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A Trustworthy Classification Model for Intelligent Building Fire Risk

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ABSTRACT The occurrence of intelligent building fires causes huge economic losses to the country and society, and even people's safety. It is necessary to accurately assess the degree of intelligent building fire risk so that the fire emergency management department can make scientific decisions. In this paper, a trustworthy classification model for intelligent building fire risk is proposed, which provides a scientific and reasonable model supporting the classification assessment of intelligent building fire risk. The model integrates Bayesian Network (BN) and software trustworthy computing approach. BN is used to calculate the risk value of attributes that describe the fire risk situation of the intelligent building from 7 profiles. Based on the fire risk attribute values, trustworthy computing is adopted to classify the fire risk into 5 ranks which indicates the severity degree of building fire risk: the higher the rank is, the greater the harm is. Taking the Shanghai Jing'an 11.15 fire as an example, the result confirms that the method proposed in this paper has good theoretical significance and practical value. In addition, we compare our method with 3 fire risk assessment methods in the reference. The comparisons illustrate that the trustworthy classification model proposed in this paper is more comprehensive, rational, and scientific.

INDEX TERMS Intelligent building, fire risk assessment, fire risk trustworthy classification model, Bayesian network, trustworthy computing.

I. INTRODUCTION

In order to meet the needs of people's production and life, the functions of urban intelligent buildings are becoming more and more complex, and the scale of buildings is expanding. People's awareness of fire protection needs to be strengthened, so many potential fire risks will inevitably arise in urban intelligent buildings. Once a fire accident occurs, it will easily cause huge losses and even casualties to the national society. Therefore, evaluating the fire risk of urban buildings has become one of the hot topics in the field of fire research [1]. Intelligent buildings in this paper refer to intelligent monitoring equipment such as sensors and cameras installed in buildings, which are connected through the Internet of Things (IoT) platform to realize real-time monitoring and prediction of fire risk information in buildings. Intelligent buildings also support big data processing. The fire big data monitored by smart devices and sensors can be calculated by the edge or uploaded to the cloud computing center for unified analysis and processing, and the processing results can be preserved permanently through the database technology. The classification of fire risk of intelligent buildings is a key link in the construction of urban intelligent fire protection, which has great practical significance. From the perspective of risk monitoring, in the practice of urban intelligent fire protection, the intelligent equipment in the intelligent building is mobilized to monitor and predict the fire risk accurately in real-time, and the emergency command center can obtain the risk distribution of intelligent buildings in real-time, and conduct risk investigation on high-risk buildings, thus reducing the frequency of fire accidents. From the perspective of emergency rescue, once a fire accident occurs, the automatic fire risk classification according to the severity is beneficial for fire emergency management departments to make hierarchical decisions and improve rescue efficiency. In emergency rescue, the rescue police force will be allocated according to the fire risk level, and relevant emergency rescue resources such

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as fire protection, transportation, and medical care will be allocated.

The United States [2], China [3] and Hong Kong, China [4], and other countries and places have successively issued fire alarm classification systems for building fires. These systems generally classify fires according to their severity or danger, and each level corresponds to the corresponding emergency rescue level. Once a fire breaks out, the corresponding level of emergency aid resources will be allocated according to the fire alarm level. However, these national standards are relatively rough. On this basis, it is necessary to introduce a strict quantitative risk assessment system. The key to an accurate assessment of urban building fire risk lies in the establishment of a scientific fire risk assessment system. Many quantitative, semi-quantitative, and qualitative building fire risk assessment models have been studied. Zhou [5] puts forward a FRAME (Fire Risk Assessment Engineering Method) model to evaluate and classify the fire risk of urban residential buildings. This method proposes three fire risk factors and classifies the risk levels respectively. Xu *et al.* [6], [7] take the development of fire accidents as the mainline and construct an index system of building fire risk assessment by using analytic hierarchy process (AHP). By dividing the evaluation index into static and dynamic parts, the dynamic evaluation of building fire risk is realized. Liu *et al.* [8] use the consequence probability estimation method to divide fire risk into three dimensions: the number of serious injuries, the number of deaths, and the direct property loss, and evaluate the fire risk value and grade of building cluster by estimating the probability of risk dimensions. Dong and Wang [9] adopt the method of combining Bayesian Network and Fuzzy Fault Tree to analyse the fire risk factors of the high-rise building. Zhang and Yu, [10] propose a Bayesian network analysis model of the fire in the dormitory of colleges and universities, establish a relevant index system, build a Bayesian model for fire risk analysis. Matellini *et al.* [11] represent a three-part BN to simulate the different stages of ordinary residential fires from fire to extinguish. Liu *et al.* [12] construct a BN model to predict the fire risk of urban buildings to calculate the probability of building fires. Shu *et al.* [13] divided building fires into four stages and identified fire risk assessment factors from both dynamic and static aspects. The Bayesian method is used to predict the risk of each fire stage, and then the additive model is applied to assess the fire risks. In addition, building fire risk is modeled from the perspective of fire spread and emergency evacuation [14]–[17].

Building fire risk data collection is the premise of its assessment. In recent years, the development of IoT technology has made it possible to intelligently collect building fire risk data: intelligent buildings are equipped with many sensors and cameras, etc. With the help of these devices, intelligent buildings can collect daily fire risk data through the IoT platform and process them through various algorithms for fire risk analysis [18]. For non-intelligent buildings, there are other research methods that can assist data collection. Tresa Sangeetha *et al.* [19] develop an IoT-based smart sensing and alarming system with robotic assistance to provide immediate monitoring and alerts for emergency evacuation. Lazreg *et al.* [20] introduce a BN model that derives the condition of fire risk and predicts its future circumstance dependent on smartphone sensor data gathered within the fire area. Australian firefighter Shan Raffe [21] puts forward an empirical model for reading fire scenes: BE-SAHF (building, environment, smoke, airflow, heat, and flame) model. Combining risk indicators and environment context to make empirical judgments on important fire information. An intelligent multi-sensor detection system [22], [23] is established for monitoring building fires. Deep learning [24] and neural network [25] methods are adopted to process diverse sensor signals in real-time. The firebird model [26] proposes a data-driven method to extract information about fire risk and introduces time-related dynamic risks, which can be updated by fire inspection checks every time. Tsai *et al.* [27] develop an automation tool for a home fire safety check, image sensors are adopted to automatically build an environmental model and reduce the labor burden for a fire safety check. The fire risk assessment and data collection methods in these researches have important reference value for our work. However, these research methods are mainly aiming at the stage of indoor fire identification or the detection of fire occurrence, and can not comprehensively assess building fire risks.

In this paper, we focus on the classification problem for intelligent building fires. Our research objective is to assess the fire risk of intelligent buildings and classify the fire according to its severity. To address this issue, we propose a comprehensive classification approach that combines Bayesian network and trustworthy computing. This method evaluates building fire risk from the 7 attributes of fire stage(FS), fire evaluation(FE), burned area(BA), building fire risk rating(BFRR), fire spread rate(FSR), cluster fire possibility(CFP) and trapped toll(TT). Attributes are decomposed into metric elements and the corresponding monitoring system is built to obtain the fire risk data in real-time. Based on the results of attribute decomposition, the Bayesian network is established to calculate the risk value of 7 attributes. Based on the attribute values provided by BN, a trustworthy assessment and classification model are constructed to calculate the fire risk value and risk rank respectively. This approach gives full play to the advantages of BN in dealing with the uncertainty of intelligent building fires and the advantages of trusted computing in dealing with quantitative classification problems.

We take the Shanghai Jing'an 11.15 fire as an example to evaluate our approaches. The experiment result confirms that the method proposed in this paper has good theoretical significance and practical value, and can provide a reference for fire rescue work. We further compare our proposed methods with the existing methods including BN + fuzzy fault tree approach [9], BN + 4D Radar chart approach [13], and BN method [20]. The comparisons illustrate that our

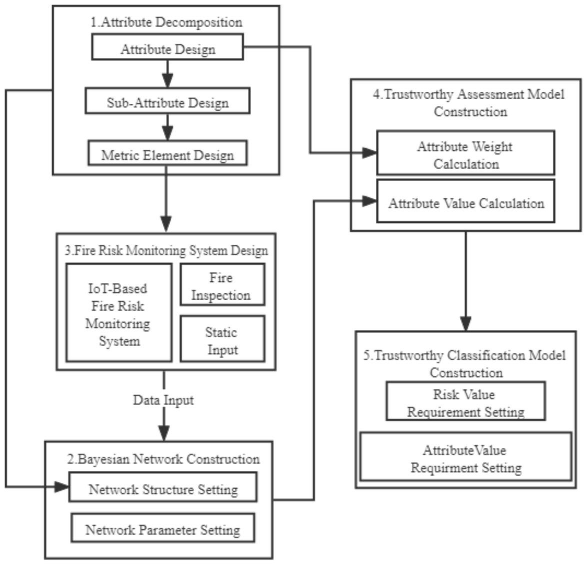

FIGURE 1. Evaluation framework of intelligent building fire risk. It consists of 5 parts: 1. Attribute decomposition; 2. Bayesian network construction; 3. Fire risk monitoring system design; 4. Trustworthy assessment model construction; 5. Trustworthy classification model construction.

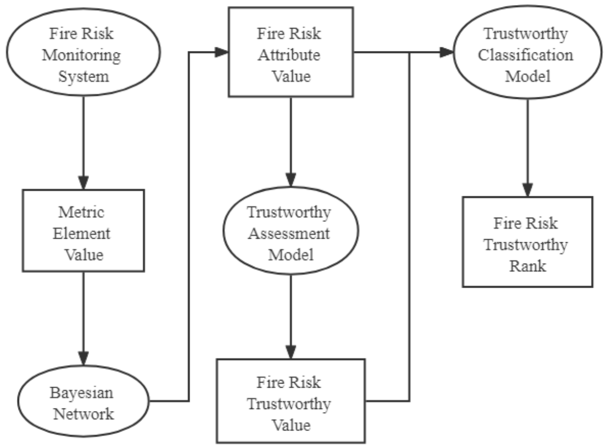

FIGURE 2. Data flow diagram of assessing fire risk rank. Firstly, the fire risk data monitored by the fire risk monitoring system need to be preprocessed to obtain the metric element value accepted by the BN model. Secondly, the metric element values are integrated into 7 attribute values through the BN model. Then, the risk value is calculated through the trustworthy assessment model. Finally, the risk rank is output through the trustworthy classification model.

proposed method makes the entire fire risk classification process more comprehensive, rational and scientific.

The organizational structure of this paper is as follows: Section II introduces the risk evaluation framework of intelligent building fires. Section III introduces the fire risk monitoring system. Section IV introduces the attribute value calculation based on BN. Section V introduces the fire risk classification based on trustworthy computing. Section VI takes the Shanghai Jing'an 11.15 fire as an example to conduct a case study of this method and compare it with 3 fire risk assessment methods in the reference. The last part summarizes this paper and gives the future research contents.

II. EVALUATION FRAMEWORK OF INTELLIGENT BUILDING FIRE RISK

The risk evaluation framework of intelligent building fires is shown in figure 1. The evaluation framework shows the main work of this paper, which can be divided into the following 5 parts:

1.Attribute decomposition. This paper defines attributes as indicators for assessing the fire risk of intelligent buildings. The definition of attributes is relatively macro, sometimes difficult to evaluate directly, and needs to be broken down to sub-attributes that are more detailed. First-level sub-attributes are generated after the first decomposition and the first-level sub-attribute can be decomposed several times as required. For each sub-attribute, design related metric elements which can be easily monitored or observed.

2.Bayesian network construction. Based on the results of attribute decomposition, a Bayesian network structure is established which describes the dependencies between fire risk nodes. We also set the network parameters which present the probability of occurrence of the event corresponding to each node. Finally, the attribute values are calculated based on the probability distribution of the attribute node in BN.

3. Fire risk monitoring system design. The monitoring system is constructed based on the designed metric elements to obtain real-time fire risk data as the input to the Bayesian network. It consists of 3 monitoring methods with different update frequencies.

4.Trustworthy assessment model construction. This model calculates the risk value of intelligent building fires, which is positively correlated with the attribute value and its weight. The weight of attributes in this paper is computed by AHP(Analytic Hierarchy Process) method. And the value of the attribute is calculated through the Bayesian network.

5.Trustworthy classification model construction. This model is designed to classify fire risk into different ranks. To this end, this model sets the corresponding risk value and attribute value requirements for each fire risk rank.

Figure 2 demonstrates the corresponding data flow for assessing the fire risk rank. First, monitor the fire risk in real-time through the corresponding means of the monitoring system to obtain the value of the metric element. Secondly, BN is used to fuse these multivariate and heterogeneous metric values, output the fire risk attribute value. Then, use the trustworthy assessment model to calculate the trustworthy value of fire risk. Finally, the fire risk trustworthy rank is output by the trustworthy classification model based on the risk value and attribute value. Note that the calculation of fire risk value and rank depends on trustworthy computing methods, so this paper defines these two outputs as 'trustworthy value' and 'trustworthy rank'.

With the input of metric element values, the model will automatically calculate the risk value and rank of intelligent building fires. With the real-time change of fire risk data, the risk value will also change dynamically. Note that after the risk value is increased, if it does not meet the next rank standard, the fire risk rank will not change.

III. FIRE RISK MONITORING SYSTEM

Building fire is a dynamic development process, and the risk factors related to fire risk assessment, such as smoke density, the water pressure of pipes, and the number of construction personnel, are constantly changing. Dynamic fire risk assessment needs to consider the risk factors in the whole life cycle of fire occurrence and development. Especially, the relationship between fire development trends and building fire protection facilities, environment, and personnel characteristics should be considered.

According to the sensitivity of fire risk to time, this paper divides it into two categories: dynamic risk and static risk. Dynamic fire risk changes in real-time with the change of time, which can be obtained by controlling the smart IoT devices and sensors in intelligent buildings and can be calculated through real-time collected data, such as smoke velocity, pipeline water pressure change, etc. Static fire risk is not sensitive to time and will not change with time. The system only needs to collect and input once, such as building height and building fire resistance rating. Dynamic fire risk data can be monitored by different means. For fire risk data that need to be collected in real-time, it can be monitored in real-time by establishing IoT-based fire risk monitoring systems [7]. For example, use a smoke sensor to monitor the smoke density; The camera sensor can be used to collect the mobility of personnel and the occupation of emergency exits; Use the water level monitoring device to monitor the real-time water level of the fire water tank, etc. For dynamic fire risks with a large time span that cannot be collected or updated in real-time, it is considered that its value will not change in a fire-fighting cycle, and it can be updated regularly by means of fire-fighting inspection [15]. The static fire risk is input by the system static collection method.

According to the update frequency, there are three main ways to update the fire risk data of intelligent buildings in this paper: 1. Real-time update through IoT-based fire risk monitoring system of intelligent buildings; 2. Regular update through fire inspection; 3. System static input. There are 63 factors affecting the fire risk of intelligent buildings to be monitored in this paper, as shown in figure 3. Generally speaking, the fire risk data of intelligent buildings are mainly collected in real-time and monitored dynamically by the IoT-based fire risk monitoring system of intelligent buildings, while the risk data is missing, the manual experience can be used to assist the input of missing data.

The monitoring system provides input for BN. There are two kinds of node variables in BN: discrete variable and continuous variable [28]. BN uses discrete tables for probabilistic reasoning. In practical application, each BN node corresponds to a physical event, and the state of the node represents the value of the physical event. It is necessary to

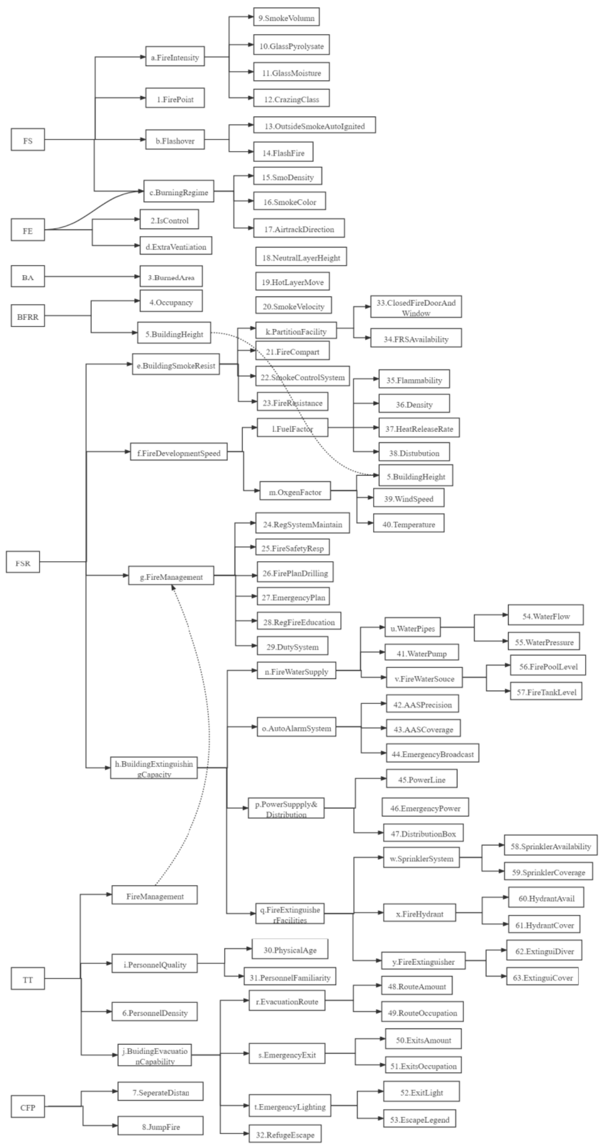

FIGURE 3. The process of attribute decomposition. The fire rank is directly influenced by 7 attributes. The attributes are more complicated and sometimes difficult to evaluate directly. They are broken down into sub-attribute nodes, marked with lower case letters. For each sub-attribute node, the relevant metric elements are designated, marked with Arabic numerals. As model input, metric element represents a basic fire risk event, which is associated with the intelligent fire risk monitoring system and updated in real-time. Attributes represent the integration of metric elements and are used to calculate the fire risk value.

define the discrete state of each metric element (BN node)in advance and save it in the database, stipulated that each metric element can only take values from its defined discrete state. The value state of the node after discretization is called the metric element value.

For a continuous variable, discretize them through data grouping [29]. When the upper and lower boundaries of each group of data are clear, the mainly used discretization methods of this paper include equal width, equal frequency, and custom rules discretization. Equal width means that the upper and lower bounds of each group of data are equal in width. Equal frequency refers to the variable that each group of data has the same frequency although its width is different, and the custom rule set the upper and lower bounds of each group of data as needed. For continuous data whose upper and lower bounds are not clear, use machine learning discretization method [22] to divide it into different groups. For discrete data, it can be regarded as a simple state classification task, and the corresponding classification situation of each state can be designed in advance. For the input data of the video stream, the video stream can be divided into image frames, and the input node data can be classified into discrete states using an image classification algorithm [23]. These discretization algorithms can be embedded in the IoT devices and implemented by edge computing, or the monitoring data can be transmitted to the cloud for cloud computing.

For reasons of space, this paper only introduces the discretization process of variables of two representatives BN input node(metric element) in figure 3. The Smoke Density node of metric element No.15 in figure 3 can be monitored by smoke sensors, and it is divided into three grades by setting the boundary of value range: dark, middle, and light, which are the three discrete states of the node, respectively corresponding to the variation of smoke density in the air. The Smoke Color node of metric element No.16 can be monitored by the image detector, the node input is a video stream format. Three discrete states, black, gray, and white, are defined to correspond to the color of smoke. The image classification algorithm can be used to monitor the color of smoke in real-time to realize the discretization of node input.

IV. ATTRIBUTE VALUE CALCULATION BASED ON BN

A. ATTRIBUTE DEFINITION

At present, the assessment of building fire risk rank is mainly based on the evaluation of casualties and property losses. In order to comprehensively assess the fire risk of intelligent buildings, this paper sets up 7 attributes to evaluate fire risk from the three aspects of fire, building, and personnel. Attributes are indicators for evaluating fire risk conditions. The definition of the 7 attributes are as follows:

(1)Fire Stage(FS), is used to determine the stage of an intelligent building fire. In the fire emergency rescue work, the commander's first task is to correctly analyze the fire stage and formulate corresponding fire extinguishing strategies.

(2) Fire Evaluation(FE), is used to measure the flame size in intelligent buildings. This attribute can be judged by the factors such as the burning regime, ventilation, and control situation of fire.

(3)Burned Area(BA), one of the important indicators of fires, is used to measure the area of the flame burned in an intelligent building.

(4)Building Fire Risk Rating(BFRR), is used to measure the risk of intelligent buildings. The risk characteristics of intelligent buildings are mainly considered from two aspects of building occupancy and building height.

TABLE 1. The update method of metric elements.

Update Method	Metric Element Number
A.IoT Method	1-3,6,8-20,33,39-41,45-46,49,51,54-57
B.Fire Inspection	22,24-31,34-38,42-44,47,52-53,58-63
C.Static Input	4-5,7,21,23,32,48,50

(5)Fire Spread Rate(FSR), is used to measure the speed of fire spread in intelligent buildings. The speed of building fire spread is affected by many factors. It depends not only on the development speed of fire itself, the smoke resistance ability, the fire extinguishing ability of intelligent buildings, and the fire management level of building managers will obviously affect the speed of building fire spread.

(6)Cluster Fire Possibility(CFP), is used to measure the probability of building cluster fire. With the uncontrolled development of fire and the catalysis of external environment, fire may spread to adjacent buildings and become a building cluster fire. The measurement factors of this attribute mainly include the fire separation distance of nearby buildings, whether there is a jump fire, and the wind speed.

(7) Trapped Toll(TT), which is used to measure the number of trapped people in an intelligent building fire. The level of trapped people is mainly considered from two aspects: personnel and building conditions. Personnel conditions include personnel quality and density, and building conditions include fire management level of intelligent buildings and evacuation capability of buildings.

B. ATTRIBUTE DECOMPOSITION

Attribute decomposition is based on daily fire-fighting practice and related work [6]–[9], [18], [25], [27], as well as the Chinese fire alarm and emergency rescue classification standard [3]. The process of attribute decomposition is demonstrated in figure 3. There are 7 attributes, 25 sub-attributes, and 63 metric elements in this paper. As model input, the metric element represents a basic fire risk event, which is associated with the intelligent fire risk monitoring system and updated in real-time. The attribute is the output of the BN model, which represents the integration of fire risk. It is also the input of the trustworthy computing model, which is used to calculate the fire risk value.

1) METRIC ELEMENT DESIGN

The metric element represents a basic fire risk event, which is considered from four dimensions of fire situation, building, environment, and personnel. It is the input of the classification method proposed in this paper, which is associated with the intelligent fire risk monitoring system and updated in real-time. As mentioned in Section III, there are three main ways to update the fire risk data of intelligent buildings: 1. Real-time update through IoT-based fire risk monitoring system of intelligent buildings; 2. Regular update through fire inspection; 3. System static input. Table 1 lists the update method of 63 metric elements.

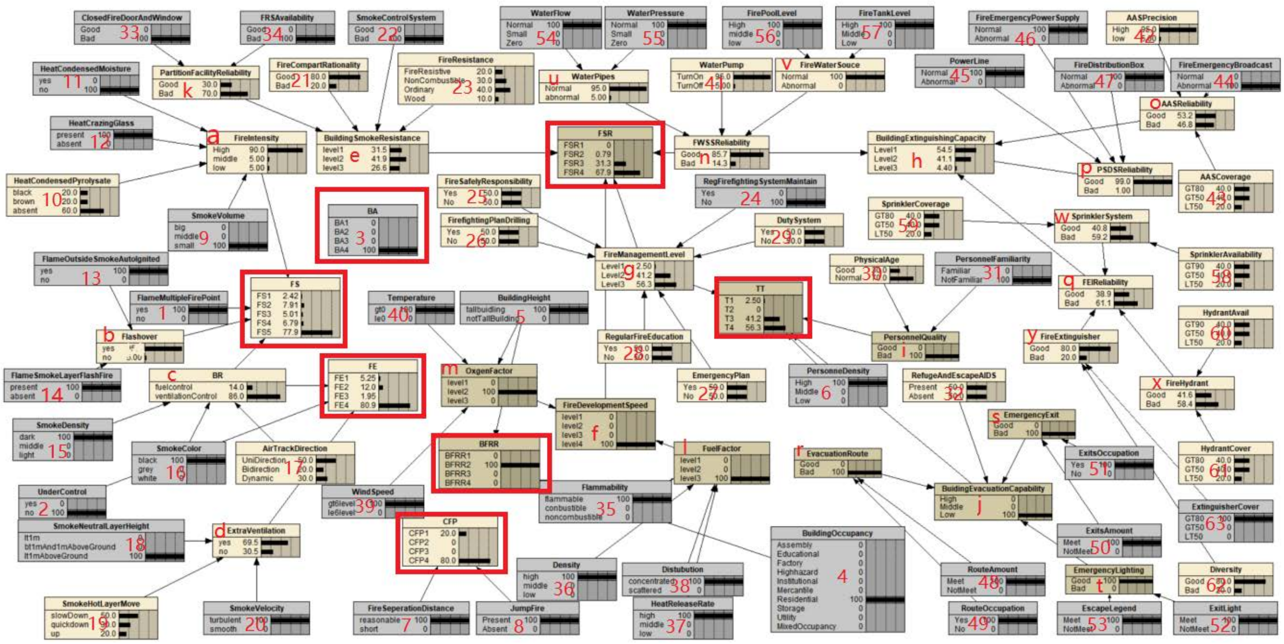

FIGURE 4. Bayesian network for fire risk attribute assessment of intelligent buildings (unit: %). The Bayesian network is constructed on the basis of attribute decomposition defined in figure 3. The yellow node means the node has no input. The gray node represents that the corresponding physical system has detected the relevant metric element(fire risk factor) value and the state corresponding to the "100%" confidence is the physical monitoring state of the node. After inputting the metric element values provided by monitoring system, the model will automatically calculate the probability distribution of 7 attribute node states(red box nodes) to output the attribute values.

2) DECOMPOSITION PROCESS

Due to space reasons, this paper only introduces the decomposition process of FS attribute in figure 3. The fire stage [30] attribute can be judged by the fire intensity, the number of fire points, the occurrence of extreme fire phenomena such as flashover, the ventilation situation, and the burning regime of the fire(whether the fuel is fully burned). So far, we have decomposed FE attribute for the first time. The number of fire points can be detected by image sensors in the building, so it is a metric element of the FE attribute. The other three nodes are sub-attributes of FE attribute that need to be further decomposed. For example, as an extreme fire phenomenon, the time of flashover is short and it is difficult to observe directly. This fire phenomenon can be judged by whether the smoke outside the building is auto-ignited(detected by roadside monitoring equipment) and whether there is a flash fire inside the building (monitored by a building video camera). In this way, we have designed the metric elements for the 'Flashover' sub-attribute. Finally, the FS attribute is decomposed into 3 sub-attributes and 10 metric elements.

C. BAYESIAN NETWORK CONSTRUCTION

Bayesian network is a directed acyclic graph. The nodes are connected by unidirectional straight arrows representing causality, and the parent node (cause) points to the child node (result) [31]. Due to the combination of existing knowledge and support complex field of uncertainty reasoning, BN is an effective theoretical model for uncertain reasoning and knowledge representation [32]. The Bayes construction and calculation in this paper is completed by Netica software [33].

1) DETERMINE THE NETWORK STRUCTURE

Based on the results of the fire risk attribute decomposition shown in figure 3, this paper constructs the corresponding BN structure for attribute value evaluation, as shown in figure 4. The information contained in each node in figure 4 is the node name, the discrete state of the node (physical scene state), and its probability from top to bottom. The numerical unit in the node is "%", which represents the confidence degree of the state (occurrence probability). The yellow node means the node has no input. The gray node represents that the corresponding physical device has detected the relevant metric(fire risk factor) value and the state corresponding to the "100%" confidence is the physical monitoring state of the node. At the same time, each node in the network implies the conditional probability table (CPT) of the node. After the metric element value is input, the probability of the whole network can be updated by using the automatic update function of Netica software.

There are 63 input nodes(metric elements) of Bayesian network, which are the leaf nodes distributed around the four peripheral boundaries in figure 4. The output nodes(attributes) are the red box ones in figure 4. The model will automatically calculate the posterior probability values (ranging from 0 to 1) of these 7 attribute nodes.

2) DETERMINE NETWORK PARAMETERS

Bayesian network uses CPT to quantify all causal relationships defined in BN structure probabilistically. Each

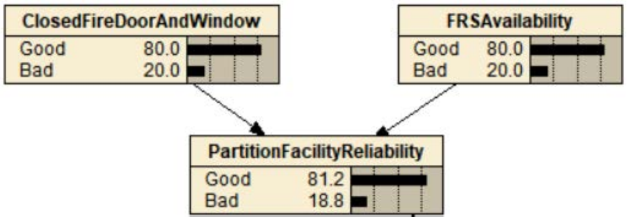

FIGURE 5. The partial BN structure of "Partition Facility Reliability" node. Each node corresponds to a physical event that affects the fire risk of the building. From top to bottom, the information contained in each node is the node name(event name), the discrete state of the node (physical state of the event), and its probability. The numerical unit in the node is "%", which represents the confidence degree of the state (probability of the event in that state).

table describes the probability distribution of variables. The table lists the conditional probabilities of nodes under all conditional combinations of all their parents, and the probability values represent the confidence of node states. The leaf node has no parent node, so the probability value is its prior probability. This section takes the partial Bayesian network composed of nodes in the upper left corner of figure 4 (node of ClosedDoorAndWindow, FRSAvailability, and PartitionFac-ilityReliability) as an example to illustrate the method of setting network parameters. The partial network is shown in figure 5, the state of the network is before compilation (when there is no input state).

a: SETTING PRIOR PROBABILITY

Firstly, it is necessary to estimate the prior probability of 63 leaf nodes(input nodes). The prior probability in this paper came from fire data analysis, expert knowledge, and on-site sampling statistics of urban buildings over the past years [9], [11], [13], [20]. As shown in figure 5, the node ClosedDoorAnd-Window shows that normally fire-prevention doors and windows should be closed during fire inspection. Let Good and Bad correspond to two discrete states, namely, good closing and poor closing situation of fire-prevention doors and windows. The prior probability of these two states came from the fire inspection data of fire-prevention doors and windows of buildings. The proportion of the two states in the fire inspection is their prior probability value [9]. The prior probability distribution of node ClosedDoorAndWindow is Good(80%) and Bad(20%). In the same way, the prior probability distribution of fire resisting shutter integrity rate(FRSAvailability) in two discrete states is Good (80%) and Bad (20%).

b: SETTING CONDITIONAL PROBABILITY TABLE

The CPT lists the probability distributions of child nodes under the condition combination of all parent nodes, which endows BN with reasoning ability when dealing with complex situations. The CPT specifies in detail what events happen under what conditions and how the state probability distribution is. The more detailed setting of CPTs, the more information stored in the network, the more intelligent the decision system will be. Even if the information available to the outside world is incomplete, the fire risk information has been stored in the form of a conditional probability table. Therefore, even if the information is missing, because of the strong fault tolerance of BN, uncertain reasoning can still be carried out. CPT can be defined by experts, learned from data, or created by a combination of the two [32]. Since the existing basic fire data cannot meet all the parameters designed in this paper, the CPTs in this paper is given by expert knowledge and risk change characteristics [34]. Taking the node PartitionFacilityReliability in figure 5 as an example, the setting of CPT is shown in table 2. On the left side of the table is the state combination of the two parent nodes. On the right side of the table is the conditional probability distribution of node PartitionFacilityReliability relative to the state combination of its parent node. As shown in the first row of table 2, when the state of ClosedDoorAndWindow node is Good and the state of FRSAvailability node is Good, the state confidence of the PartitionFacilityReliability node is Good(0.96), and Bad (0.04). It can be determined that the fire partition facilities of the building are reliable under this combination of parent node conditions. As shown in figure 5, combining the probability distribution of the parent node and the conditional probability table of the child node, the probability distribution of node PartitionFacilityReliability can be calculated by Bayes formula. The posterior probability confidence of the two node states automatically calculated by Netica software is Good(81.2%) and Bad(18.8%). This node will be the parent node of another node, and its posterior probability distribution will continue to pass down until the posterior probability calculation of seven fire risk attribute nodes is completed.

TABLE 2. The CPT of "Partition Facility Reliability" node. On the left side is the state combination of the two parent nodes. On the right side is the conditional probability distribution of node The probability distribution of child node relative to the state combination of its parent node.

State of Parent Node		State Confidence of Node Partitionfacilityreliability	
ClosedDoorAndWindow	FRSAvailability	Good	Bad
Good	Good	0.96	0.04
Good	Bad	0.76	0.24
Bad	Good	0.63	0.35
Bad	Bad	0.21	0.79

D. ATTRIBUTE VALUE CALCULATION

The quantitation between the seven attribute states and the attribute value is shown in table 3, which also lists the physical scenes corresponding to each attribute state. Among them, the information of the burned area and the number of trapped people can be counted accurately in the case of a small number. Therefore, the physical scenes corresponding to the risk states of these two attributes have quantitative data.

For the output state of attribute nodes, the maximum posterior probability criterion is adopted, that is, the output state of the node is the state with the highest posterior probability. However, in order to participate in the calculation of the fire risk value(equation 2), it is necessary to quantify the value of the attribute state. The fire risk attribute state

TABLE 3. Quantification criteria for building fire risk attributes. The table lists the quantitative relationship between the seven attribute states and the attribute value and also lists the physical scenes corresponding to each attribute state.

Risk Attribute	Attribute State	Physical Scene Description	Attribute Value
Fire Stage (FS)	FS1	The fire is in the indoor incipient stage.	2
	FS2	The fire is in the indoor growth stage.	5
	FS3	The fire is in the indoor decay stage with a hot temperature.	7
	FS4	The fire is in the indoor fully developed stage after flash over.	9
	FS5	The fire is breakthrough and in the spread stage.	10
Fire Evaluation (FE)	FE1	The fire is well contained before the fire brigade came	2
	FE2	The fire is not under control, but is in the fuel control stage.	7
	FE3	The fire is not under control, ventilation control, no extra ventilation.	9
	FE4	The fire is not under control and extra ventilation is presented.	10
Burned Area (BA)	BA1	Small area on fire ($\leq 500m^2$)	2
	BA2	Middle area on fire ($500m^2 - 1000m^2$)	7
	BA3	Large area on fire ($1000m^2 - 2000m^2$)	9
	BA4	Extremely large area on fire ($\geq 2000m^2$)	10
Building Fire Risk Rating (BFRR)	BFRR1	Low damage.e.g. normal building on fire.	2
	BFRR2	Middle damage.(e.g. tall building on fire.)	7
	BFRR3	High damage.(e.g. storage building on fire.)	9
	BFRR4	Extremely high damage.(e.g. high hazard building on fire.)	10
Fire Spread Rate (FSR)	FSR1	The fire can be extinguished in the first time.	2
	FSR2	The fire develops slowly.	7
	FSR3	The fire develops relatively rapidly.	9
	FSR4	The fire develops rapidly.	10
Cluster Fire Possibility (CFP)	CFP1	Small probability of spread to nearby buildings.	2
	CFP2	Middle probability of spread to nearby buildings.	7
	CFP3	Large probability of spread to nearby buildings.	9
	CFP4	Extremely large probability of spread to nearby buildings.	10
Trapped Toll (TT)	TT1	0-50 people are trapped, no casualties.	2
	TT2	50-100 people are trapped, 1-5 casualties	7
	TT3	100-300 people are trapped, 5-10 casualties	9
	TT4	More than 300 people are trapped, with more than 10 casualties.	10

defined in BN is graded according to the severity degree to quantify the state of risk attributes, and each state corresponds to an attribute risk level and a quantified value. The higher the risk level, the higher the risk degree of this attribute, and the greater the harm caused. It is the basic principle of risk management to seek advantages and avoid disadvantages. Once the risk level is found to rise, people tend to reduce risks. In fact, the higher the risk level, the smaller the probability of occurrence.

Therefore, this paper adopts the method of decreasing the proportion of the value from the lowest attribute risk level to the next level to approximate the golden section which means that the higher the attribute risk level, the lower the probability [35]. Specifically, if the attribute node defined in BN has four states, it means that the attribute risk is divided into four levels, and the attribute risk value range is set to {2,7,9,10}. According to this criterion, if the number of attribute risk states defined in BN is five, the attribute risk value range is set to {2, 5, 7, 9, 10}.

V. FIRE RISK CLASSIFICATION BASED ON TRUSTWORTHY COMPUTING

Trustworthy computing provides a measurement model and a classification model for software trustworthy evaluation. Because of its strict demonstration, it has been successfully applied in many fields such as artificial intelligence [36], aerospace [37], social networks [38] and computing platform [39], etc.

A. FIRE RISK TRUSTWORTHY ASSESSMENT MODEL

According to the trustworthy measurement characteristics of multi-dimensional attribute software systems, Tao *et al.* [40] designed a software trustworthy measurement model based on the product of power functions. This model embodies the barrel principle and series connection rules of trustworthy attributes and ensures the importance of each attribute. The model divides the software trustworthiness into five ranks, which is consistent with the five-level classification goal of building fire risk in this paper. Therefore, this model is adopted in our paper. The model accepts the input of fire risk attribute value and outputs the fire risk trustworthy value. In this paper, the risk trustworthy measurement model of intelligent building fires is defined as follows:

$$\mathrm{T} = \prod_{i=1}^{7} y_i^{\alpha_i} \tag{1}$$

where,

1) y_i is the degree of trustworthy attributes and α_i is its weight, $y_i \in \{2, 5, 7, 9, 10\}$, $0 \leq \alpha_i \leq 1$, $\sum \alpha_i = 1$;
2) T is the fire risk trustworthiness measure function regarding $y_1, \ldots, y_7$.

There are seven fire risk attributes in this paper, which are: 1. fire stage (FS), 2. fire evaluation (FE), 3. burned area (BA),4. building fire risk rating (BFRR), 5. fire spread rate (FSR),6. cluster fire possibility(CFP), 7. trapped toll(TT), and

TABLE 4. Weight combination of risk attributes of intelligent building fires.

Attribute	FS (y_1)	FE (y_2)	BA (y_3)	BFRR (y_4)	FSR (y_5)	CFP (y_6)	TT (y_7)
Weight	0.21	0.22	0.21	0.05	0.13	0.10	0.08

attribute risk values are marked with $y_1, y_2, y_3, y_4, y_5, y_6$ and y_7 respectively.

In this paper, AHP weight calculation method introduced in [41] is used to calculate the weight of fire risk attributes. The weight reflects the importance of fire risk attributes to the risk degree of intelligent building fires. The main process [6] of calculating attribute weights by AHP method is shown in figure 6. The two most important steps of AHP are to establish a pairwise comparison matrix and check the consistency of the calculation results. The elements in the pairwise comparison matrix reflect people's understanding of the relative importance of each fire risk attribute and generally use 1-9 scale to quantify its relative importance. The consistency test is a vital basis of the pairwise comparison method, which is performed to ensure that the decision maker is being logical in his/her pairwise comparisons. Each group of pairwise comparison matrices that passes the consistency test corresponds to a combination of attribute weights. In order to objectively obtain the AHP pairwise comparison matrix and eliminate the influence of subjective factors to the greatest extent, this paper uses the group decision method to make it into a questionnaire survey. It is issued in the fire protection forum, people with fire-fighting experience are invited to compare and score in pairs according to the importance of the risk attribute to the risk of intelligent building fires, and finally collect back the surveys and calculate the weight. The calculated combination of attribute weights is shown in table 4.

After the calculation of attribute weights, the following fire risk trustworthy measurement model with fixed weight combination is as follow:

$$T = y_1^{0.21} \times y_2^{0.22} \times y_3^{0.21} \times y_4^{0.05} \times y_5^{0.13} \times y_6^{0.1} \times y_7^{0.08} \quad (2)$$

B. RISK TRUSTWORTHY CLASSIFICATION MODEL

In view of the fact that when most of the fires just broke out, If the fire alarm is reported in time and the fire is extinguished scientifically, the fire risk level is low, and the impact and harm are small. With the increase of fire duration and scope, the fire risk level will rise correspondingly. From the perspective of probability, most fires can be extinguished in time. The proportion of serious fire accidents caused by untimely discovery is small. Numerically, according to the fire data [42] released by the Fire and Rescue Bureau of the Ministry of Emergency Management of China, 252,000 fires were reported nationwide in 2020, including 63 relatively serious fires, 1 serious fire, and no extremely serious fire. It can be seen that the higher the fire risk level, the smaller its proportion and the smaller the probability of its occurrence. So the measurement distance between fire risk

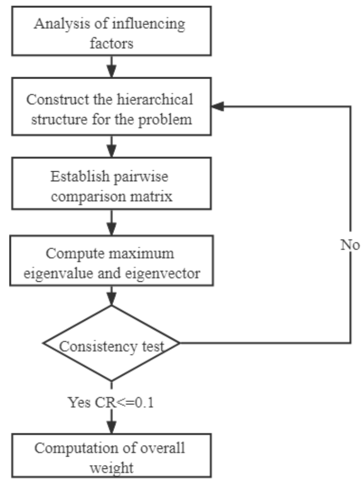

FIGURE 6. The main flow chart of the analytic hierarchy process [6]. This is the method used in Attribute Weight Calculation(figure 1.4).

TABLE 5. Fire risk trustworthy classification model. The table defines the minimum trustworthy value and the corresponding attribute value requirements of each rank of fire risk. When grading the risk of intelligent building fires, it is not only necessary to meet the requirements of trustworthy value to reach the rank, but also the attribute value needs to meet the corresponding rank requirements.

Risk Value	Attribute Requirements	Risk Rank
9 <= T	1. No more than 2 fire risk attributes with value less than 9; 2.No fire risk attribute with value below 7.	V
9 <= T	1.more than 2 fire risk attributes with value less than 9; 2.No fire risk attribute with value below 7.	IV
7.5 <= T <9	1. No more than 2 fire risk attributes with value less than 7; 2.No fire risk attribute with value below 5.	III
4.5 <= T <7.5	1.No more than 2 fire risk attributes with value less than 5;	II
T<4.5	1.No requirement.	I

trustworthy ranks should be non-equidistant, and the higher the trustworthy rank, the smaller the measurement distance of this risk rank.

Therefore, this paper constructs a risk trustworthy classification model of intelligent building fires, as shown in table 5. This table defines the minimum trustworthy value and the corresponding attribute value requirements of each rank of fire risk. When grading the risk rank of intelligent building fires, it is not only necessary to meet the requirements of risk value to reach the rank, but also the attribute values need to meet the corresponding rank requirements. First, the risk rank will be initially determined based on the risk value (the 4th and 5th ranks are distinguished according to the first item of the attribute requirements). When all the attribute requirements are met, the final risk rank is the initial rank corresponding to the risk value. When the attribute requirements are not met, it will automatically drop by one level as the final risk rank. In this paper, the risk of intelligent building fires is divided into five trustworthy ranks, corresponding to the five-level standards for fire alarm and emergency rescue in China [3]. The risk of building fires is divided into one to five ranks from low to high, of which one is the lowest and five is the highest. From one to five, the severity and hazard of fire accidents increase.

VI. CASE STUDY

In this paper, a typical fire case, the Shanghai Jing'an 11.15 fire, is selected as the experimental fire case to verify the method proposed in this paper. The case study shows that the method in this paper has good theoretical significance and practical value for fire risk assessment of urban intelligent buildings.

The general situation of the fire is: On November 15, 2010, in Jing'an District, Shanghai, a fire disaster broke out, 58 people dead and more than 70 people injured. From an intuitive point of view, it is a very serious fire, and the fire level is the highest. China's fire alarm and emergency rescue classification [3] rank it as a five-level fire alarm, which is the highest level of fire alarm. China's fire accident classification standard [43] classifies it as a particularly serious accident, which is also the highest level of fire accident.

A. FIRE RISK METRIC ELEMENT VALUE INPUT

Due to the lack of real IoT devices' monitoring data and fire inspection data, this paper is based on the investigation report [44] of the fire accident to simulate the fire risk data to construct the input of the metric element value of this fire. For the fire risk metric elements included in the model directly mentioned in the investigation report, we extract them as the input of the model; and for those metric elements not directly mentioned in the report, reasonable assumptions are made on the basis of the fire facts. Finally, the metric element value input of Shanghai Jing'an 11.15 fire is demonstrated in table 6.

There is strong uncertainty in the risk information of intelligent building fires. In real fire scenes, due to equipment damage and other reasons, the lack of fire risk data is very common. The model needs to have the ability to make judgments and reasoning under the condition of missing risk data. BN supports uncertainty reasoning, stores knowledge in the form of a conditional probability table. The more network node is, the more information the whole network stores. Even in the case of incomplete external information, BN can make intelligent inferences based on pre-stored knowledge. This explains why the total number of metric elements is 63, and the input of metrics, in this case, can be 42. If more fire risk data can be obtained in the future, more accurate assessment results will be obtained.

Input the metric element values defined in table 6 into the BN project constructed by Netica software, and the result is shown in figure 4. Among them, the input nodes (leaf nodes) which are not mentioned in the investigation report are yellow nodes in figure 4, which represent that the monitoring status of the fire risk metric element is abnormal. The model will use the prior probability distribution of these input nodes to participate in the posterior probability calculation of the whole network. The input nodes of metric elements defined in table 6 are gray in figure 4, which means that the monitoring status corresponding to this node is operating normally. After the metric element value is input into the Bayesian network, the model will automatically update the posterior probabilities of all nodes in the entire network.

TABLE 6. Metric element value input of Shanghai Jing'an 11.15 fire. There are three inputs per line. Id represents the number of metric element defined in figure 3; State represents the input value of metric element.

Id	State	Id	State	Id	State
1	yes	16	Black	45	normal
2	no	18	0.5m	46	normal
3	Ba4	20	turbulent	47	normal
4	residential	22	bad	48	meet
5	Tall-building	24	yes	49	yes
6	high	31	Not Familiar	50	meet
7	reasonable	33	bad	51	yes
8	present	34	bad	52	meet
9	small	35	flammable	53	meet
11	no	36	high	54	normal
12	present	37	high	55	normal
13	yes	38	concentrated	56	high
14	present	39	Gt6level	57	high
15	dark	44	abnormal	63	Gt80

B. CALCULATION OF FIRE RISK ATTRIBUTE VALUE

The red border nodes in figure 4 are fire risk attribute nodes. After the input is complete, the posterior probabilities of each state of the seven attribute nodes are automatically updated by the Netica software. According to the maximum posterior probability criterion, the ouput state of the attribute node is set to the attribute state with the maximum posterior probability. Taking the TT attribute in figure 4 as an example, it can be seen from table 3 that the four states of the attribute are {TT1,TT2,TT3,TT4}. The corresponding risk attribute values of each state are $\{2,7,9,10\}$. In figure 4, the confidence of these four states are $\{2.5\%, 0, 41.2\%, 56.3\%\}$. The attribute states with the highest confidence value are TT4, so the corresponding attribute value of TT attribute is 10. Thus, the risk value of each attribute is obtained as shown in table 7.

C. CALCULATION OF FIRE RISK TRUSTWORTHY VALUE AND RANK

By substituting the seven fire risk attribute values into formula 2, the trustworthy assessment value of the fire risk can be obtained as follows:

$$*{-}0.5pc\mathrm{T} = 10^{0.21} \times 10^{0.22} \times 10^{0.21} \times 7^{0.05} \times 10^{0.13} \times 10^{0.1} \times 10^{0.08} = 9.86$$

Combined with the fire risk trustworthy value and the seven attribute values, the risk trustworthy rank of the fire can be obtained. According to the fire risk trustworthy classification model defined in table 5, it can be seen that:

1. The risk trustworthy value of this fire case is greater than 9;

2. The number of attributes with an attribute value of less than 9 is one. And there are no attributes with a value less than 7.

According to the fire risk trustworthy classification model (table 5), the Shanghai Jing'an 11.15 fire risk is rank V.

TABLE 7. Risk attribute value of Shanghai Jing'an 11.15 fire. After the input is complete, the posterior probabilities of each state of the 7 attribute nodes are automatically updated by the Netica software. According to the maximum posterior probability criterion, the output state of the attribute node is set to the attribute state with the maximum posterior probability. The quantitative relationship between Attribute Sate and the Attribute value is shown in Table 3. The risk assessment value T = 9.86, combined with the attribute values, the risk level is rank V, which is the highest level of fire.

Attribute	FS (y_1)	FE (y_2)	BA (y_3)	BFRR (y_4)	FSR (y_5)	CFP (y_6)	TT (y_7)
Weight	0.21	0.22	0.21	0.05	0.13	0.10	0.08
Attribute Sate	FS5 (77.9%)	FE4 (80.9%)	BA4 (100%)	BFRR2 (100%)	FSR4 (67.9%)	CFP4 (80%)	TT4 (56.3%)
Attribute Value	10	10	10	7	10	10	10

D. ANALYSIS OF EXPERIMENTAL RESULTS

It can be seen from table 7 that

1. The output state of FS attribute is FS5, from the physical scene corresponding to this state in table 3, it can be known that the fire has broken through the fire compartment and spread to the entire building. Meanwhile, the sub-attribute and metric element information affecting the risk of this attribute can be determined through the hierarchical structure in figure 3. Analysis of these factors can provide targeted guidance for rescue work. For example, attention should be paid to observing the distribution of flame points during rescue and increasing the allocation of fire-fighting resources;

2. The output state of FE attribute is FE4. As above, it can be seen that the fire has not been effectively controlled. At this time, the fire is of ventilation control type, which is prone to extreme fire phenomena(e.g. flash over and explode). Special attention should be paid to the ventilation situation of the fire site, and cooling measures should be taken before rescue;

3. The output state of the BA attribute is BA4, which indicates that the affected area of the building is extremely large, and the distribution of fire fighting and rescue equipment and rescuers should be increased;

4. The output state of BFRR attribute is BFRR2. It shows that although the risk factor of the building itself is not high, it is necessary to pay attention to the usual fire inspection work and improve the fire-fighting ability of the managers.

5. The output state of the FSR attribute is FSR4, which shows that there are many combustibles in the building and the combustion-supporting conditions are good. The building's fire and smoke prevention capabilities and the building's fire extinguishing capabilities are defective. In normal times, the inspection frequency of fire-fighting facilities should be increased to ensure that these facilities are in good working condition. Do not stack combustible materials in the building and reduce the number of them;

6. The output state of the CFP attribute is CFP4, which indicates that the risk of nearby construction is high, and the fire is likely to spread to surrounding buildings. Attention should be paid to the weather changes during fire-fighting and rescue work. And the fire prevention and isolation of nearby buildings should be done at the same time;

7. The output state of the TT attribute is TT4. The large number of people affected by this fire shows that the building's fire management level and safe evacuation ability are poor. At this time, more medical resources should be increased to rescue the wounded. Usually, it is also necessary to strengthen the fire-fighting training of personnel and regularly check the reliability of emergency evacuation facilities.

The risk trustworthy assessment value of the Shanghai Jing'an 11.15 fire calculated in this paper is 9.86, and the fire risk trustworthy level is rank V, which is consistent with the fire situation and the classification result of China's fire alarm rating standards. Generally speaking, the fire has the characteristics of large fire intensity, large burning area, rapid fire spread, easy to spread to other buildings, and high casualties, which means that it is a fire with high severity and great social harm.

E. COMPARISON

We further compare our proposed method with the existing methods in [9], [13] and [20]. The comparison results are shown in table 8.

1. The method in [9] designs 24 fire basic events as BN input to evaluate the probability of fire occurrence(BN output) in high-rise buildings. The BN nodes defined in [9] include two states of State0 (represents the probability that an event occurs) and State1. The fire accident occurrence is the output node of BN, which is influenced by fire probability and personnel operation factors. The FSR attribute(figure 3) in our method considers risk factors similar to those in [9]. For example, the evaluation of 'f.FireDevelopmentSpeed' and 'g.FireManagement' sub-attributes is related to fire and personnel operation factors. We define FSR3 and FSR4(table 3) as State0 of fire accident occurrence. The post probability of FSR3 and FSR4 is 31.3% and 67.9%. The output of Shanghai Jing'an 11.15 fire by the method in [9] is State0(99.2%). It indicates that the fire incident occurs, with 99.2% confidence.

2. The method in [13] evaluates building fire risk from fire situation. It divides building fires into 4 stages of FireOmen(R1), FireAlarm(R2), FireBehavior(R3), and FireSpread(R4), and uses the area of a 4-dimensional radar chart to calculate the risk of building fire. The fire risk calculation function is. Reference [13] divides attributes into 2 states of high-risk(participate in risk assessment) and low-risk states. However, we have 7 attributes in our method, among which the 4 attributes of FS, FE, BA, and FSR are designed according to the fire situation. We define the state with an attribute value of more than 7 (including 7) in table 3 as a high-risk state, and the probabilities of these states are summed as the high-risk probability. The high-risk probability values of the 4 fire situation attributes(FS,

TABLE 8. Comparison results for Shanghai Jing'an 11.15 fire.

Assessment method	Application scenarios	BN input	BN output	Result
1.BN+fuzzy fault tree in [9]	High-Rise Building fires	24	1	State0(99.2%)
2.BN+ 4D Radar chart in [13]	Building fires	16	4	0.841
3.BN in [20]	Indoor fire detection	4	1	FS5(77.9%)
BN+trustworthy computing (our method)	Intelligent building fires	63	7	9.86, rank V

FE, BA, FSR) are 0.847, 0.829, 1, 0.992 respectively(the probability of attribute is in figure 4). Finally, the risk assessment result of the Shanghai Jing'an 11.15 fire by the method in [13] is R = 0.841. The fire risk range is [0,1]. According to the risk value, the risk level of fire situation can be roughly judged.

3. The method in [20] constructs a BN to classify the stage of indoor fire. The BN has 4 inputs: temperature, humidity, visibility, and pressure which are collected by smartphone sensors. The output of BN is the stage of indoor fire. The indoor fire is divided into 5 stages of dormant, growing, developed, decaying, and burnt-out, which is similar to the FS attribute classification(table 3) in our method. It can be seen from table 7 that the output state of FS attribute is FS5(77.9%), it indicates that the fire spread outside the room, but [20] only focuses on indoor fire and has no corresponding state. So the output of Shanghai Jing'an 11.15 fire by the method in [20] is FS5(77.9%). It indicates that the fire spread outside the room, with 77.9% confidence.

Compared with the above methods, the advantages of the method in this paper are the following three points:

(1) This paper is more capable of comprehensively assessing building fire risks. It can be seen from table 8 that we designed 7 attributes(BN output) and the 63 related metric elements(BN input) to evaluate the building fire risk rank. From comparison 1-3, our method includes the risk factors considered by other methods and is more comprehensive.

(2) The risk assessment model in this paper is more reasonable. We adopt a multi-attribute evaluation method that embodies the barrel principle and series connection rules of risk attribute to ensure the importance of each attribute, and the degree of importance is reflected by weight. From comparison 2, the method in [13] is only suitable for 4-dimensional attribute evaluation and lacks scalability.

(3) This paper realizes the classification assessment of fire risk, that is, to classify the fire risk according to its severity. The classification process is scientific and rational, so the classification result is trustworthy, which can provide a reference for fire rescue work.

VII. CONCLUSION

This paper introduces a novel approach that combines BN and trustworthy computing approach to assess and classify the fire risk of intelligent buildings. The model comprehensively considers the basic risk factors involved in intelligent buildings from four dimensions of fire situation, building, environment, and personnel. An intelligent fire risk monitoring system is built to monitor the basic fire risk factors and obtain fire risk data in real-time. We use BN to assess the attribute value of fire risk. Based on the attribute value, we adopt trustworthy computing to classify fire risk into 5 ranks. This approach gives full play to the advantages of BN in dealing with the uncertainty of intelligent building fires and the advantages of trusted computing in dealing with quantitative classification problems. The case study verifies the theoretical significance and practical value of the method in this paper. The proposed model in this paper offers many useful suggestions to fire rescue work for urban intelligent buildings and plays a decisive role in reducing fire risk.

Different quantification methods of attribute risk value will be tried to compare in the future. At the same time, a fire protection big data platform will be built to accumulate learning data, thereby improving the efficiency of model performance. In addition, how to determine the level of emergency rescue and the allocation of resources by fire risk rank and attribute risk value is also an urgent problem to be solved in the future.

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