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Preventive Monitoring and Early Warning of Fire Risks in Timber Heritage Buildings: A Case Study of Hualin Temple in Fuzhou, China

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ABSTRACT

In building fires the protection of life is priority to buildings, which normally considered as guidance rather than strict codes. However, in cases of heritage buildings, which are at extremely high risk of irreplaceable loss, fire alerts may issue warnings based on low criteria as a significant threat appears to the building. In China, the oldest existing heritage buildings are mainly wood structures, which often have extremely high fire hazards with aged low moisture timbers and the unique wood frame system making it extremely difficult to quickly salvage the building when fire occurs. To realize the preventive conservation (PC) of ancient timber structures, this study focuses on predicting the probability of fire events. Firstly, the frequency data of heritage fire events in China over the past seventy years were collected to isolate the common fire triggers. Secondly, to assess the credibility of each fire risk factor, Hualin Temple, a typical Song Dynasty wood-frame architectural heritage in Fuzhou City, Fujian Province, was selected as a case. Thirdly, fire time series data were obtained using FDS software to establish a fire dynamics model with local temperature and humidity data to simulate two fire conditions: summer and winter. Subsequently, the data were analyzed in a fuzzy inference system to predict the probability of fire occurrence. The preliminary results suggest to issue a warning when the fire confidence level is about 0.24 or more and to issue an alarm when the fire confidence level is approaching 0.5.

1. Introduction

As an important part of cultural heritage, heritage buildings are exposed to seven types of the most common hazards that may lead to a disaster: meteorological, hydrological, geological, astrophysical, biological, human-induced and climate change [1]. Among them, human-induced and meteorological hazards are the most complex and can cause fires, which are extremely destructive and one of the most serious risks in heritage conservation. In recent years, there have been cases around the world where heritage buildings have been severely damaged or even completely destroyed by fire. On May 23, 2023, the Central Post Office building in Philippine, caught fire, and it took more than 30 hours for

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the fire to be extinguished. On August 6, 2022, the Wan'an Bridge, China's longest wooden-arch corridor bridge, in Pingnan County, Ningde, Fujian Province, suffered a fire that caused it to collapse and burn down. On April 15, 2019, the top tower of Notre Dame in Paris, France, caught fire, and the 855-year-old central tower collapsed in the fire.

China's oldest existing heritage buildings are mainly wood-framed, and are widely distributed and numerous throughout the country. Due to the long period of time and the low moisture content of building timber, ancient wood-framed building materials are highly flammable. Furthermore, the wood-framed frame system provides better combustion conditions, which also makes the risk of fire extremely high. Without preventive conservation (PC), the heritage could be easily lost in the event of a fire.

In the 1950s, Cesare Brandi proposed the term “preventive restoration” in his book Teoria del Restauro, and the concept of PC has gradually entered the field of heritage building conservation in subsequent decades. Since 2018, China’s conservation policy has begun to transform from salvage protection only to both salvage and preventive protection, and from focusing on the protection of heritage only to the overall protection of heritage with its surrounding environment. As such, research on the preventive protection of heritage buildings against fire needs to be strengthened urgently.

Nevertheless, most of the existing heritage protection research is about the burning behavior of buildings after fire, or the fire risk prediction of a large area [2-6]. A more specific fire prediction research on the heritage itself is rare. Meanwhile, the rapid development of artificial intelligence (AI) technology has paved the way for the applicability of AI algorithms to heritage building fire prediction.

This study takes Hualin Temple in Fuzhou City, Fujian Province, China, as a case to explore the fire early warning method and alarm thresholds for wood-framed heritage buildings. The fire model and fuzzy inference algorithm are used, in an attempt to realize the real-time fire prevention of the Hualin Temple Main Hall building to serve as a reference for the research on disaster prevention of heritage buildings in the international arena.

1.1 Literature Review

Heritage buildings face higher fire risks than ordinary buildings due to their unique structural and material characteristics. Currently, there are relatively few international studies on fire prediction in heritage buildings, and they mainly focus on the analysis of combustion behavior after a fire has occurred, or the assessment of fire risk in a large area. Although these studies provide some experience and data, there is still much room for research on fire prediction in specific heritage buildings, especially in early warning before fire.

In recent years, with the rapid development of artificial intelligence technology, especially the application of machine learning algorithms, the accuracy and efficiency of fire prediction have been significantly improved. Computers can identify the characteristics of fire occurrence and potential patterns by learning and training a large amount of data, and realize a certain degree of prediction of fire characteristics. There are three main types of related research, fire image recognition, fire time series research, and fire probability research.

In terms of real-time fire detection, current research is mainly based on intelligent image recognition, capturing fire and smoke images, etc. For instance, in order to analyze the risk of wildfires in 20 monasteries of the Holy Mountain of Assos, Greece, Giorgos et al. determined the spatial extent of fuel types using high-resolution imagery, using the FlamMap software's Minimum Travel Time (MTT) algorithm to evaluate the Burning Probability (BP), Conditional Flame Length (CFL), and Flame Size(FS), and etc. [7]. Vikram & Sinha used a detector that senses temperature, humidity, and drought conditions, and a camera that captures images of the area. A multi-modal framework for identifying forest fire prone areas was developed using a sensor model based on neuro-fuzzy classification and an image model with CNN, respectively [8].

For time series research, Li developed a neural network model that can predict smoke dispersion and temperature distribution at corridor locations in real time based on transposed convolutional neural network and FDS numerical simulation method, and the results proved that the prediction model has high accuracy [9]. Meng *et al*. used fire dynamics simulation software (FDS) to establish fire scenarios, and then utilized a convolutional neural network (CNN) with a long short-term memory network (LSTM) to construct a real-time prediction model for fire source strength, and the final verification of the prediction accuracy reached 99.18% [10].

As for the fire probability, the relevant research was mainly to learn historical or simulated data with the help of neural network algorithms, combined with real-time data parameters such as temperature and humidity to complete the fire probability prediction. For example, Zhang fused a weighted estimation method based on weighted estimation, and a multi-sensor fusion fire early warning algorithm based on neural network, and developed a ship fire early warning simulation system software, which is able to predict the probability of fire under three environments of the ship [11]. Emmanuel *et al*. utilized the Mamdani inference system, and proposed an early fire fuzzy model for detection and control of real fire incidence (EFIP) can be predicted by setting six parameters: temperature, humidity, flame, CO, CO_2 and O_2, and building a multisensory fuzzy logic operational model [12]. Saily et al. collected time domain data such as maximum temperature, cloudiness, humidity, precipitation, and wind speed of wildfires occurring in India during a year. The collection was carried out and the data was trained and simulated with the help of LSTM algorithm model which predicts the occurrence of forest fires [13].

While existing studies have used neural network algorithms to predict the time and probability of fire occurrence, fewer studies have been conducted on fire prediction for heritage buildings, and most of them are limited to the prediction of fire events in a wide range of built-up areas based on historical data, and there may be a lack of accuracy in terms of the fire risk at a particular point. For example, heritage buildings have different structural and material properties and complex fire occurrence and development patterns, which require more refined and personalized prediction models. In addition, how to integrate and process large amounts of data from multiple sensors and monitoring systems is an issue that needs to be addressed to achieve effective fire prediction.

This study focuses on the prediction of fires by incorporating the early characteristics of fires in specific heritage buildings, simulating the physical processes at the onset of fires, and combining fuzzy logic to deal with non-linear and uncertain information.

1.2 The case

Wooden structure is the most common structural type of ancient Chinese buildings. Although wood-framed buildings are beautiful, earthquake-resistant, and of high architectural value, they are

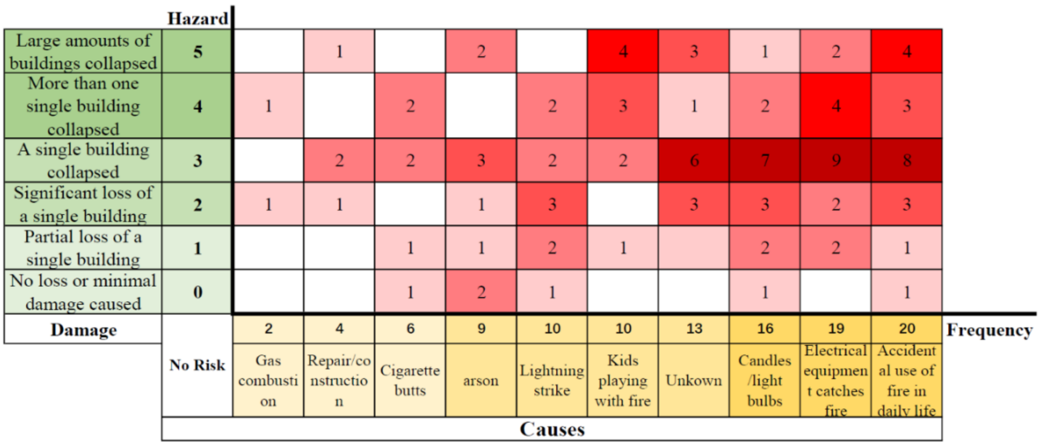


Fig.1. Distribution of fire causes and damage in China, 1950-2023

also vulnerable to natural disasters and the risk of human damage. Fire, in particular, often causes irreparable damage when it occurs due to the flammability of wood. From 1950-2023, there were 132 published (including papers and news) heritage building fire incidents, as shown in **Fig. 1**., indicating that human-induced are the main cause of fires in ancient timber frame buildings. The prediction of fires should catch the signs of fires in advance as well as minimize the false alarms.

The specific case studied in this paper is Hualin Temple in Fuzhou, built during the Northern Song Dynasty (964 A.D.), the oldest surviving all-wooden heritage building south of the Yangtze River in China and a national heritage. Its Main Hall has a single-eave hermitical roof, a width of three rooms, a depth of eight rafters, four pillars for front and back medical devices. The depth of the building is about 14.6 m; the overall width is 15.85 m; and the highest point is 15.5 m [14]. The current fire warning equipment in the building consists of only four smoke alarms without lightning rods and lightning wires and a few bio-infrared detectors are installed inside and outside the main hall. Although these devices can provide early warning to a certain extent, there is the possibility of false alarms and can hardly comprehensively assess the fire risk.

2. Research Method

This paper adopts fire dynamics simulation combined with fuzzy inference algorithm in two major steps. Firstly, establish the data set with three fire characteristic indexes of temperature, CO concentration and smoke concentration by multi-case simulation with the digital model of Hualin Temple Main Hall. Secondly, the dataset is inputted into the fuzzy inference system for fuzzification. The temporal temperature change characteristics are defuzzified and transformed into the probability of fire to assist the fire signal monitoring judgment and behavioral intervention. The structure diagram is shown in **Fig. 2**.

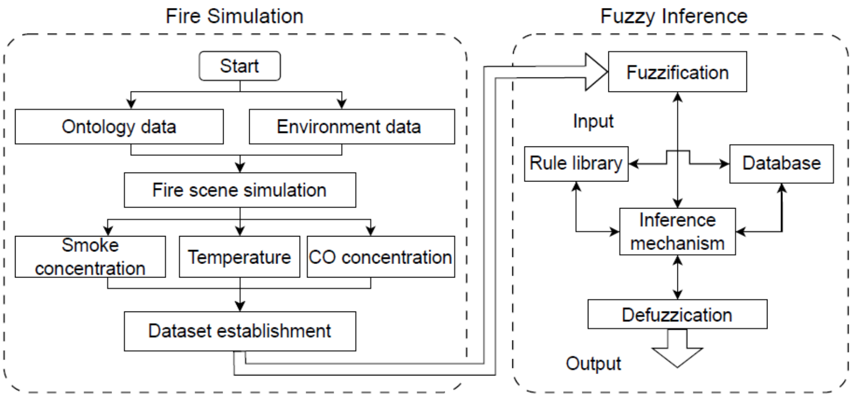


Fig.2. Block diagram of the research program

2.1 Fuzzy Inference

Fuzzy inference system is also known as fuzzy rule system, the biggest feature of this system is that it is based on the control experience and knowledge of the experts expressed as linguistic control rules, which are utilized to control the system, which is suitable for the system which is unknown, complex and nonlinear. Fire probability as an unknown and complex kind of concept is more suitable for this system. Previously, many scholars have conducted the analysis of fire data using fuzzy inference, and all of them have better results [15-17]. The fuzzy inference system mainly consists of five functional modules: fuzzification, rule base, database, inference mechanism, and defuzzification [18].

The fuzzy inference model in this study was implemented using the scikit-fuzzy library provided by python and the python program was written through Pycharm. The inputs to the input layer of the fuzzy inference system were set as temperature (T), CO concentration (CO), smoke concentration

(SO); and the outputs were probability of fire (PF). The more important processes in the process are fuzzification of the database, logical reasoning on the fuzzified data and defuzzification of the fuzzified database to arrive at a probabilistic conclusion.

2.1.1 Fuzzification

Due to the different length of the unit values of the input quantities, it is necessary to first limit the value domain of the input quantities to the (0,1) interval by means of the affiliation function, and at the same time, this step also completes the training set normalization process. Secondly, the fuzzification layer also divides the input variables into three linguistic variable values, low, medium and high, and then assigns the corresponding affiliation function to them, in this study, the affiliation function is all taken as a Gaussian function for fuzzification, their response curves are shown schematically in **Fig. 3**.

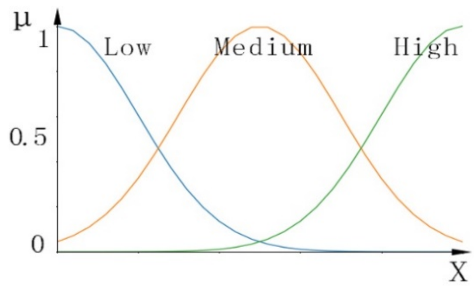


Fig. 3. Schematic of the curve of the affiliation function

2.1.2 Inference Mechanism

The logical inference process is mainly based on the formulated fuzzy rule base, which calculates and reasons about the fuzzified inputs. Based on experience, this paper assigns four linguistic identifiers to each of the three input quantities: none (N), low (L), medium (M), and high (H); the output quantities are the same, and finally 64 rules are compiled. The related partial rule list is shown in Table 1, where T refers to temperature, CO refers to CO concentration, SO refers to smoke concentration, and PF refers to fire probability.

Table 1 Rule sheet of fire probability (partial)

T	CO	SO	PF
N	N	N	N
L	N	N	L
M	N	N	M
H	N	N	H
N	M	H	L
L	M	H	M
M	H	H	H
H	H	H	H

2.1.3 Defuzzification

The output and input of a fuzzy control system are also fuzzy quantities, in order to make the output of the fuzzy controller can control the controlled object, it is necessary to convert its output fuzzy quantities into precise quantities, the process of defuzzification. There are various methods for defuzzification, among which the Centroid Method, also known as the moment method, is the most widely used defuzzification method. It is characterized by the comprehensive consideration of the relevant information of the fuzzy quantity, and at the same time, it is easier to perform the operation. Therefore, the Centroid Method is used for defuzzification in this paper.

2.2 Fire simulation

Fire dynamic simulator (FDS) is the most widely used commercial fire simulation software, widely used in building fire simulation analysis [19]. The main functions of FDS include determining target boundary parameters and data files, determining calculation areas, dividing simulation grids, setting fire source start time, fire source power, combustion material parameters, etc. In addition, there is a simulation result display software Smokeview, which outputs the results for analysis.

2.2.1 Modeling

According to the data of Sun Chuang [14], this paper used Sketchup to build a digital model of Hualin Temple in equal scale, which was converted to FBX format and imported into FDS for fire simulation. The model mainly contains three parts: the stone foundation, the wooden frame, the roof tiles, and the bamboo wall. In the model, the combustible wooden frame material is set to be similar to “yellow pine”, and the masonry foundation, the roof tiles, and the bamboo wall are non-combustible, which are equivalent to “concrete”. The masonry foundation, roof tiles and bamboo wall are not combustible, so they are equivalently set as “concrete” material.

In addition, FDS needs to mesh the experimental scene, the model will be divided into several tiny grids for simulated fire simulation calculations, the appropriate mesh size needs to be decided according to the diameter of the fire source features, and its related formula is shown in (1).

$$\boldsymbol{D}^{*} = \left[\boldsymbol{Q}/\left(\boldsymbol{\rho}_{\infty}\boldsymbol{c}_{\boldsymbol{p}}\boldsymbol{T}_{\infty}\sqrt{\boldsymbol{g}}\right)\right]^{\frac{2}{5}} \tag{1}$$

Where D* is the characteristic diameter of the fire source; Q is the heat release rate of the fire source (kW), $\boldsymbol{\rho}_{\infty}$ is the ambient density (kg/m^3), $\boldsymbol{c}_{\boldsymbol{p}}$ is the constant-pressure specific heat capacity kJ/(kg·K), $\boldsymbol{T}_{\infty}$ is the ambient temperature (K), and g is the acceleration of gravity (m/s^2).

According to the U.S. NIST test, the simulation results are more accurate when the grid size is 1/16~1/4 of D* [9]. In this study, the fire release rate of 1MW was used, and the grid size of 0.5m*0.5m*0.5m was finally selected by considering the calculation accuracy and time cost.

2.2.2 Setting fire conditions

The situation of fire will be different under different environmental data, considering the size of the calculation and the fact that FDS only supports static data simulation with fixed environmental state, this study has simplified the environmental data. According to the climate of Fuzhou, the average temperature and humidity of August and December, which are representative of summer and winter, were selected and brought in to perform the calculation (the data were quoted from weather-atlas.com, and the specific data were as follows: the average temperature of August in Fuzhou City was 29.2°C, and the average humidity was 77%; the average temperature of December was 13.9°C, and the average temperature and humidity was 70%.).

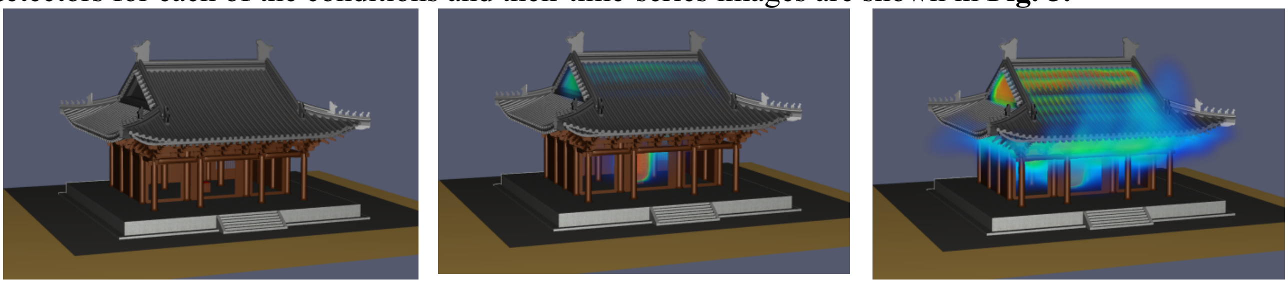
Hualin Temple is now a museum used for exhibitions, of which door is always open, so in the simulation is also set to open the door ventilation model. There is a booth in the middle of the temple, about 1.0 m height, 2.0 m long and 1.0 m wide, on which the wooden model of Hualin Temple is placed. In this experiment, the fire point was set on the top surface of this booth. According to NEPA regulations, this type of fire (fire caused by burning of wood panels and other materials) can be considered as a fast-growing type, and the time for the ignition source to release power to reach 1055kw needs to be 150s [20]. Meanwhile, temperature (°C) detectors, CO concentration (ppm) detections and smoke concentration (%/m) detectors were arranged at a height of 3.0 m to collect time series data.

Therefore, 2 working conditions were collected in conjunction with the months of August and December, containing three data sets: temperature, CO, and smoke concentration. This data is integrated to become the required data set for the study, which can be processed by the fuzzy inference system.

3. Results

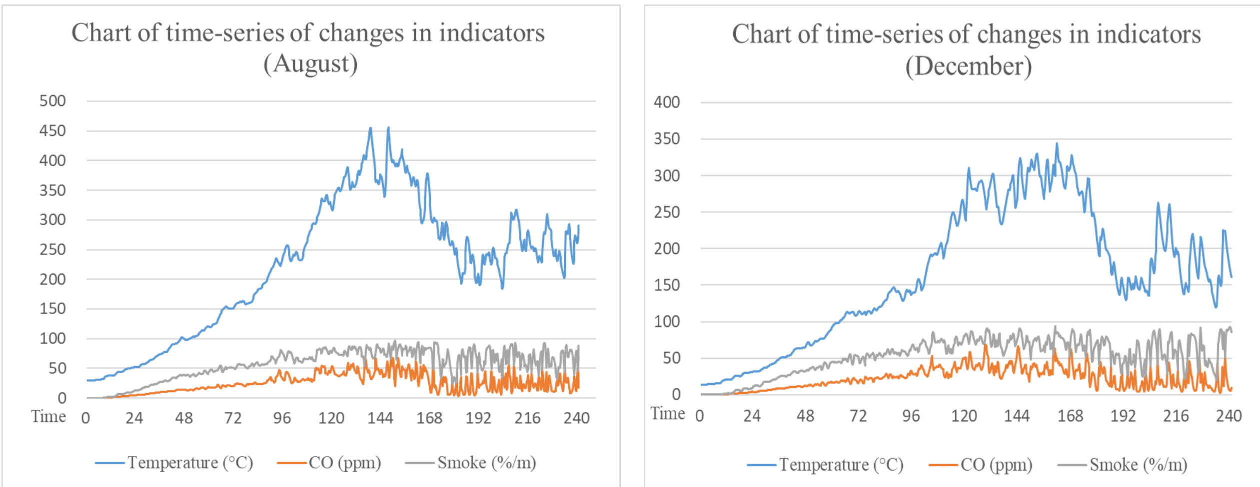
3.1 FDS data

The study was conducted using FDS software to simulate the two conditions, as shown in **Fig. 4** for the temperature visualization images of the fire initiation process simulating the winter conditions in the Great Temple; in addition, the data captured by the various temperature, CO, and smoke detectors for each of the conditions and their time-series images are shown in **Fig. 5.**



(a) (b) (c)

Fig. 4. Fire simulation temperature visualization images in December (a) initial state (b) status at 60s (c) status at 120s.



(a) (b)

Fig. 5. Chart of time-series of changes in indicators (a) Working condition in August (b)Working conditions in December.

Temperature-wise it appears that the August data are clearly higher than those of December, the former reaching 260°C around the 106s and the latter at the 117s; and they rise rapidly around thereafter, remaining at around 320°C. After that there were large fluctuations, with a downward trend around 160s. It may be due to the unstable combustibles in the room or affected by more ventilation.

As for carbon monoxide concentration, the values basically equalized around 120s, but there was a short-lived decreasing trend around 170s, possibly due to a larger fire, which reduced the concentration of CO after fully reacting with the air.

In the smoke concentration index, it can be seen that the growth trend is similar to that of CO, which tends to stabilize around 120s, and the extinction rate basically stabilizes in the range of about 80%/m.

3.2 Fuzzy inference results

The flash fire temperature of wood is approximately 260°C, and if it encounters an open flame, it will be immediately ignited [21]. Therefore, in this working condition, the early warning response time is set as the time before the flash fire temperature arrives by default under the principle of early intervention, i.e., the data samples of 0-105s and 0-115s were selected for the August and December working conditions, respectively, for the test and fire probability prediction. The sample lengths were set in terms of the maximum and minimum values within the dataset, respectively, for normalization purposes. The input quantities are temperature range (13.9, 260), CO concentration range (0, 55), smoke concentration range (0, 100), and the output quantity fire probability range (0, 1). After importing the data, the fuzzy system measurements were able to obtain the time series fire probability scenarios as shown in **Fig. 6.**

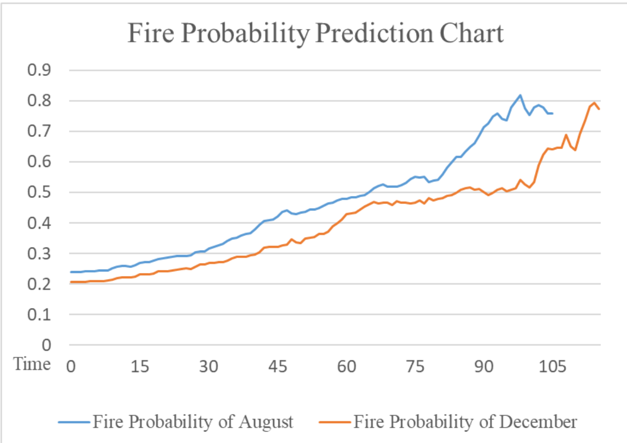


Fig. 6. Fire Probability Prediction Chart

As can be seen from the probability curves, both have roughly the same trend, with some degree of fluctuation in each after 90 seconds. In addition, the initial fire probability is significantly higher in summer compared to winter, which may be mainly influenced by the ambient temperature in the case where the CO concentration and smoke concentration are initially 0.

3.3 Discussions

From the FDS simulation data, in general, it can be seen from the data that the indicators rise slowly, and the highest value of the indicators can be reached around 150s. After this point, there are fluctuations, but the values tend to be balanced, which aligns with the standard of the initial heat release rate. In the later study of fire prediction, the two cases of winter and summer were divided, and 105s and 115s were chosen as the time nodes. This approach ensures a comprehensive study of the early stage of the fire and avoids unnecessary work. However, the curves of the three indicators are generally in line with the experimental expectations. However, perhaps because of the ventilation, the data fluctuates a lot in the later stage. More studies could be carried on the fire conditions in different corners of the building or the fire data situation in the non-ventilated state.

For the simulation results of fuzzy inference, based on the national standard test fire data, as well as data from published journals and dissertations [22-25], appropriate data were selected as samples to compare the effectiveness of the system. From the simulation results, it is evident that for the judgment of fire, the system is mostly able to approach the expected value. The samples and the results of the simulation are shown in the following table (the sample data are normalized):

Table 2 Sample data and simulation results

Sample data				
Temperature	CO	SMOKE	Expected output	Fire Probability
0.20	0.68	0.53	fireless	0.37
1.00	1.00	0.25	fiery	0.79
0.45	0.60	0.15	fiery	0.48
0.20	0.10	0.30	fireless	0.30
0.93	0.25	0.18	fiery	0.75
0.10	0.74	0.66	fireless	0.39
0.20	0.80	0.75	fiery	0.24
0.98	0.80	0.20	fiery	0.78

On this basis, current standards of Stand-alone smoke detection alarms (GB 20517-2006) and Stand-alone temperature-sensitive fire detection alarms (GB 30122-2013) were referred to [26-27], with the commonly used temperature detector alarm threshold at 70°C. The temperature detector alarm threshold is 40 ppm for CO concentration detectors and 10%/m for smoke detectors.

Combined with the data of August and December, it seems that the smoke concentration reaches the alarm threshold at the earliest, 22s and 23s respectively; followed by the temperature which reaches the threshold at 34s and 47s respectively; and lastly, the CO concentration, which reaches the threshold at 93s and 99s respectively. Therefore, the smoke concentration is the most sensitive value before a fire occurs. The data (partial) and corresponding fire probabilities obtained from the simulation in August are shown in Table 3.

Table 3 Three indicators of fire and corresponding fire probabilities (August)

serial number	Time	Temperature (°C)	CO (ppm)	SMOKE (%/m)	Fire Probability
71	20.82	50.09	3.73	8.96	0.23
72	21.10	50.37	3.91	9.03	0.24
73	21.38	50.63	4.01	9.25	0.24
74	21.66	50.89	4.08	9.61	0.24
75	**21.94**	**51.16**	**4.11**	**10.08**	**0.24**
76	22.22	51.40	4.12	10.62	0.24
112	33.02	67.81	8.44	23.16	0.39
113	33.35	68.64	8.63	23.35	0.41
114	33.67	69.69	8.86	23.70	0.42
115	**33.90**	**70.60**	**9.02**	**24.11**	**0.42**
116	34.26	71.49	9.14	24.64	0.43
117	34.62	72.37	9.22	25.33	0.43
310	92.44	235.37	35.93	61.42	0.84
311	92.73	232.77	36.52	65.36	0.84
312	**93.03**	**229.44**	**39.25**	**67.70**	**0.83**
313	93.32	228.12	43.47	68.59	0.82
314	93.61	226.25	47.06	70.32	0.84
315	93.96	223.66	45.74	74.88	0.83

After considering the three metrics, the experimental environment should reach the minimum alarm threshold in about 22 s, so at least a 0.24 probability of fire is needed for the observation requirement, and at most no more than 99 s, i.e., when the probability is 0.5, the manual alarm intervention is raised.

The results of the fuzzy reasoning seem that the fuzzy system can basically recognize the presence or absence of fire according to the existing experimental control. However, there is no exact reference standard for the fire probability in this scenario, and its accuracy needs to be verified by combining more accurate experimental samples or conducting simulation experiments. In addition, the fuzzy inference system may be able to integrate other algorithms to predict the fire probability in a more intelligent way.

4. Conclusions

This paper investigated the early warning building fire detection technology in two major steps. Firstly, by analysing historical data, the situation of clearly documented heritage fire incidents in China over the past 70 years was collected, and it was concluded that most of them were caused by man-made, electrical, and candle fires, and most of them were emergencies, so there is a need to capture the signs of fire as early as possible. Secondly, the study focused on a case study of the Grand Hall of Hualin Temple, a thousand-year-old timber-framed heritage building in Fuzhou, which was digitally modelled using FDS software, and subsequently the fire probability was estimated in conjunction with a fuzzy inference system.

The fire simulation of the building was carried out in summer (August) and winter (December) by setting up the corresponding working conditions with the booth combustion with a heat release rate of 1000 KW as a possible scenario. The fire probability was predicted by combining fuzzy inference. The results show that, for the fire prevention prediction of Hualin Temple, if the booth in the middle of the building is on fire, and when the smoke detector measures 10%/m (fire confidence 0.24), an observation signal is issued; and it is recommended that when the CO detector obtains a value of 40 ppm (fire confidence 0.5) to trigger the fire alarm.

Although this study might have shed some lights on fire risk prevention simulations in heritage buildings with fuzzy inference system, which theoretically can be useful in predicting the fire probability of a specific heritage building, it has several major limitations.

Firstly, due to the huge computational demand and other problems, only a few fire scenarios have been explored in multiple environments and conditions, and only one ignition point and two seasonal scenes were simulated. Secondly, the simulated FDS model is an ideal model, the temperature, smoke and CO concentration detectors used in the model collect theoretical values in the absence of real-time environmental disturbances. Thirdly, although the fuzzy inference system can deal with fuzzy probability problems with the experience of the experts, it cannot distinguish the specific type of fire yet. The accuracy need to be further improved. Furthermore, the model is only at the theoretical level and cannot be directly used for fire prediction in heritage for the time being.

In future studies, in order to improve the accuracy of the fire risk assessment, the model may be able to explore more fire scenarios and incorporate richer standard fire samples to optimize the structure and parameters of the fuzzy inference system. Moreover, to improve the overall performance of the fire prediction, the fuzzy inference system could be paired with other machine learning algorithms to form a fusion model in order to take advantage of each part's strengths. Furthermore, to heritage protection literally, hardware devices can be incorporated to establish a set of realize real-time fire predicting systems.

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