INTELLIGENT IDENTIFICATION OF LARGE SPACE FIRES BASED ON ADAPTIVE WEIGHTED FUSION UNDER THE CONSTRUCTION OF INTELLIGENT FIRE PROTECTION

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Abstract

The vast expanse of large spaces allows for the accommodation of many individuals, and incidents involving fire often present complex and diverse rescue challenges. However, the current fire protection system lacks the ability to predict fire condition changes effectively. This research introduces an intelligent fire recognition plan for large areas and a novel adaptive weighted fusion algorithm for combining multi-sensor data. By combining data from three types of detectors, temperature, smoke concentration, and carbon monoxide content, the study provides a novel and comprehensive method of acquiring fire information to improve the accuracy of fire warnings. Simulation tests on similar detectors demonstrated the algorithm's efficiency in reducing external white noise interference on detection data. In a medium-sized rehearsal space, it successfully integrated data from over six detectors, enhancing fire recognition efficiency by approximately 80 s. The studio experiment indicated that the recognition scheme significantly improved fire index judgment, with regional monitoring aiding in enhancing the prediction of fire changes. Compared to the traditional identification methods, the identification efficiency of the proposed method increased by an average of 55.78%. The results show that the proposed fusion algorithm resists external noise interference, enhancing system robustness and reliability. This intelligent fire identification scheme is effective for large spaces, improves fire information utilisation, and holds value for indoor fire emergencies like in broadcasting halls.

Key Words

Intelligent fire protection, weighted fusion, multiple sensors, intelligent fire identification, fire prediction

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1. Introduction

The rapid progress of artificial intelligence has led to the concept of intelligent city management being proposed, and products of the information age, such as smart buildings and smart cities have quickly gained widespread attention. Smart firefighting is crucial for smart cities, which achieves early warning and effective management of fires through the integration of IoT, big data and other technologies, improves emergency management capabilities, optimises firefighting resource allocation, and enhances fire prevention efficiency and overall safety in cities [1], [2]. At the same time, how to efficiently achieve fire warning, judgment, and rescue is a new research hotspot in the intelligent construction of smart cities [3], [4]. Traditional fire protection methods are commonly used in Chinese building designs, but they often lack data collection, analysis, and warning systems, leading to inaccurate fire risk assessment and prediction. These systems also suffer from information silos, impeding efficient fire management. Moreover, many buildings' fire protection equipment, due to its long service life and lack of maintenance, fails to function properly during fires, causing significant losses. Improvements in intelligent fire protection, particularly in warning and identification, are crucial. Multi-sensor information fusion (MSIF) is highly valuable for fire warnings [5], [6]. This study introduces an adaptive weighted fusion (AWF) algorithm to integrate data from various fire detectors in large spaces. Simulations were conducted in theater rehearsal and studio spaces with fire protection systems. The overall structure of the study consists of five parts. Part 1 summarises the research achievements and shortcomings of FII technology. Part 2 studies and designs a large space FII method based on AWF. Part 3 conducts experiments and analysis on the proposed FII method. Part 4 discusses the proposed method and experimental results. Part 5 summarises the experimental results and indicates directions for future research.

2. Related Works

With the development of computer computing, people's research on the mechanism of fires continues to deepen. The FII technology, based on big data analysis and constructed using computer vision and geographic information systems, has been widely studied by industry scholars [7]. Taspinar *et al.* [8] introduced a three-stage fire detection framework that employs basic image processing to extract flames and convolutional neural networks (CNNs) for recognition, achieving a 98.8% success rate in training data. Tan *et al.* [9] created a path planning algorithm that incorporates image processing techniques and the A-Star algorithm while introducing a particle swarm optimised CNN for the identification and localisation of fire sources in the input image. Ren *et al.* [10] created an affordable smart fire detection system for small to medium buildings that uses multi-info fusion and fuzzy logic to pinpoint arc faults in low-voltage systems, enhancing fire safety. Qian and Lin [11] combined Yolov5 and EfficientDet for enhanced forest fire detection through parallel training and weighted fusion, surpassing traditional methods in feature extraction and boosting detection accuracy and model recognition. Li *et al.* [12] developed YOLOv8-EMSC, a lightweight model that reduces parameters, boosts inference speed, and achieves 95.6% accuracy in fire detection, improving on existing models.

Data fusion refers to the combination or combination of data or information collected from multiple sensor information sources to obtain more accurate estimation information [13]. Ali *et al.* [14] presented an efficient underwater robot positioning method through competitive/split input modulation neural networks, achieving optimal fusion with an average error of 1.2704 m and a computational cost of 2.2 ms. Wang *et al.* [15] enhanced a sparse Bayesian learning model to tackle big data heteroskedasticity and uncertainty in structural health monitoring, improving decision-making and prediction for large suspension bridges like the Tsing Ma Bridge in extreme events. Wang *et al.* [16] improved a Gaussian process for structural health monitoring by addressing heteroskedasticity, extending applicability, and using an out-of-sample prediction algorithm to estimate high volatility from non-stationary typhoon responses.

Current research on FII is predominantly aimed at small spaces and outdoor settings, with limited focus on large indoor environments. This study introduces an innovative AWF algorithm to address this gap. Utilising AWF, a large space FII scheme is developed for multi-sensor data fusion. The scheme incorporates a neural network to assess the likelihood of open flames and smoldering, and employs fuzzy inference to calculate the Fire Hazard Index (FHI), enhancing building fire recognition and protection strategies, and advancing smart fire protection development.

3. Design of Large Space FII Based on AWF

Firstly, based on the distribution of fire detectors, neural networks are introduced to judge the probability of open flame and shadow ignition of on-site fires, and fuzzy reasoning to predict the fire danger index. Secondly, a large space intelligent identification scheme based on AWF algorithm is designed.

3.1 Design of Fire Information Fusion Based on Adaptive Weighted Estimation

In order to improve the estimation accuracy and detection of multi-sensors, the study was designed to evaluate the results of AWF using the mean square error. In this case, the expression of the detection value of a single sensor is shown in (1).

$$A_j(t) = A(t) + d_j(t) \tag{1}$$

In (1), A represents an unknown variable. A_j represents the detection values of each sensor. $A(t)$ represents the actual signal of the sensor. $d_j(t)$ represents the cumulative increase in white noise. When there is no offset in the detected values and they are independent of each other, the estimation formula for unknown variables is shown in (2).

$$\begin{cases} \widehat{A} = \sum_{j=1}^{N} \omega_j A_j \\ \sum_{j=1}^{N} \omega_j = 1 \end{cases} \tag{2}$$

In (2), $\widehat{A}$ represents the estimation formula for unknown variables. ω_j represents the weighting coefficient. N represents the number of sensors. j represents sorting. Therefore, the expression of the estimated variance and weighted coefficients for a single sensor is shown in (3).

$$\begin{cases} \partial^2 = \sum_{j=1}^{N} \omega_j^2 \partial_j^2 \\ \omega_j = \frac{\lambda}{\partial_j^2} = \frac{1}{\partial_j^2 \sum_{j=1}^{N} \frac{1}{\partial_j^2}}, j = 1, 2, \ldots, N \end{cases} \tag{3}$$

In (3), ∂^2 represents the estimated variance. ∂_j^2 represents the white noise variance of the sensor. λ represents the weighting factor. On this basis, the study calculates the variance estimate using the corresponding algorithm based on the information of the detection data obtained from the sensors. Taking a group with two sensors as a reference, the corresponding detection errors of the two sensors are uncorrelated with the detection values and are uncorrelated with each other, and the average value between the two errors is set to be 0. Therefore, the formula of the correlation coefficient is shown in (4).

$$\begin{cases} B_{\mathrm{ij}} = D((A_i - \mu_i)(A_j - \mu_j)) \\ B_i = D((A_i - \mu_i)^2) = D(A^{\ 2}) + D(d_i^2) - \mu^2 \end{cases} \tag{4}$$

In (4), B_{ij} represents the correlation coefficient between two detectors. B_i represents the auto-correlation coefficient of a single detector. D represents the set of all errors. μ represents a constant. From this, the MSE formula for white noise can be obtained, as shown in (5).

$$\partial_i^2 = D(d_i^2) = B_i - B_{\mathrm{ij}} \tag{5}$$

When the number of sensor detection reaches a certain number, the time-domain estimates of the correlation coefficients of two sensors and the auto-correlation coefficients of a single sensor are shown in (6).

$$\begin{cases} B_{\text{ij}}(k) = \frac{k-1}{k} B_{\text{ij}}(k-1) + \frac{1}{k} C_i(k) C_j(k) \\ B_i(k) = \frac{k-1}{k} B_i(k-1) + \frac{1}{k} C_i(k) C_i(k) \end{cases} \tag{6}$$

In (6), k represents the number of times the sensor has detected it. $B_{\text{ij}}(k)$ represents the time-domain estimate of B_{ij}. $B_i(k)$ represents the time-domain estimate of B_i. C_i and C_j represent the time-domain detection values of the detector, respectively. The more detections there are, the more accurate the correlation coefficient is in estimating the time domain. Therefore, this study further extends to a group of multiple sensors based on (6). The average of all time-domain estimated values of the correlation coefficient between sensors can be used as the estimated value for the group. The specific expression formula is shown in (7).

$$B_{\text{ij}} = \overline{B}_{\text{ij}}(k) = \frac{1}{n-1} \sum_{\substack{i=1 \\ j=1}}^{n} B_{\text{ij}}(k) \tag{7}$$

In (7), n represents the number of detectors. The white noise variance estimation of the detector is crucial for the AWF algorithm. The study was carried out with a group of three detectors of the same type and the estimated number of detections was set to be five. The detection values are shown in (8).

$$\begin{cases} A_1(t) = A(t) + d_1(t) \\ A_2(t) = A(t) + d_2(t) \\ A_3(t) = A(t) + d_3(t) \end{cases} \tag{8}$$

For example, the formula for a detectors estimated auto-variance and its covariance with others is presented in (9).

$$\begin{cases} \widehat{B}_1(k) = \frac{\sum_{t=k=4}^{k} (A_1(t) - \mu_1)^2}{5} \\ \qquad\quad = \frac{4}{5} \widehat{B}_1(k-1) + \frac{1}{5} (A_1(k) - \mu_1)^2 \\ \widehat{B}_{1j}(k) = \frac{\widehat{B}_{12}(k) + \widehat{B}_{13}(k)}{2} \end{cases} \tag{9}$$

Based on the estimated values of auto-variance and covariance, the variance estimates of white noise for multiple detectors can be obtained. Furthermore, the adaptive weighted value of a single detector at a specific time can be obtained based on its auto-correlation coefficient. Based on the above, the calculation steps of the AWF fusion algorithm are shown in Fig. 1.

3.2 Design of Large Space Intelligent Recognition Scheme Based on AWF

To accurately achieve intelligent identification and fire warning for large space fires (LSF), this study proposes an intelligent fire protection scheme for large spaces based on AWF.

In Table 1, in large areas or rooms with high demand for fire prevention, a single detector is difficult to meet the

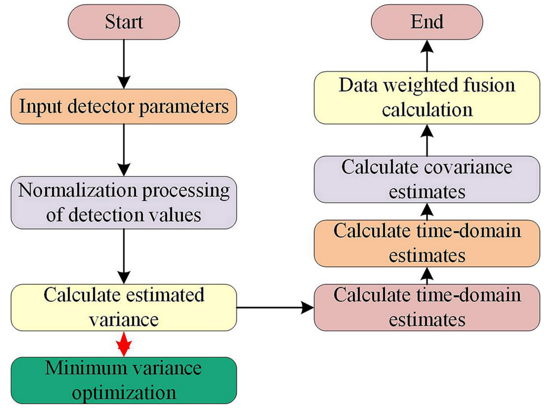

Figure 1. The calculation steps of AWF algorithm.

efficiency and accuracy of fire detection work. A detector group with multiple detectors is needed to achieve effective fire warning. Therefore, this study utilises AWF to fuse the information collected by the same type of detector group. As shown in (10).

$$\begin{cases} |X(i,j) - X(i-1,j)| \le \alpha \\ |X(i,j) - X(i+1,j)| \le \alpha \\ |X(i,j) - X(i,j-1)| \le \alpha \\ |X(i,j) - X(i,j+1)| \le \alpha \end{cases} \tag{10}$$

In (11), X represents the sample value. α represents the set threshold for detecting outliers. The mean of adjacent detectors of the same type is used as a supplement to the detection related data. The mean formula for adjacent detectors of the same type is shown in (11).

$$X(i,j) = \frac{\begin{array}{c} X(i-1,j) + X(i+1,j) \\ +X(i,j-1) + X(i,j+1) \end{array}}{4} \tag{11}$$

Based on the above, this study takes the rehearsal room and studio of a theater as examples, and the layout of fire detectors in a large space is shown in Fig. 2.

Figure 2(a) illustrates the fire detector layout in a theater rehearsal room, comprising three CO and three smoke detectors as a combined system. Due to the limited range of temperature detectors, six are placed in overlapping pairs across the room. Figure 2(b) shows an increased detector count in a broadcasting hall with a zoning protection design for grouped fire detection. To address the limitation of detectors relying on single-sided fire information, neural networks assess the probability of flames and smoldering, while fuzzy reasoning predicts and judges the fire situation.

Figure 3(a) depicts a neural network model, which varies by topology, neuron traits, and training methods. Figure 3(b) illustrates the backpropagation (BP) network structure. Using reverse network data from the fire scene and the building's fire protection level, fuzzy reasoning estimates the FHI for appropriate response actions. The specific process is shown in Figure 4.

Table 1
Selection and Design Specification Requirements for Three Types of Fire Detectors

Types of Fire Detectors	Room Height h (m)	Ground Area S (m^2)	The Detection Range A and Detection Radius r of a Single Detector					
			Room Slope θ					
			$\Theta > 30°$		$15° < \theta \leq 30°$		$\Theta > 30°$	
			A (m^2)	r (m)	A (m^2)	r (m)	A (m^2)	r (m)
Smoke/CO detector	$h > 12$	$S \geq 80$	80	8.0	80	7.2	80	6.7
	$6 < h \leq 12$		120	9.9	100	8.0	80	6.7
	$h \leq 6$	$S < 8$	100	9.0	80	7.2	60	5.8
Heat detector	$h \leq 8$	$S \leq 30$	30	5.5	30	4.9	30	4.4
	$h > 8$	$S > 30$	40	6.3	30	4.9	20	3.6

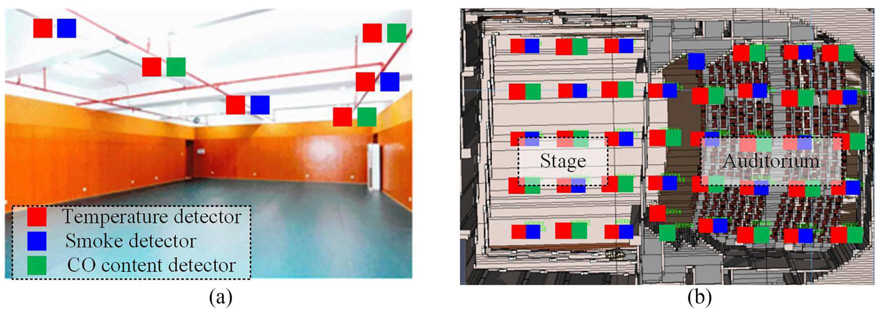

Figure 2. Layout of large space fire detectors.

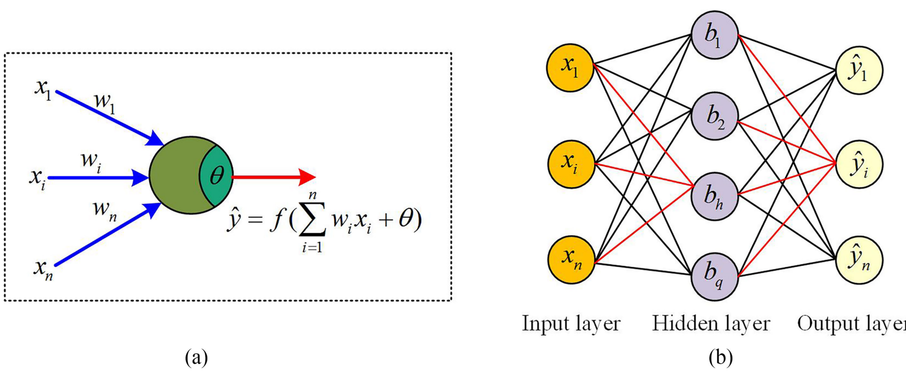

Figure 3. Neuron models and reverse network structures.

The fluctuation range of open flame and smoldering probabilities for input parameters is set to (0,1), and the degree of fuzziness is divided into three levels: high (H), medium (M), and low (S). The output is used as the final judgment of the FHI by the controller, and a Gaussian function is used to calculate the probability fuzziness of open flames and smoldering, while a triangular function is used to calculate the fuzziness of the output. Among them, the Gaussian membership function formula is shown in (12).

$$f(x, y, z) = \exp\left(-\frac{(x-\varepsilon)^2}{2z^2}\right) \tag{12}$$

In (12), x represents the sample. y represents a normally distributed parameter. z represents the standard deviation of a normal distribution. ε represents the mean of a normal distribution. The membership function of a triangle is shown in (13).

$$f(x, a, b, c) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ \frac{c-x}{c-b} & b < x \leq c \\ 0 & x > c \end{cases} \tag{13}$$

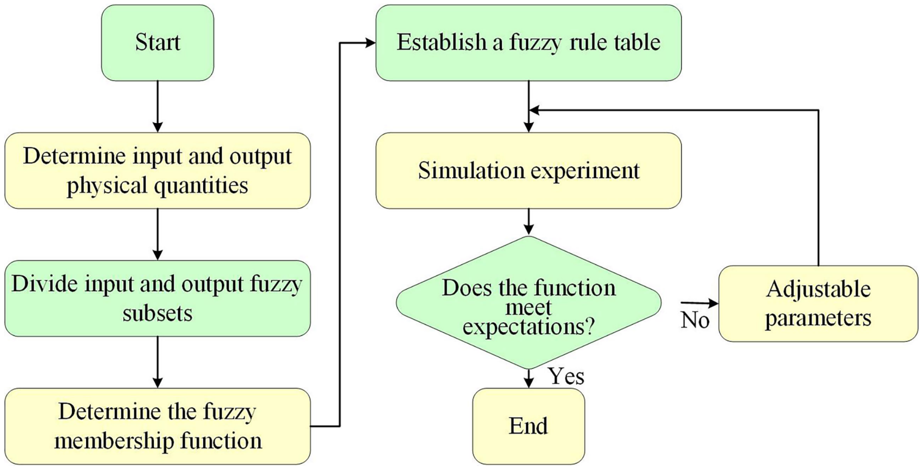

Figure 4. Design process of fuzzy reasoning model.

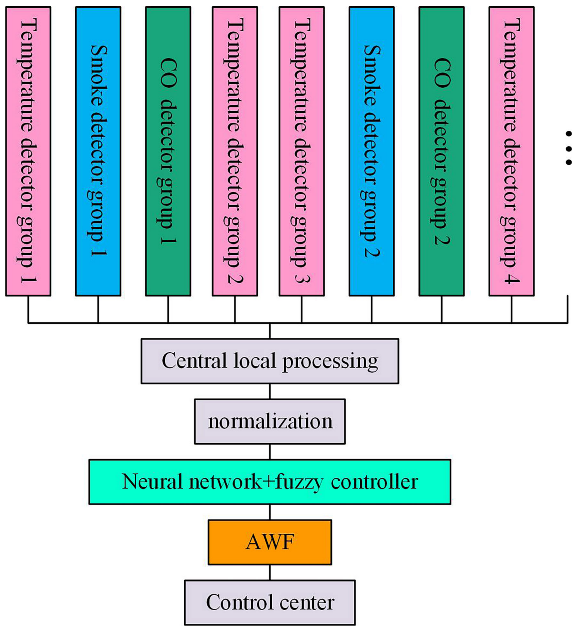

Figure 5. Intelligent recognition model for LSF.

In (13), a, b, and c represent parameters, where a and c represent the "feet" of the triangle, and b represents the "peak" of the triangle. Broadcasting halls and similar large spaces pose challenges for fire prevention due to their size and population density. Figure 5 presents a large space MSIF FII scheme that integrates AWF distribution, neural network-based real-time fire scene judgment, and FHI prediction through fuzzy reasoning.

4. Large Space FII Simulation Experiment Based on AWF

This study conducted simulation experiments on the proposed AWF algorithm and FII scheme in two large and medium-sized spaces, the rehearsal room and the studio, respectively. The intelligent recognition of LSF was achieved by comparing the detection values and fusion effects of three detectors, the intelligent recognition scheme of open flame and smoldering probability at the fire scene, and the judgment of FHI.

4.1 Validation Analysis of AWF Algorithm

To verify the effectiveness of the AWF algorithm, this study detects time invariant systems by simulating detectors. The experiments are conducted in a university theatre building which is used as the experimental site for the design of the smart fire protection system. The theatre building is modelled 1:1 using building information modelling (BIM) technology, including the arrangement of fire detectors and the associated design of the fire protection system. A numerical simulation of fire was conducted using Fire Dynamics Simulator (FDS) software to simulate a variety of fire scenarios, including a slow fire in a confined space, a fast fire in a confined space, and a medium to LSF. In the simulation experiment, the size of the physical quantity to be detected is set to 100, the number of detectors is three, and three calculated white noises are introduced, with variance values of 4.00, 4.84, and 9.00, respectively. The specific processing results are shown in Fig. 6.

Figure 6(b)–6(d) shows detectors' values heavily impacted by white noise, detector 3 the most. Figure 6(a) presents AWF-processed values matching the unprocessed mean, showing less noise interference and superior results. This demonstrates AWF's effectiveness in minimising external noise impact by fusing sensor data, enhancing detection accuracy and reliability. In Fig. 6(e), detector 3 has the most white noise, receiving the lowest weights in fusion, reducing its influence and improving overall data fusion. This study further simulates and detects time-varying systems using AWF, and the calculation results are shown in Fig. 7.

Figure 7(a) demonstrates the superior data fusion of a time-varying system over individual detectors. Figure 7(b)–7(d) depicts simulations for detectors 1–3, with detector 3 showing the most white noise, suggesting greater environmental sensitivity. These results highlight AWF's enhanced fusion in dynamic systems, effectively mitigating noise and bolstering multi-detector resilience without altering sample counts.

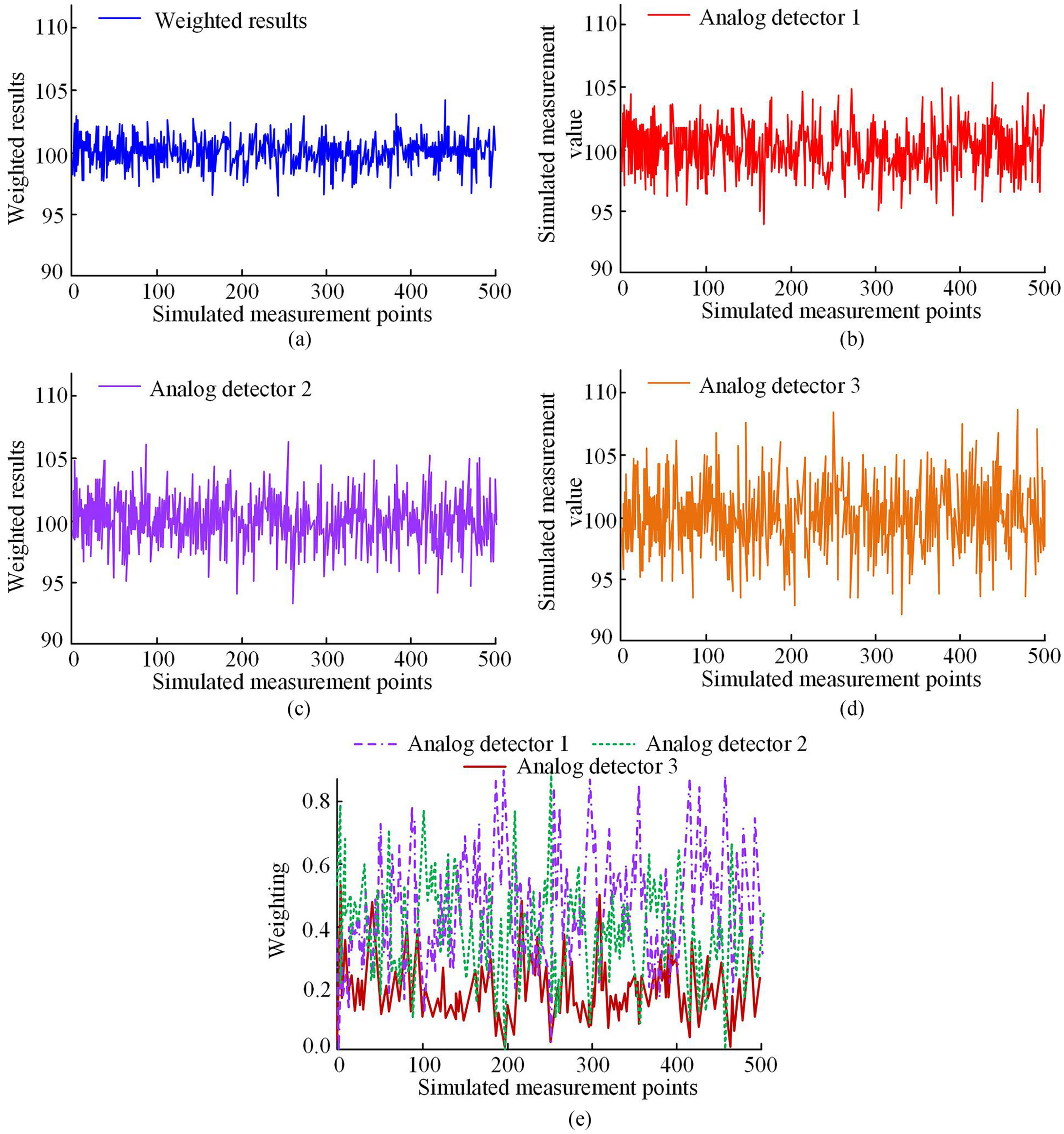

Figure 6. Simulation of fixed value sensor fusion results.

4.2 Simulation Analysis of LSF Information Fusion

Through simulation verification of time invariant and time-varying systems, the efficient fusion ability of AWF for data collected from multiple detectors has been confirmed. Therefore, this study further conducts fusion simulation experiments in large spaces such as rehearsal rooms. The processing results of the fusion algorithm for four sets of fire detectors within 300 s are shown in Fig. 8.

Figure 8(a) and (b) shows smoke detector values stabilising post-fusion. Figure 8(c) and 8(d) indicate reduced CO detector fluctuations, maintaining overall trends. The comparison in Fig. 8(e), (g) with (f), (h) reveals AWF's effective averaging on temperature detector data, highlighting its robust performance in complex, fire-prone buildings. Meanwhile, the robustness of AWF in the process of spatial fire information fusion is verified, as shown in Fig. 9.

Figure 9(a) and 9(b) shows similar fire development trends for two temperature detectors, but Group 1's fire probability changes at 100 s, while Group 2's change is around 120 s, suggesting Group 1 is closer to the fire source. Figure 9(c) displays FHI recognition from fused data, with Group 1 changing at 95 s and Group 2 lagging. These results show AWF reduces detector failures due to faults and interference, enhancing fire system robustness.

4.3 Simulation Analysis of Intelligent Fire Protection Schemes for LSF

Based on the proposed intelligent fire protection scheme for LSF, this study takes the broadcasting hall as an example and designs the ignition point as the front row of the seat for simulation analysis. The entire studio space is divided into 26 intelligent fire protection small areas, and each area is equipped with three smoke concentration and CO detectors, as well as four temperature detectors. According to the detection values collected by the detector, the fusion algorithm processes the data of the three types of detectors as shown in Fig. 10.

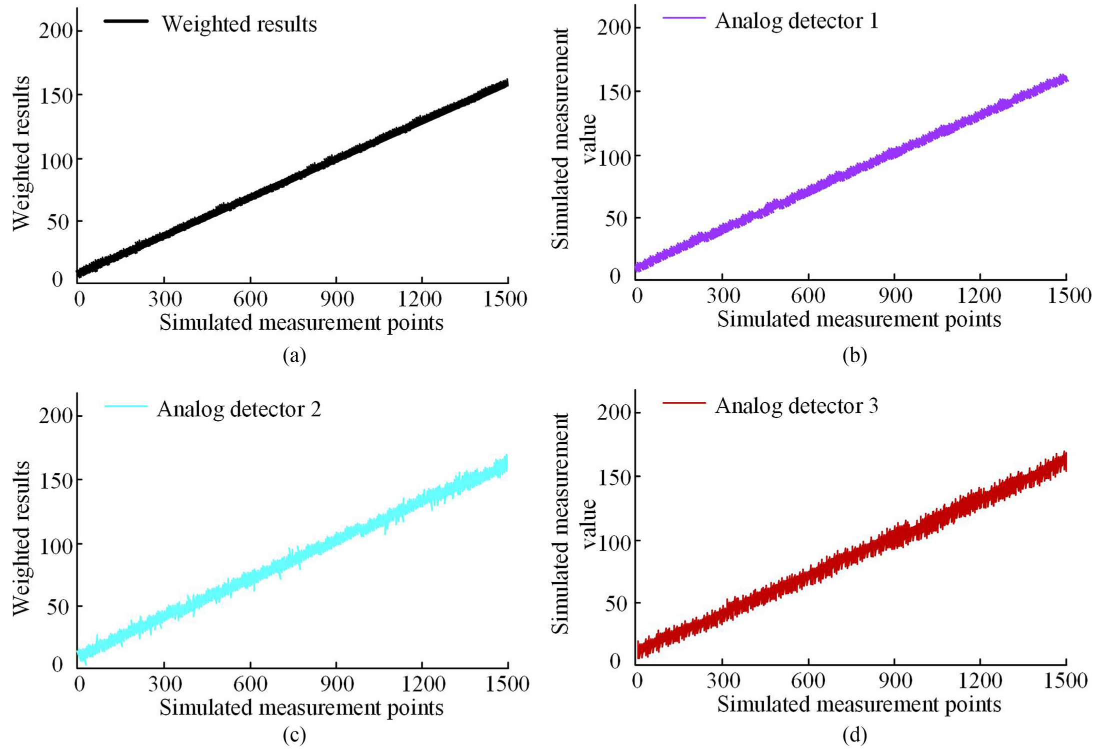

Figure 7. Simulated linear time-varying sensor fusion results.

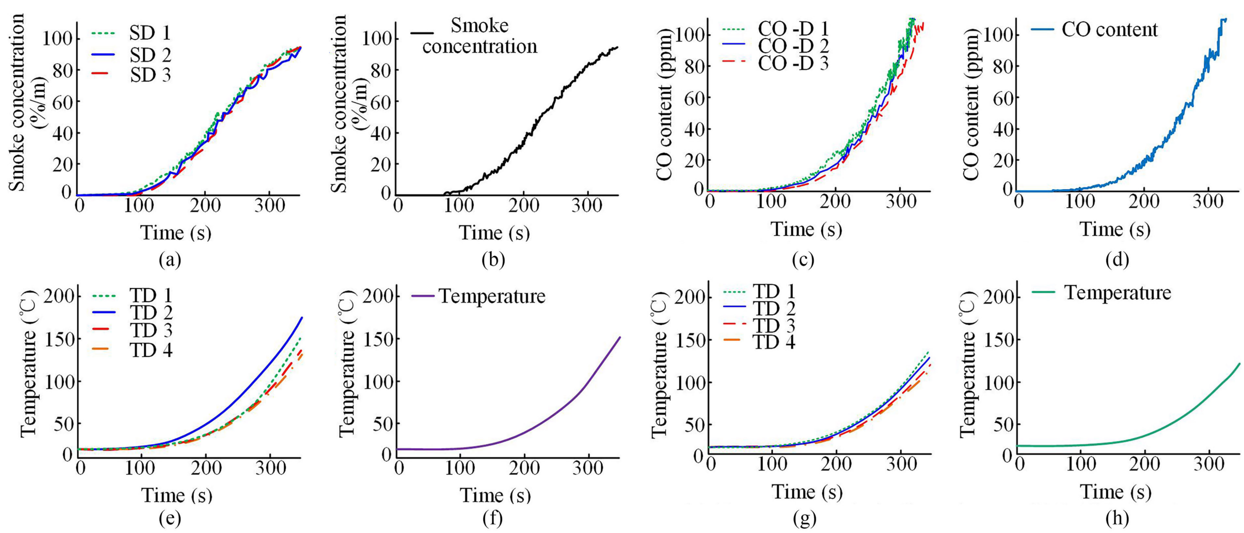

Figure 8. Data fusion results of various detector groups in the rehearsal room.

Figure 10(a) and 10(d) demonstrates a more harmonious temperature trend post-fusion. Figure 10(b) shows the smoke detector's erratic numerical changes, contrasting with the smoother trend in Fig. 10(e) after fusion. Figure 10(c) details CO content fluctuations within 1500 s, with notable variations in some areas. Fusion, as shown in Fig. 10(f), results in more averaged and smoother data, highlighting AWF's value in enhancing large space FII and fire protection efficiency.

Figure 11(a) and 11(b) reveals that areas near the ignition point peak in smoldering probability at 160 s, with open flame probability fluctuating around 120 s before rising. Farther areas peak in smoldering around 290 s, with open flames fluctuating at 250 s. Proximity to the ignition point affects fire system response times, with areas closer prompting earlier activation of sprinklers, smoke exhaust, and alarms by about 130 s. Figure 11(c) shows the FHI increasing at 120 s for the closest area, while Fig. 11(d) shows it at 250 s for the farthest. This demonstrates the effectiveness of regional fire monitoring and the superior intelligent recognition of synchronised protection responses. Finally, the study further compares the efficiency of approach recognition in rehearsal room and studio between the traditional recognition method and the proposed method of the study, as shown in Table 2.

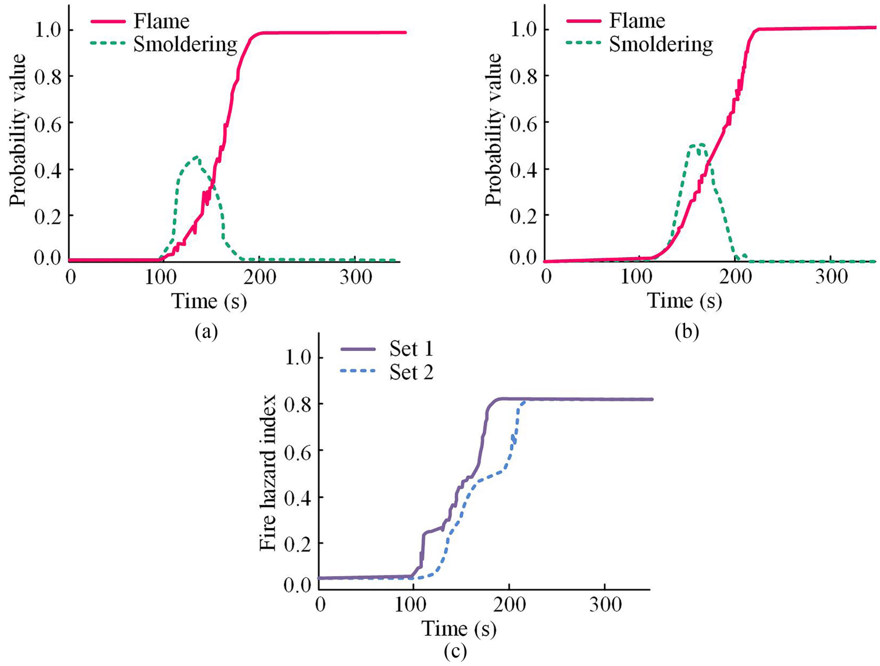

Figure 9. Neural network and fuzzy inference recognition results.

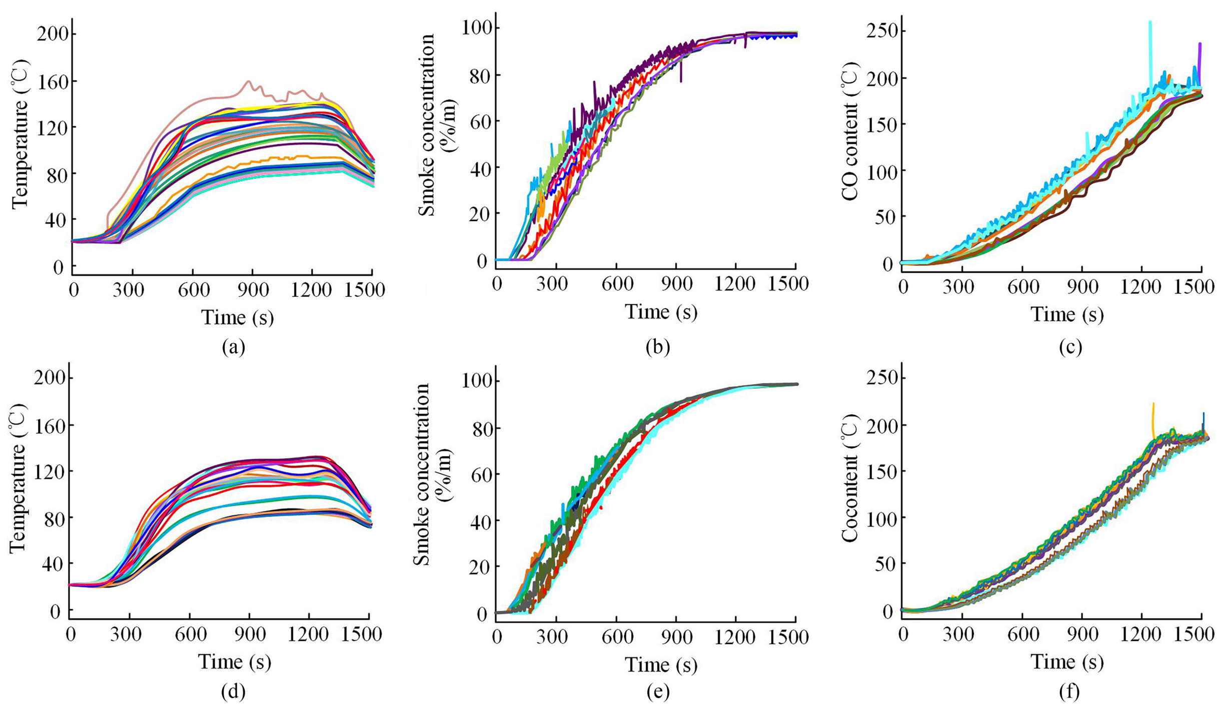

Figure 10. Weighted fusion processing results of fire data for front seats in the studio.

Table 2
Comparison of the Efficiency of the Research Method and Traditional Method

Method	Rehearsal Room			Broadcasting Studio		
	Recognition Time (s)	False Positive Rate (%)	Under-reporting Rate (%)	Recognition Time (s)	False Positive Rate (%)	Under-reporting Rate (%)
Traditional method	203.53	5.23	12.33	243.87	7.87	13.45
Research method	80.24	1.45	3.01	119.58	2.04	3.59

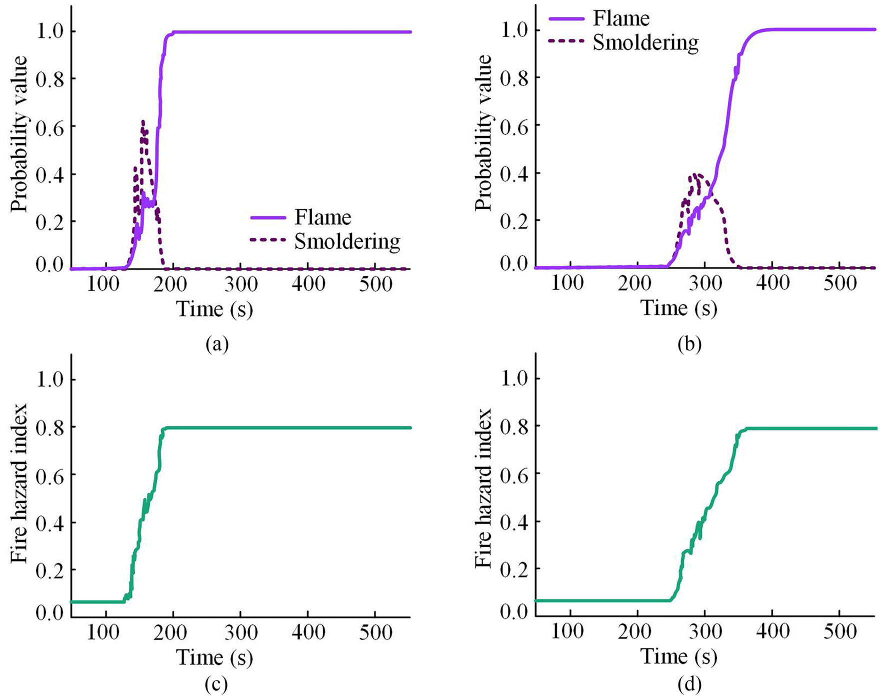

Figure 11. Comparison results of neural networks and fuzzy reasoning between the nearest and farthest regions of the ignition point.

In Table 2, the research method improves the recognition time in rehearsal room and studio by 60.58% and 50.97%, respectively compared to the traditional recognition method. Comparison of the false alarm and missed alarm rates of the two methods shows that the research method is more advantageous. This indicates that the method of neural network and fuzzy inference combined with AWF can effectively reduce the false alarm situation and improve the intelligent recognition of fire.

5. Discussion

The AWF algorithm excels in multi-sensor data fusion, reducing external noise interference and improving fire recognition efficiency by about 80 s. on average in medium-sized spaces. It outperforms traditional methods by 55.78% on average. The algorithm dynamically adjusts sensor weights to minimise outlier and noise impacts, enhancing system robustness with outlier detection thresholds between sensors. It dynamically weights data using time-domain correlation coefficients, improving noise suppression. By integrating multi-sensor data, the AWF algorithm increases system accuracy and reduces reliance on single data sources, which are prone to errors. Incorporating neural networks and fuzzy inference, it comprehensively assesses fire scene complexity, improving fire situation predictions. Overall, the AWF algorithm boosts fire recognition precision, reduces false alarms and omissions, and supports regional monitoring for early fire warnings and rapid responses.

Currently, the concept of utilising smart cities to achieve modern urban governance in China has matured. Gao and Zhao [17] investigated the complexity of the urban spatial structure of Pingdingshan based on an improved non-dominated sorting genetic algorithm-II algorithm. Their results pointed out that smart technologies are extremely important in modern urban governance, which is consistent with the results obtained from the study. Wu and Wang [18] proposed a multi-stage stochastic programming model to address the issue of how to coordinate multiple circular economy supply chain projects to improve their operational efficiency and value. By analysing typical circular economy supply chain projects in China, coordinating multiple circular economy supply chain projects provides a powerful tool for logistics companies and third-party logistics companies to optimise their investment decisions. Hao [19] proposed an improved algorithm based on deep reinforcement learning to address the problem that traditional algorithms are poorly adapted to intelligent driving in smart cities. In response to the challenges of low efficiency and high energy consumption in large-scale distribution in smart cities. Wang [20] proposed a two-stage intelligent distribution model that integrates dual-loop material distribution and taboo search. In this regard, the proposed method reduces energy consumption through intelligent fire recognition technology and has positive applications in smart city governance.

6. Conclusion

Given the unpredictable nature of fires, traditional methods struggle to predict fire changes effectively. This study introduces an AWF algorithm, combined with neural networks and fuzzy reasoning, to create a large-space FII scheme. It demonstrates that AWF reduces noise interference and enhances data fusion reliability, enabling fire identification about 80 s before an open flame. Studio experiments showed the scheme could monitor regional fires and detect open flames in about 120 s, increasing identification efficiency by 55.78% over traditional methods. The results show that the proposed AWF algorithm can effectively reduce the interference of external noise on fused data and improve the robustness, safety, and reliability of fire protection systems. The designed intelligent recognition scheme for large spaces has superior anti-interference and reduced false alarm rates.

This study concentrated on LSF identification and alarms, not evacuation. Future work will expand AWF for smart evacuation in large areas and assess its broader smart firefighting value. Research will focus on enhancing AWF's real-time capabilities for swift responses to fires and aiding emergency protocols. It will also explore integrating diverse sensors for more comprehensive fire data and higher recognition accuracy, and test AWF's applicability in industrial safety and environmental monitoring.

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