing information systems, such as mine safety production and equipment management platforms. This breaks down information barriers, enhances data processing efficiency, and elevates cross-system collaboration, providing robust technical support for fire analysis, decision-making, and dynamic prediction.

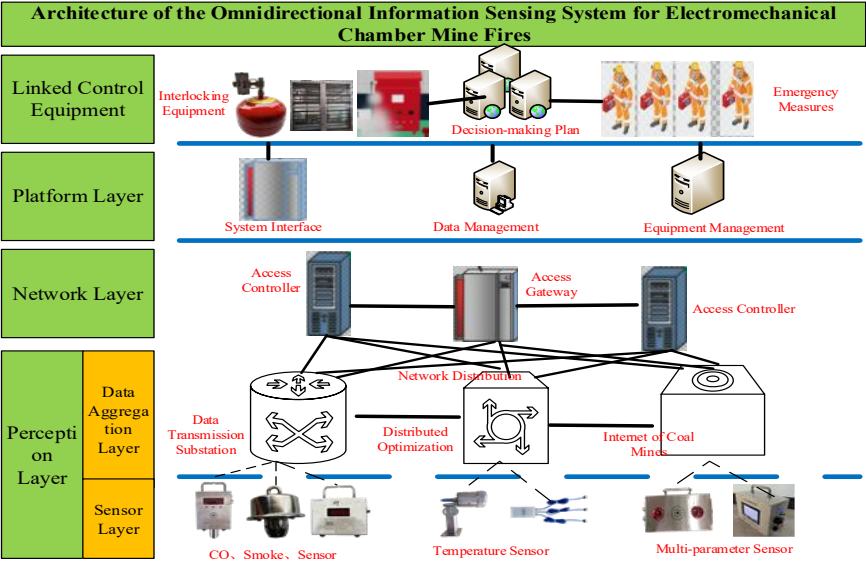


Fig.2 Architecture of the Full-Dimensional Perception and Linked Control System

(4) Application Layer

This layer integrates various fire suppression technologies—including inert gas, aerosols, dry powder, water mist, and airflow control—to improve the efficiency of emergency firefighting. Simultaneously, a unified IoT management platform is established for leadership decision-makers and various management departments. This enables visualized monitoring and collaborative control over the entire process and all ele.

2.2 Technology Roadmap

Aligning with the development trends of intelligent coal mines in China and the demands for intelligent collaboration in mine fire management, this study proposes an integrated approach encompassing fire perception, early warning, prevention & control, and emergency response. By deeply integrating Artificial Intelligence (AI), the Industrial Internet of Things (IIoT), and big data technologies into coal mine fire safety, an intelligent prevention and control system is established. This system possesses core capabilities such as comprehensive perception and real-time interconnection. Drawing on the concepts and methodologies of Smart Firefighting and Smart Cities, the proposed technical roadmap is illustrated in Fig 3.

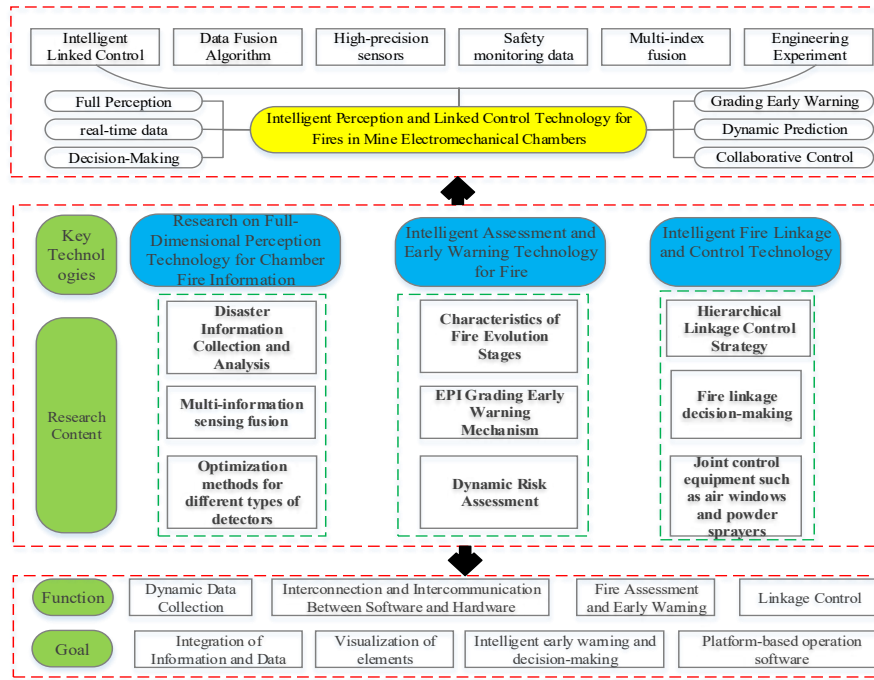


Fig 3 Technology Roadmap

3.Comprehensive Perception Technology for Fires in Electromechanical Chambers

3.1 Development of a Multi-Parameter Sensor for Fire Detection in Electromechanical Chambers

To address the challenges of traditional fire monitoring in mine electromechanical chambers—such as dispersed sensors, limited functionality, and low monitoring efficiency—an integrated, intelligent, and highly adaptable multi-parameter sensor has been developed. This sensor enables real-time synchronous monitoring of critical gas parameters and equipment operating conditions, establishing a reliable data perception foundation for unattended chambers.

3.1.1 Functional Design

The multi-parameter sensor incorporates multiple optimization designs at the hardware architecture level, focusing on three core modules: gas sampling, gas analysis, and power management. These enhancements improve performance while ensuring portability and extended battery life. Key design features are as follows:

(1) Gas Sampling Module: A chemically inert pipeline and a micro-diaphragm pump are used to construct the sampling pathway, combined with a dust/hydrophobic composite filter to effectively prevent gas sample adsorption and contamination, ensuring sample integrity. An integrated flow sensor enables real-time monitoring of the sampling flow rate, with automatic alarms triggered under abnormal conditions to ensure sampling stability.

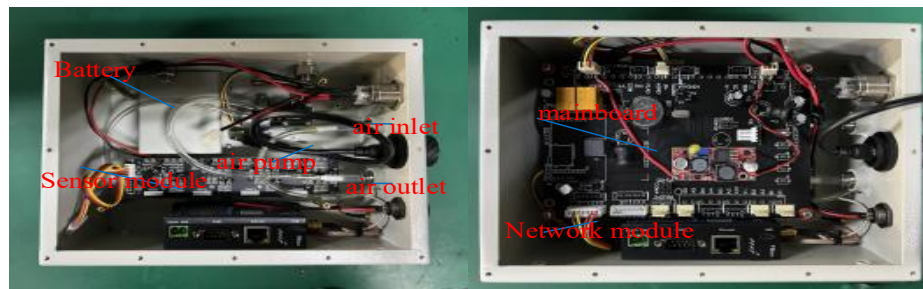


Fig 4 Internal structure diagram

(2) Gas Analysis Module: A temperature-controlled gas chamber is added to eliminate the impact of ambient temperature fluctuations on sensor detection sensitivity. A 24-bit high-precision ADC (Analog-to-Digital Converter) is incorporated to accurately capture and convert weak gas detection signals, enhancing detection precision.

(3)Power Management Module: A four-cell Samsung INR18650-35E lithium battery pack serves as the core power source, paired with the TI BQ25895 charging management chip and the TPS63000 buck-boost converter to construct a hierarchical power management system. Combined with dynamic power optimization strategies—such as CPU sleep mode, intelligent backlight adjustment, and intermittent pump operation—the system reduces energy consumption. Under continuous operation with the pump and display screen always on, the device achieves a battery life of ≥ 8 hours and a total weight of ≤ 3.5 kg, meeting on-site portability requirements. The core technical parameters and validation methods for the sensor are shown in Table 1.

Tab 1: Core Technical Parameters and Validation Methods

Technical Parameter	Function	Validation Method
Target Gases	SO ₂ , HCL, CO, O ₂	Standard gas testing
Measurement Range	SO ₂ : 0-100ppm; HCL: 0-50ppm; CO: 0-1000ppm; O ₂ : 0-25%vol	Standard gas testing
Response Time	≤ 15 s	Dynamic gas distribution testing system
Indication Error	$\leq \pm 5\%$ FS	Comparison with standard concentrations
Operating Humidity	0–95% RH (non-condensing)	Constant temperature and humidity chamber
Protection Capability	Dustproof, splash-proof, shock-resistant	IP54 testing, vibration testing
Battery Life	≥ 8 hours (pump and screen always on)	Discharge testing under actual working conditions

3.1.2 Circuit Design

The sensor's circuit system is built around a low-power MCU (Microcontroller Unit) as the core, forming a multi-channel signal acquisition and processing architecture. Dedicated detection channels are designed for smoke, temperature, and fire-specific gases such as CO, SO₂, and HCl. Operational amplifiers and instrumentation amplifiers are used to condition and amplify raw signals from each channel, effectively enhancing the identification capability of weak signals.

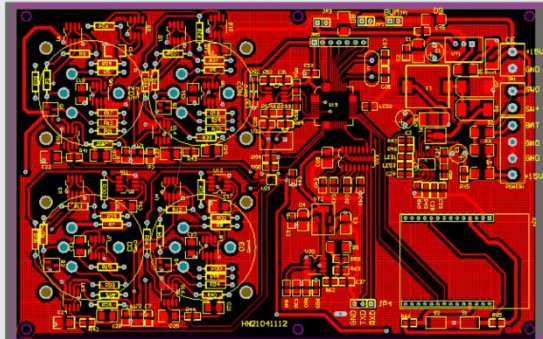


Fig 5: System Circuit Schematic Diagram

The circuit design integrates power management, multi-standard communication interfaces, and a watchdog circuit. The power management module ensures stable power supply to all components, the communication interfaces enable efficient transmission of monitoring data, and the watchdog circuit effectively prevents system

crashes. These features collectively enhance the circuit system's anti-interference capability and long-term operational stability at the hardware level.

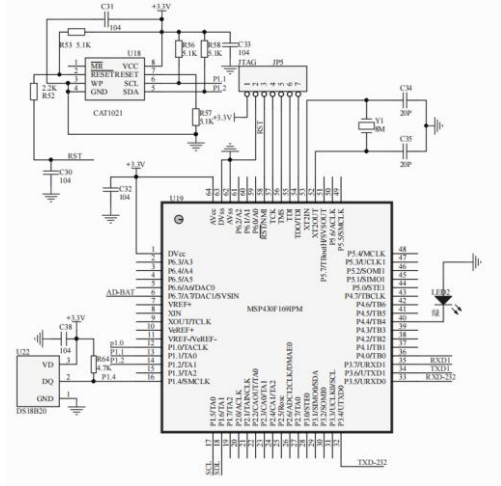


Fig 6: Partial PCB Design Diagram of the Main Board

3.1.3 Data Processing and Intelligent Interaction

The device uses a high-performance ARM Cortex-M series microcontroller as its core processing unit, equipped with a 24-bit high-precision ADC to support synchronous signal acquisition, digital filtering, and temperature compensation for multi-channel sensors. Built-in calibration curves enable the direct output of accurate gas concentration values, improving data reliability and consistency.

The device features a 4.3-inch embedded touchscreen that supports real-time curves, instrument panels, and other graphical display modes, allowing on-site personnel to intuitively grasp environmental conditions. Additionally, it incorporates intelligent functions such as audible and visual alarms for threshold exceedance and fault self-diagnosis, achieving a functional leap from "single data acquisition" to "on-site intelligent sensing terminal."



Fig 7: Device Interface Display and Prototype Physical Image

3.2 Flame Detection Technology for Mechanical and Electrical Chambers

Traditional fire monitoring in mechanical and electrical chambers relies on threshold alarms from gas, temperature, and smoke sensors, which suffer from response lag. Conventional infrared image recognition is also prone to interference from mobile light sources underground. To achieve early and accurate fire identification, a flame detection model adapted to the complex underground environment is constructed based on deep learning object detection algorithms, thereby compensating for the shortcomings of traditional monitoring methods.

3.2.1 Selection of Flame Object Recognition Algorithm

Currently mainstream object detection algorithms are primarily divided into two categories: two-stage detection algorithms (represented by the R-CNN series) and single-stage detection algorithms (centered on the YOLO series). Although two-stage detection algorithms offer high detection accuracy, their slow inference speed fails to meet the engineering requirements for real-time video monitoring underground, making it impossible to promptly report potential fire hazards. In contrast, YOLO series algorithms innovatively transform the object detection task into an end-to-end regression problem, simultaneously outputting the target's coordinates, category information, and

confidence level through a single convolutional neural network. This approach has significant advantages in real-time performance and compact model size, making it more suitable for engineering deployment and mobile device applications underground.

As the most widely used single-stage object detection algorithm currently, YOLOv5 can flexibly adjust network depth and width coefficients to adapt to different training scenarios and hardware requirements. The algorithm's model structure is mainly composed of three parts: the backbone network, the neck network, and the head network. After input image preprocessing and resizing, the backbone network completes feature extraction and fusion, providing reliable feature support for subsequent object recognition. YOLOv5 introduces Mosaic data enhancement technology and the CIOU loss function, effectively improving the model's detection accuracy and robustness for flame targets in complex environments, thus better adapting to the complex conditions of underground mechanical and electrical chambers.

3.2.2 Optimization of Fire Detection Algorithm Based on YOLOv5

Addressing the practical characteristics of underground fires—specifically the microscopic scale of initial flames and the abundance of environmental interference factors—this paper implements three targeted optimizations to the baseline YOLOv5 algorithm. These improvements aim to enhance the model's detection capability for extremely small flame targets and its adaptability to complex underground environments, thereby resolving the shortcomings of the original algorithm in underground applications.

Regarding the selection of attention mechanisms, a performance comparison among three mainstream mechanisms (SE, CBAM, and ECA) revealed that the ECA attention mechanism is superior. By eliminating fully connected layers and utilizing 1D convolutions for adaptive learning of channel weights, ECA not only effectively improves detection accuracy but also reduces computational load. The optimization effect is most pronounced when this mechanism is inserted immediately before the SPPF module in the backbone network.

In terms of detection layer optimization, a fourth detection head utilizing $4\times$ downsampling was added to the original three detection heads. This enables the effective detection of extremely small flame targets ($\geq 4\times 4$ pixels). Furthermore, by matching priors (anchor boxes) with halved dimensions to this new detection layer, the issue of missed detections for tiny initial flames in the original model is effectively resolved.

Concerning model training optimization, the model is initialized using YOLOv5s weights pre-trained on the CO dataset. This approach effectively compensates for the insufficient sample size of underground flame datasets, accelerates model convergence, and significantly enhances generalization capability, making the model more adaptable to the complex and dynamic underground environment.

(1) Model Evaluation Metrics

In object detection algorithms, mean Average Precision (mAP) is commonly used to evaluate training effectiveness, measuring the alignment between predicted bounding boxes and ground truth boxes. In fire detection algorithms, since the task involves single-class detection, results are categorized into four scenarios. The experimental results employ five evaluation metrics: Precision, Recall, Intersection over Union (IoU), Average Precision (AP), and mAP.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

Recall represents the proportion of true positive samples among all actual positive samples that were correctly predicted as positive by the model. It measures the model's ability to retrieve all positive samples. The calculation method is as follows:

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

Where: TP (True Positive): Correctly identifying a flame as a flame. TN (True Negative): Correctly identifying a non-flame scene as non-flame. (Note: The original text contained a typo stating "correctly identified as flame"; this has been corrected to logical consistency). FN (False Negative): Incorrectly classifying a scene containing a flame

as having no flame. FP (False Positive): Incorrectly identifying a non-flame scene as containing a flame.

IoU is frequently used as an indicator of prediction accuracy. When the IoU between the ground truth bounding box area and the predicted bounding box area reaches a set threshold, the model is considered to have correctly predicted the detection target.

The IoU is the ratio of the intersection area to the union area of the target bounding box and the ground truth bounding box, calculated as follows:

$$\text{IoU} = \frac{\text{Area}_{\text{pred}} \cap \text{Area}_{\text{gt}}}{\text{Area}_{\text{pred}} \cup \text{Area}_{\text{gt}}} \quad (3)$$

To derive the comprehensive metric mAP, the Average Precision (AP) for each category must be calculated, using the area under the Precision-Recall (PR) curve as the standard. Generally, precision and recall exhibit an inverse relationship.

$$\text{AP} = \int_0^1 P \, dR \quad (4)$$

The prediction accuracy for a single category ranges from 0 to 1. By varying the IoU threshold, precision and recall values under different IoU conditions can be obtained. Typically, the AP under each threshold is calculated using the following equation:

$$\text{AP} = \frac{1}{11} \sum_{r \in \{0,0.1,\dots,1\}} \text{AP}_r = \frac{1}{11} \sum_{r \in \{0,0.1,\dots,1\}} \max_{r' \geq r} p(r') \quad (5)$$

(Note: The formula in the source text contained formatting errors regarding the summation range; it has been corrected to the standard 11-point interpolation method usually denoted as $\{0,0.1,\dots,1\}$).

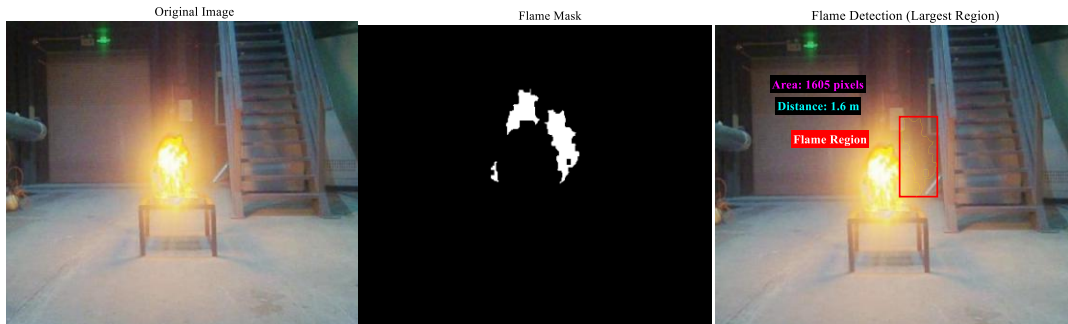
AP evaluates the object detection performance for a single category, whereas mAP evaluates the overall detection performance of the entire model. The mean Average Precision is the average of the AP values across all categories:

$$\lim_{n \rightarrow \infty} \frac{\text{AP}_1 + \text{AP}_2 + \dots + \text{AP}_n}{n} \quad (6)$$

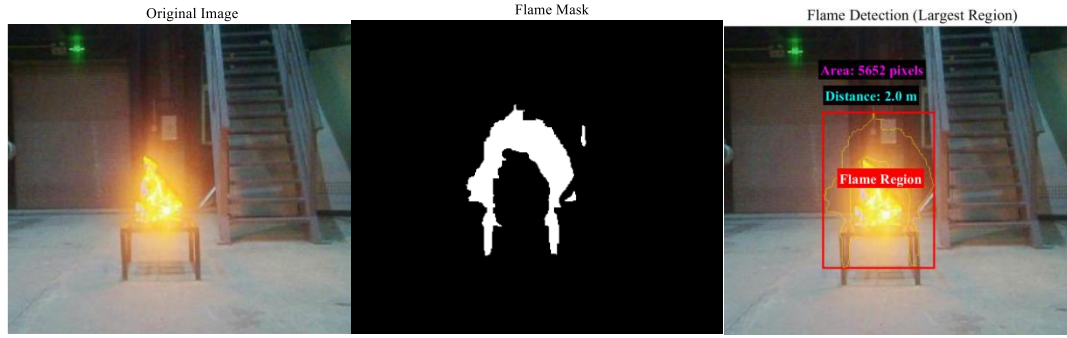
Where AP_n represents the precision for each detection category.

3.2.3 Flame Recognition and Distance Detection Experiments in Mechanical and Electrical Chambers.

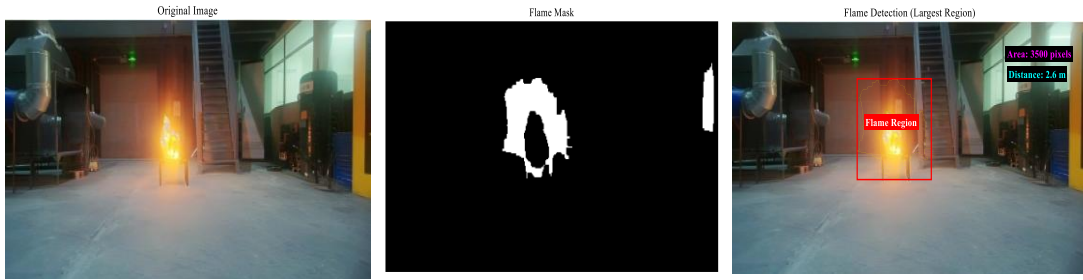
In this experiment, fire sources were photographed at varying distances. To simplify the experimental procedure, the depth (Z-coordinate) of the camera relative to the fire source was strictly controlled. The initial distance was set to 1 meter, with increments of 20 cm. Given that the camera baseline distance is 6 cm, the experiments were conducted within a short range to maintain accuracy, with a maximum shooting distance of 5 meters. After image acquisition, the images were input into the model to derive the three-dimensional coordinates of the fire source point, where the Z-coordinate value represents the depth distance. Partial specific output results are illustrated in Figure 8.



(a)1.6



(b) 2.0



(a) 2.6

Fig 8 Analysis of Flame Recognition Results at Various Distances

Based on Figure 8, it can be observed that under normal lighting conditions, the algorithm achieves excellent flame recognition performance, with ranging errors controlled within 0.1 meters. However, at a distance of 1.4 meters under excessively strong ambient light, flame recognition occasionally fails, indicating that the algorithm retains a certain sensitivity to extreme lighting conditions.

In the original image sub-figure, the raw morphology and distribution of the flame are clearly visible. The flame mask sub-figure displays the binarization results obtained after color thresholding and morphological optimization. This mask effectively preserves the primary contour features of the flame while filtering out background interference, demonstrating that the HSV space threshold selection is reasonable and capable of accurately capturing the typical color characteristics of flames.

In the detection result sub-figure, the algorithm successfully identifies the bounding box and contour of the largest flame region. The red bounding box prominently highlights the main flame area, while the yellow dotted contour precisely outlines the flame's edge morphology, validating the accuracy of the region growing and contour extraction algorithms. Furthermore, the algorithm clearly annotates distance and area information above the bounding box.

3.3 Optimization of Sensor Layout

Addressing the challenges within mechanical and electrical chambers—characterized by strong electromagnetic interference, high dust concentrations, humid environments, and dense equipment arrangements—traditional sensor layout methods often suffer from significant monitoring blind spots, severe data redundancy, and low wireless communication reliability. These limitations make it difficult to meet the demands for precise monitoring under complex operating conditions. To overcome these issues, this section proposes a sensor layout methodology that integrates 3D spatial value modeling with multi-objective intelligent optimization. By incorporating the numerical simulation patterns of fire evolution in mechanical and electrical chambers, this approach enables precise sensor placement and multi-parameter collaborative monitoring. Consequently, it significantly enhances monitoring efficiency within the chamber while reducing operation and maintenance costs.

3.3.1 Sensor Layout Optimization Method

(1) Sensor Layout Optimization Approach

The optimization of sensor layout in mechanical and electrical chambers begins with the construction of a precise spatial model. The entire three-dimensional space of the chamber is discretized into multiple voxel units. Each unit is assigned a corresponding monitoring value weight to establish a 3D model of the chamber. The space is divided into a voxel grid, and the monitoring value for each grid is calculated as follows:

$$V_i = \alpha_i \times \beta_i \times \gamma_i \quad (7)$$

Where: α_i Equipment Importance Coefficient, reflecting the criticality of the equipment located within the unit. β_i Failure Probability, representing the likelihood of equipment malfunction or fire initiation in that unit. γ_i Environmental Weight, which accounts for environmental factors influencing risk. The overall coverage rate of different layout configurations is evaluated using Monte Carlo simulations to ensure optimal placement.

(1) Intelligent Algorithm Solution Based on Multi-Objective Optimization

Sensor layout optimization is fundamentally a multi-constraint, multi-objective optimization problem. It balances three key indicators: monitoring coverage, deployment cost, and network energy consumption, as formulated in Equation (8):

$$\begin{cases} \max f_1(x) = \sum_{i=1}^N V_i \cdot C_i(x) \\ \min f_2(x) = \sum_{j=1}^M c_j x_j \\ \min f_3(x) = \sum_{k=1}^K E_k(x) \end{cases} \quad (8)$$

Where: $C_i(x)$: The state function indicating whether point i is covered. c_j the deployment cost of the j -th sensor. E_k The energy consumption of the k th communication link.

Given the conflicting nature of these objective functions, traditional single-objective optimization algorithms struggle to find effective solutions. To address this, the proposed method utilizes Fast Non-dominated Sorting and Crowding Distance Calculation. This approach enables the acquisition of a set of Pareto optimal solutions in a single run. In practical implementation: Chromosome Encoding: A binary string is used to represent sensor deployment locations (where '1' indicates a sensor is placed and '0' indicates otherwise). Fitness Function: Constructed based on the weighted sum of the three objectives to guide the evolutionary search towards optimal trade-offs.

$$Fitness = w_1 \cdot f_1 - w_2 \cdot f_2 - w_3 \cdot f_3 \quad (9)$$

The weight coefficients w_i can be dynamically adjusted using the Entropy Weight Method.

3.3.2 Numerical Simulation Study on Temperature Variation Laws in Mechanical and Electrical Chambers

The modeling is based on an actual underground electrical machinery chamber as the prototype, establishing a three-dimensional geometric model as shown in Figure 9. To simplify calculations and align with engineering practice, the model dimensions are simplified to 20 m in length, 10 m in width, and 5 m in height, with adiabatic boundary conditions applied at the model boundaries. The medium inside the chamber is air, with an initial ambient temperature set at 25°C and an initial atmospheric pressure at standard pressure. The fire simulation adopts a combination of steady-state and transient approaches. The fire source is assumed to originate from a typical electrical equipment fire inside the chamber, with an initial power of 500 kW. This setup is used to simulate the temperature variation patterns at different stages of a fire in the electrical machinery chamber, providing a foundational model for subsequent analysis of temperature field distribution and fire early warning research.

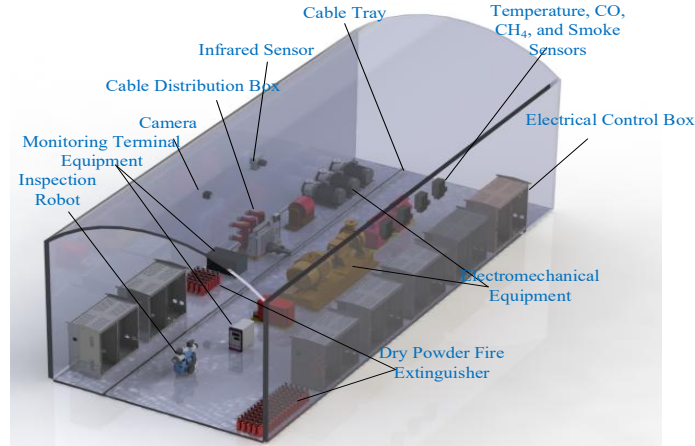


Fig 9 Geometric Model of the Mechanical and Electrical Chamber

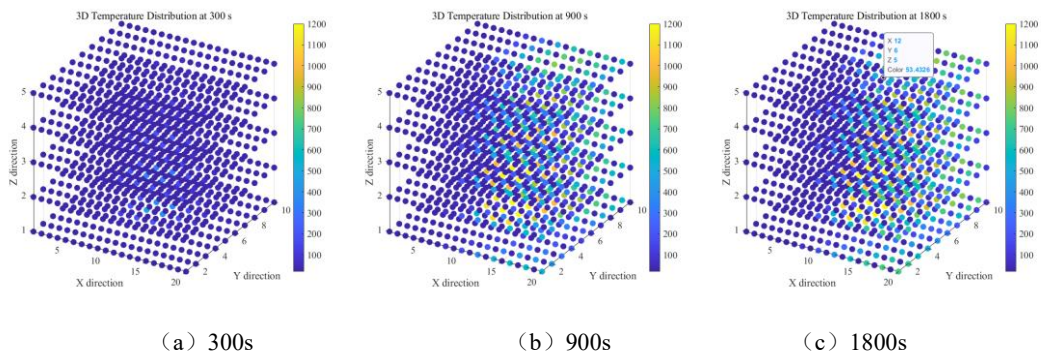


Fig 10 Temperature contours of the fire evolution in the chamber

Figure 10 presents the three-dimensional temperature distribution of the chamber fire at 300 s, 900 s, and 1800 s after ignition. As can be seen from the figure, a high-temperature core region forms at the fire source, where isothermal surfaces are densely packed and the temperature gradient is extremely large; as the distance increases, the temperature gradually decreases, and the spacing between isothermal surfaces widens. In the vertical direction, the buoyant rise of hot smoke causes the ceiling area to have significantly higher temperatures than the floor, forming a stable thermal stratification. In the horizontal direction, influenced by the chamber geometry and ventilation, local features appear at air inlets and corners. During dynamic evolution, the temperature spread exhibits distinct directionality: a thermal plume rapidly forms a high-temperature channel above the fire source, and a ceiling jet spreads along the ceiling and deflects upon encountering obstacles. These patterns reveal heat accumulation and high-temperature channels, providing key insights for understanding fire spread paths, optimizing ventilation and smoke exhaust design, and formulating fire suppression strategies.

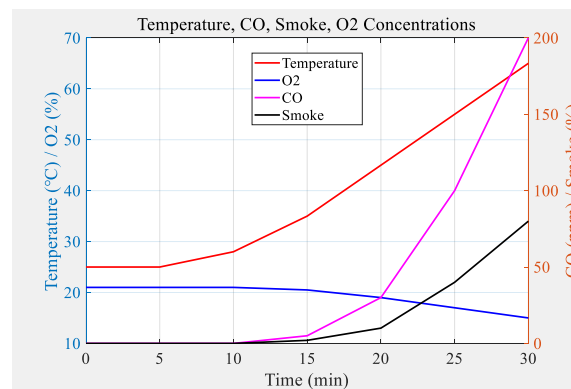


Figure 11 Time histories of production parameters at monitoring points

Figure 11 illustrates the evolution of four core fire parameters within the electromechanical chamber over a 30-minute period. As can be seen from the curves: the temperature rises slowly between 0 and 10 minutes (from 25°C to 28°C), accelerates between 10 and 20 minutes (from 28°C to 45°C), and then increases sharply after 20 minutes, reaching 65°C, exceeding the warning threshold ($T_0=30^\circ\text{C}$) and approaching the dangerous temperature ($T_{\text{max}}=60^\circ\text{C}$). The oxygen concentration is negatively correlated with temperature; it remains stable at 21% in the early stage but drops rapidly to 15% after 20 minutes, reaching the hypoxia risk threshold. The CO concentration and smoke concentration are nearly zero before the 15-minute mark, begin to increase significantly after 15 minutes, and show exponential growth after 20 minutes, reaching 200 ppm and 80% respectively at 30 minutes, indicating that incomplete combustion and smoke generation have entered a violent stage. This figure clearly delineates the three phases of fire development: the incubation period (0–10 min), the early stage (10–20 min), and the intense stage (20–30 min). It provides a reliable time-series data foundation for subsequent graded warning analysis.

3.3.3 Analysis of Sensor Layout in Electromechanical Chambers

Based on three-dimensional fire dynamic simulation, this study analyzes the distribution patterns of the temperature field, smoke diffusion, and hazardous gases at different fire development stages. Accordingly, the sensor layout scheme for electromechanical chambers has been optimized. By integrating numerical simulation with visualization technology, an optimization configuration table (Table 2) is generated. This table evaluates the effectiveness of monitoring point data and verifies the rationality of the sensor layout, thereby providing a theoretical basis and technical support for the design of fire monitoring systems in electromechanical chambers.

Table 2 Optimization of configuration

Detector Type	Monitoring Parameters	Placement Location t	Spacing Requiremen
Heat Detector	Dynamic changes in temperature field	0.5m below the roof, areas with dense equipment	$\leq 8\text{m}$
Smoke Detector	Smoke concentration, diffusion speed	Ventilation paths, roadway intersections	$\leq 10\text{m}$
Gas Detector	CO/O ₂ concentration	Personnel activity area, return air side	$\leq 15\text{m}$
Flame Detector	Fire source location	1m above flammable equipment	line-of-sight coverage

In the practical selection of characteristic parameters for fire detection in electromechanical chambers, too few parameters can compromise the sensitivity and reliability of detection, while an excessive number may reduce the efficiency and cost-effectiveness of the detection system. Therefore, a multi-sensor fire feature combination selection model is established. Based on the mutual information theory of information entropy, research and analysis are conducted to identify the optimal combination of multi-sensor fire features.

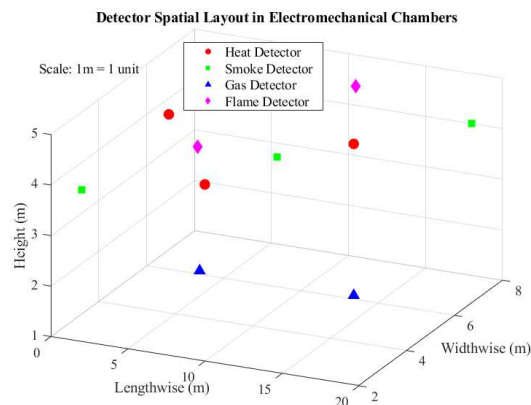


Fig 12 Optimization of equipment layout

Based on the fire characteristics and spatial structural features of the electromechanical chamber, this scheme adopts a multi-parameter collaborative monitoring layout: heat detectors are arranged at intervals of 8 m and positioned 0.5 m below the roof to primarily monitor dynamic changes in the temperature field; smoke detectors are installed at intervals of 10 m along the ventilation paths to focus on monitoring smoke concentration and diffusion;

gas detectors are placed at intervals of 15 m covering personnel activity areas and the return air side to monitor changes in CO and O₂ concentrations; flame detectors are installed 1 m directly above flammable equipment to achieve precise fire source localization; and image-type detectors are arranged on the roof of the roadway with a coverage radius of 50 m to provide panoramic monitoring capabilities. This layout scheme complies with the relevant requirements of the Coal Mine Safety Regulations. The spacing settings and installation positions of various detector types are determined based on the characteristics of their monitoring parameters and the actual operating conditions of the electromechanical chamber. The specific equipment layout optimization is shown in Figure 12.

4 Fire Assessment and Graded Warning for Electromechanical Chambers

4.1 Hybrid Model for Fire Risk Assessment

The construction of a hybrid model for fire risk assessment in electromechanical chambers requires comprehensive consideration of the dynamic variation characteristics of multi-source heterogeneous data. A hierarchical processing architecture comprising a "data layer, feature layer, and decision layer" is adopted. At the data layer, real-time environmental parameters are collected through multiple sensors, and wavelet transform and Kalman filtering are employed for noise suppression to ensure data reliability. At the feature layer, Fuzzy Neural Networks (FNN) and Grey Relational Analysis (GRA) are utilized to extract key fire features, such as sudden changes in CO concentration, abnormal temperature rise rates, and accumulation trends of smoke particulates. This is complemented by infrared thermography technology to identify the spatial distribution of high-temperature zones.

4.1.1 Dynamic Risk Assessment Based on FNN

Fuzzy Neural Networks combine the semantic representation capability of fuzzy logic with the autonomous learning characteristics of neural networks, making them suitable for the nonlinear risk assessment of fires in electromechanical chambers.

(1) Fusion Mechanism of Fuzzy Logic and Neural Networks

The core of FNN lies in integrating the semantic reasoning capability of fuzzy logic with the adaptive learning characteristics of neural networks, forming a hybrid intelligent system capable of handling uncertainty and nonlinear relationships. In the fire risk assessment of electromechanical chambers, traditional mathematical models struggle to accurately describe the complex mapping relationship between parameters such as temperature and gas concentration and the fire risk. FNN addresses this by transforming continuous input variables into fuzzy linguistic variables through membership functions, followed by approximate reasoning via a fuzzy rule base. The introduction of neural networks solves the challenges of rule extraction and parameter optimization in fuzzy systems: the feedforward network structure automatically adjusts the centers and widths of membership functions, as well as rule weights, through the backpropagation algorithm. For example, the membership function for the temperature input can adopt an adjustable Gaussian function:

$$\mu_{A_i}(x) = \exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right) \quad (10)$$

Here, c_i and σ_i are dynamically optimized using training data, allowing the define the scope of "high temperature" to adaptively adjust with seasonal changes. Research indicates that this fusion mechanism endows FNN with better interpretability than pure neural networks in mine fire risk assessment, while its accuracy is significantly higher than that of traditional fuzzy systems.

(2) Structural Design and Parameter Learning of the FNN Model

The FNN model for fire assessment in electromechanical chambers adopts a multi-input single-output structure. The input variables must cover three key categories: thermodynamic, gas, and smoke indicators. Taking a 5-input example: real-time temperature, temperature rise rate, CO concentration, smoke transmittance, and O₂ decline rate. The output is the fire risk index $RE[0,1]$. The fuzzification layer defines 3 to 5 linguistic variables for each input, with initial membership functions determined by K-means clustering. The rule layer employs a fully connected

structure, containing $3^5=243$ potential rules. During actual training, a pruning algorithm retains rules with a confidence level > 0.8 to reduce computational load.

Offline training: Historical fire data is used to optimize the antecedent parameters (c_i, σ_i) and consequent parameters through a hybrid learning algorithm. The loss function employs weighted mean squared error:

$$E = \frac{1}{N} \sum_{k=1}^N \lambda_k (\tilde{R}_k - \hat{R}_k)^2 \quad (11)$$

Here, λ_k represents the sample weight. The weight for fire samples is set to three times that of normal samples to address the issue of class imbalance.

4.1.2 Grey Relational Analysis and Multi-Index Fusion Decision-Making

Grey Relational Analysis (GRA) is an effective method for handling uncertain systems characterized by small samples and poor information. Its core principle involves determining the degree of correlation among factors based on the similarity of their geometric sequence shapes. In the fire risk assessment of electromechanical chambers, traditional GRA methods suffer from issues such as sensitivity to initial values and the subjective selection of the resolution coefficient. To address these limitations, an improved Dynamic Weighted Grey Relational Analysis model, DW-GRA, is proposed. The improved formula for calculating the relational degree is presented in Equation (12):

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \cdot w(k) \quad (12)$$

where $\xi_i(k)$ represents the correlation coefficient at the k -th time instant, and $w(k)$ is a time-varying weight.

Given the heterogeneous characteristics of the monitoring parameters (temperature, gas, smoke, etc.) in electromechanical chambers, a hierarchical correlation strategy is proposed:

Intra-parameter Correlation: The self-correlation degree of a single parameter across different time periods is calculated to identify its variation patterns. Through the construction of a time-delay correlation model, it was discovered that a sudden change in CO concentration precedes the appearance of an open flame by approximately 8 to 15 minutes, making it a critical early warning indicator.

Inter-parameter Correlation: An improved grey absolute relational degree is employed to analyze the synergistic effects among multiple parameters. The coupling correlation degree is defined as follows:

$$\gamma_{i,j} = \frac{1 + |s_i| + |s_j|}{1 + |s_i| + |s_j| + |s_i - s_j|} \quad (13)$$

Here, s_i and s_j represent the cumulative slopes of the parameter sequences. Research indicates that when the coupling correlation degree between the temperature rise rate and CO concentration exceeds 0.75, the fire risk increases significantly.

4.2 Graded Early Warning Mechanism Based on EPI for Electromechanical Chambers

Through real-time monitoring, analysis, and classification of key environmental parameters within electromechanical chambers, the objectives of pre-warning, in-process control, and post-event traceability are achieved, effectively preventing equipment failures, fires, and even major safety accidents caused by environmental deterioration.

4.2.1 Theoretical Analysis of EPI

The core of the EPI graded warning theory for fires in electromechanical chambers lies in establishing a comprehensive evaluation model based on multi-index fusion by quantifying key fire parameters. The fire early warning for electromechanical chambers typically employs a comprehensive index method based on multi-parameter fusion, with the basic form expressed as:

$$EPI = \sum_{i=1}^n (W_i \times S_i) \quad (14)$$

Where: EPI represents the comprehensive early warning index; W_i is the weight of the i -th indicator; S_i is the normalized hazard function value of the i -th indicator.

To convert the physical quantities collected by sensors into dimensionless early warning scores, hazard functions are constructed. Temperature Hazard Function:

$$= \begin{cases} 0 & T \leq T_0 \\ \frac{T-T_0}{T_{\max}-T_0} & T_0 < T < T_{\max} \\ 1 & T \geq T_{\max} \end{cases} \quad (15)$$

Where T is the measured temperature; T_0 is the warning initiation threshold temperature; $T_{\max}$ is the critical dangerous temperature.

Temperature Rise Rate Hazard Function:

$$S_R = \frac{dT}{dt} \times \alpha \quad (16)$$

Where $\frac{dT}{dt}$ represents the rate of temperature change per unit time; α is the correction coefficient.

Smoke and Visibility Impact Model: For electromechanical chambers, smoke has a significant impact on equipment, often expressed by visibility or light extinction coefficient:

$$S_V = 1 - \frac{V}{V_0} \quad (17)$$

Where V is the measured visibility; V_0 is the initial visibility.

4.2.2 Analysis Based on EPI Graded Warning

The EPI model is a multi-parameter fusion intelligent warning system. Through real-time monitoring and analysis of key parameters such as temperature, smoke, CO, and oxygen concentration, the variation of the normalized hazard function over time is analyzed according to Figure 11. This process maps each physical parameter to a dimensionless risk level, as shown in Figure 13.

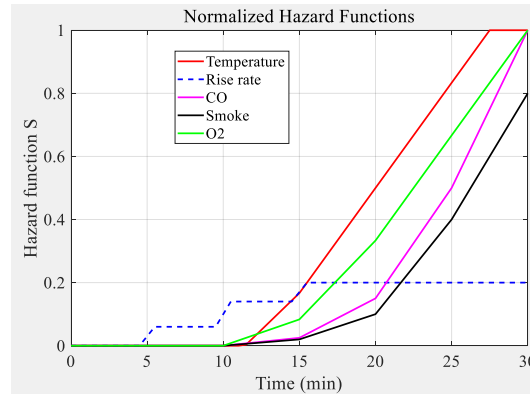


Fig 13 Mapping of physical parameters to dimensionless risk levels

Figure 13 illustrates the mapping of various physical parameters to the dimensionless risk level S , eliminating the influence of dimensionality. The temperature risk level rises rapidly to above 0.8 after 20 minutes; the temperature rise rate risk level peaks between 15 and 25 minutes, reflecting sudden temperature change signals. The CO risk level and smoke risk level increase sharply after 20 minutes, lagging behind temperature changes but with steeper slopes. The oxygen risk level grows slowly, exceeding 0.5 after 25 minutes. The temporal misalignment of these risk levels reveals the propagation sequence of fire signals: the temperature rise rate responds first, followed by temperature and gaseous products, with oxygen consumption being the last. This asynchronous variation among multiple parameters provides complementary information for integrated warning systems, effectively avoiding false alarms and delays associated with single-indicator monitoring.

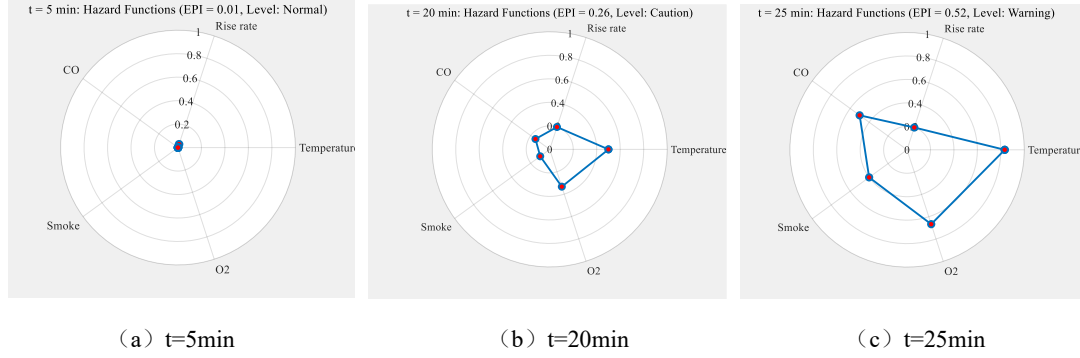


Fig 14 Radar charts at different time points

Figure 14 presents risk profiles at 5 min, 20 min, and 25 min, respectively, using radar charts to visually compare the contribution of each indicator. Figure 14(a) shows that at $t=5$ min, all indicators have risk levels below 0.1, with an EPI of 0.01, classified as "normal," indicating the chamber is in a stable state. Figure 14(b) shows that at $t=20$ min, the temperature risk level rises to 0.5, oxygen risk level to 0.4, CO and smoke risk levels to 0.15 and 0.13 respectively, and the temperature rise rate risk level to 0.25, with an EPI of 0.26, entering the "attention" level. The radar chart exhibits a "higher in the north, lower in the south" pattern (with temperature and oxygen making prominent contributions), suggesting that the fire has entered an early stage of development. Figure 14(c) shows that at $t=25$ min, the temperature risk level approaches 0.8, oxygen risk level reaches 0.6, CO and smoke risk levels reach 0.6 and 0.5 respectively, and the temperature rise rate risk level reaches 0.3, with an EPI of 0.52, rising to the "warning" level. The radar chart shows significant outward expansion along all axes, indicating synergistic deterioration of multiple parameters. The three radar charts reveal the risk evolution process from normal to warning levels, and the changes in the contribution of each indicator provide a visual diagnostic tool for warning decision-making.

5 Conclusion

This study systematically addresses key technical challenges in intelligent fire prevention and control for coal mine electromechanical chambers, focusing on multi-information sensing and graded warning technologies. The main innovative achievements are as follows:

(1) A full-dimensional information perception and linkage control system architecture was established. To overcome issues such as information isolation and delayed response in traditional monitoring systems, a four-layer architecture encompassing perception, network, platform, and application was designed. This system enables comprehensive data acquisition, real-time transmission, intelligent analysis, and collaborative control, providing a systematic solution for fire prevention in electromechanical chambers.

(2) An integrated multi-parameter intelligent sensor was developed. Through optimized design of gas sampling, analysis, and power management modules, a portable sensor supporting simultaneous monitoring of SO₂, HCL, CO, and O₂ was developed. Utilizing low-power design and edge computing, the sensor achieves ≥ 8 hours of battery life while maintaining a lightweight structure of ≤ 3.5 kg, significantly improving on-site monitoring accuracy and efficiency.

(3) An improved YOLOv5-based flame detection algorithm was proposed. Addressing the challenges of complex underground environments and small-scale initial flames, the ECA attention mechanism was introduced and a fourth detection head was added, effectively enhancing the recognition capability for small flame targets. Experiments demonstrate that the algorithm achieves ranging errors ≤ 0.1 m within 5 meters, meeting the engineering requirements for real-time underground video monitoring.

(4) A multi-objective optimization method for sensor layout was established. Combining 3D spatial value

modeling with numerical simulation, the Pareto optimal solution set was obtained using fast non-dominated sorting algorithm, achieving collaborative optimization of monitoring coverage, deployment cost, and network energy consumption. Fire evolution numerical simulations revealed the spatiotemporal distribution patterns of temperature fields, smoke diffusion, and hazardous gases, providing theoretical basis for optimal sensor placement.

(5) A hybrid fire risk assessment model based on FNN-GRA was constructed. Combining the autonomous learning capability of fuzzy neural networks with the multi-index fusion advantages of grey relational analysis, dynamic identification and quantitative assessment of fire risks were achieved. This model effectively addresses the limitations of traditional methods in handling nonlinear and small-sample data.

(6) An EPI-based graded warning mechanism was proposed. By constructing hazard functions for multiple parameters including temperature, smoke, CO, and O₂, a comprehensive early warning index (EPI) was established. Combined with radar chart visualization analysis, a tiered response system from "normal" ($EPI \leq 0.1$) to "attention" ($0.1 < EPI \leq 0.3$) and "warning" ($EPI > 0.3$) was implemented, providing scientific decision-making support for early fire intervention.

Data Availability

The data used to support the findings of this study are inclosed with the article.

Conflicts of Interest

There are no conflicts of interest regarding the publication of this paper.

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