Application of Bayesian Belief Networks for Smart City Fire Risk Assessment Using History Statistics and Sensor Data

Jinlu Sun[1,2,3](✉), Hongqiang Fang[4], Jiansheng Wu[1], Ting Sun[2,3], and Xingchuan Liu[3]

[1] School of Urban Planning and Design, Shenzhen Graduate School, Peking University, Shenzhen, China
[2] The Postdoctoral Innovation Base of Smart City Research Institute of China Electronics Technology Group Corporation, Shenzhen, China
[3] The Smart City Research Institute of China Electronic Technology Group Corporation, Shenzhen, China
[4] State Key Laboratory of Fire Science, University of Science and Technology of China, Hefei, China
sunjinlu@mail.ustc.edu.cn

Abstract. Fires become one of the common challenges faced by smart cities. As one of the most efficient ways in the safety science field, risk assessment could determine the risk in a quantitative or qualitative way and recognize the threat. And Bayesian Belief Networks (BBNs) has gained a reputation for being powerful techniques for modeling complex systems where the variables are highly interlinked and have been widely used for quantitative risk assessment in different fields in recent years. This work is aimed at further exploring the application of Bayesian Belief Networks for smart city fire risk assessment using history statistics and sensor data. The dynamic urban fire risk assessment method, Bayesian Belief Networks (BBNs), is described. Besides, fire risk associated factors are identified, thus a BBN model is constructed. Then a case study is presented to expound the calculation model. Both the results and discussion are given.

Keywords: Smart fire-fighting · Bayesian Belief Networks · Internet of Things · Urban fire · Fire risk indicators

1 Introduction

The Center of Fire Statistics of International Association of Fire and Rescue Services (CTIF) indicates that urban fires are one of the major concerns in public safety, resulting in a large number of casualties and serious property damage every year [1]. Fires become one of the common challenges faced by smart cities.

To better understand the feature of fire accidents, risk assessment is one of the most efficient ways in the safety science field, which could determine the risk in a quantitative or qualitative way and recognize the threat [2]. Many researchers have conducted studies on urban fire risk assessment for urban fire prevention and emergency response.

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The statistical approach is the most prevalent technique used to understand the feature of urban fires. Xin and Huang used fire statistics data from statistical yearbooks to analyze the urban fire risks [3]. Lu et al. applied the method of correspondence analysis to investigate the association between fire fatality levels and influential factors in the urban area [4]. Shai studied fire injury rates in Philadelphia and used multiple regression to determine significant variables in the prediction of fire injuries [5]. Furthermore, another branch of researchers, mainly from the discipline of urban planning and geography field, analyzed urban safety level by incorporating the technique of Geographic Information Systems (GIS) with its strong capabilities on spatial statistics and carried out a spatial analysis of the urban fires that occurred in Toronto [6].

However, fire is both a social and a physical phenomenon [7]. As a physical phenomenon, a fire incident can be identified with the objective attributes, such as causes of the fire, location of the fire, time of day, building types and fire brigade intervention. Meanwhile, as a social phenomenon, the fire transcends the individual, since social and economic elements of the city, such as citizen education and urban infrastructure development, show a mediating effect to the group of fire incidents in the urban area. In addition, the non-linear relation and the complex interactions among all these factors make the phenomenon even more complicated. Although the research on urban fire risk assessment mentioned above has dramatically facilitated the exploration of the relationship between fire incidents and the corresponding associated factors, urban fire risk has not been understood integrally or systemically since most studies remain fragmented and isolated. The traditional analytic methods mentioned above in different degrees confine the model to combine multidimensional factors and explain the interaction between factors, leading to limitations in quantitative risk assessment of urban fires.

With the rapid development of the Internet of Things, Cloud Computing, and Big Data, Bayesian Belief Networks (BBNs) have gained a reputation for being powerful techniques for modeling complex systems where the variables are highly interlinked [8]. BBNs have been widely used for quantitative risk assessment in different fields, including maritime transportation systems [13, 14], process industries [15, 16] and many other large infrastructure systems. As for its application to fire safety, urban fires have hitherto been rarely reported, although most of the existing literatures are related to forest fires [17–19]. Moreover, most application of BBNs for fire safety conducted only theoretical analysis due to the lack of data before. Therefore, it is of great significance to conduct an overall quantitative risk assessment of urban fires based on BBNs with data support.

This work performs the application of BBNs for smart city fire risk assessment using history statistics and sensor data, which could help preferably understand fire operation situation in smart cities. Thus, personal and property security could be better guaranteed. The dynamic urban fire risk assessment method, Bayesian Belief Networks (BBNs), is described in Sect. 2. In Sect. 3, fire risk associated factors are identified at first, thus a BBN model is constructed, then a case study is presented to expound the calculation model, then both the results and discussion are given at this section. Finally, some conclusions are summarized in Sect. 4.

2 Methodology

2.1 Dynamic Urban Fire Risk Assessment

Comprehensive fire risk is the product of probability and consequence [20]. To evaluate fire risk dynamically, both the probability and the consequence should be analyzed dynamically. Dynamic urban fire risk assessment could be achieved based on real-time updated data with the help of the Internet of Things and Big Data.

Urban fires could be influenced by many potentially relevant factors, such as basic urban attributes, urban fire rescue forces, etc. Dynamic monitoring IoT system makes it possible to monitor operation status from a distance. In addition, Big Data Platform gives a probability distribution based on historically accumulated data. The larger the amount of data accumulation, the more stable the probability distribution is, that is, the prior probability.

2.2 Bayesian Belief Networks

To evaluate fire risk dynamically, Bayesian belief networks (BBNs) are highly recommended because of the ability to combine the multidimensional factors and account for the interdependencies among the factors involved [21].

A Bayesian Belief Network (BBN), is a Directed Acyclic Graph (DAG) formed by the nodes (variables) together with the directed arcs, attached by a Conditional Probability Table (CPT) of each variable on all its parents, which could encode probabilistic relationships among the selected set of variables in an uncertain-reasoning problem [22]. Generally, the BBN structure formed by nodes and arcs is qualitative, while the probabilistic dependence attached to the nodes is quantitative.

Bayes' theorem could be stated as Eq. (1). Where A is the variables of a child node, and B is the variables of a parent node. P is the joint probability distribution of variables, in addition, various marginal probabilities, conditional probabilities, and joint probabilities could be represented by P(A), P(B), P(A|B), P(B|A), P(A ∩ B), etc.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A \cap B)}{\sum_{A} P(A \cap B)} = \frac{P(B|A)P(A)}{\sum_{A} P(A \cap B)} = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

3 Modeling

In this part, fire risk associated factors are identified at first based on the fire history statistics of Futian District in Shenzhen City over the past 11 years. Thus a BBN model structure for predicting the consequence of urban fires is constructed, with the various variables and the interaction among the variables combined in. Then the approach is applied to Extinguishing effectiveness as a case study, and the BBN calculation model is expounded therein.

3.1 Dynamic Urban Fire Risk Assessment

Since fire risk is the product of probability and consequence, urban fires risk associated factors (RAFs) include factors affecting fire occurrence rate and fire consequence, including basic urban attributes, urban fire rescue forces, and smart city fire management. Based on the fire history statistics of Futian District in Shenzhen City over the past 11 years, fire RAFs are identified. Then, the comprehensive fire risk level could be summarized by Eq. (2), where FRL is the overall fire risk level, and RL is the fire risk grades with respect to certain fire RAFs.

$$FRL = f(RL_1, RL_2, RL_3, \ldots) \tag{2}$$

Basic Urban Attributes. Basic urban attributes could reflect the probability of fire occurrence in the area, which include time of day, economic level, vocation, fire types, and causes of fire.

Urban Fire Rescue Forces. Urban fire rescue forces could effectively reduce the consequences of fires by reducing the number of casualties and property damage, which include fire-fighting equipment, fire station protection area, fire safety training, and fire safety inspection.

Smart City Fire Management. With the rapid development of the new generation of information technology, smart cities pay more and more attention to smart fire-fighting and continuously increases the investment in the construction of fire-fighting work. Personal and property security could be better guaranteed with the advance of smart fire-fighting work, such as fire detection system, fire alarm system, fire extinguishing system, etc.

3.2 BBN Model

Base on the identification of fire RAFs, a BBN model for predicting the consequence of urban fires is constructed, then the calculation based on the BBN model is introduced.

Structure Construction. The interaction between the variables is analyzed, based on the identification of fire RAFs. Consequence is the most intuitive node (variable) to evaluate the fire risk, influenced by the parent nodes (variables), Fatality and Economic loss. Similarly, Fatality and Economic loss are related to other variables, such as Extinguishing effectiveness, Local fire service, Vocation, etc. In addition, Extinguishing effectiveness, Local fire service, Vocation, and other fire RAFs are interdependent. Thus, the network structure of BBN model for predicting the consequence of urban fires is constructed as shown in Fig. 1.

Model Quantification. On the basis of the network structure of BBN model, the fire RAFs could be divided into 2 groups, the static group, and the dynamic group. The static fire RAFs, such as fire-fighting equipment within the node of Local fire service, could be updated periodically. While the dynamic fire RAFs, such as the effectiveness of the Temperature detector, could be monitored in real time with the help of dynamic monitoring IoT system.

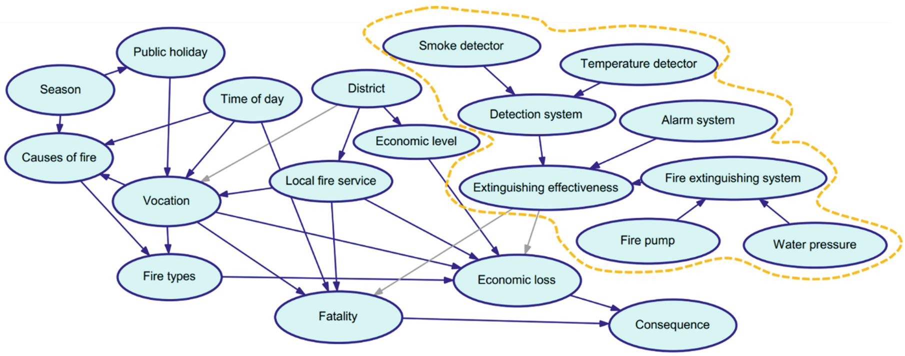

Fig. 1. The network structure of BBN model for predicting the consequence of urban fires.

Each node has a corresponding Conditional Probability Table (CPT) to indicate the probability dependencies between the node and its parent nodes. Based on the fire history statistics of Futian District in Shenzhen City over the past 11 years, the CPTs could be obtained. Table 1 reveals the CPTs for three of the root nodes, including Season, Time of day, and District. Moreover, the assumptive CPTs for other root nodes are illustrated in Table 2. The CPTs of other nodes, such as causes of fire, could also be gained based on urban fire history statistics.

Table 1. The CPTs for three of the root nodes.

Node	States and corresponding probabilities									
Season	Spring/0.2503				Summer/0.2349		Autumn/0.2328		Winter/0.2820	
Time of day	Before dawn/0.1614				Moring/0.2288		Afternoon/0.3045		Night/0.3052	
District	Area 1	Area 2	Area 3	Area 4	Area 5	Area 6	Area 7	Area 8	Area 9	Area 10
	0.0630	0.1725	0.0491	0.0847	0.0690	0.0964	0.0854	0.1921	0.0928	0.0950

Table 2. The assumptive CPTs for other root nodes.

Node	States and corresponding probabilities	
Water pressure/Fire pump	Available/0.98	Unavailable/0.02
Temperature detector	Available/0.90	Unavailable/0.10
Smoke detector/Alarm system	Available/0.95	Unavailable/0.10

3.3 BBN Calculation Model

Taking Extinguishing effectiveness as an example as shown in Fig. 2, to ensure Extinguishing effectiveness, Detection system, Alarm system, and Fire extinguishing system should all remain available. Detection system could function well when either Smoke detector or Temperature detector is available. While Fire extinguishing system could function well when both Fire pump and Water pressure are available.

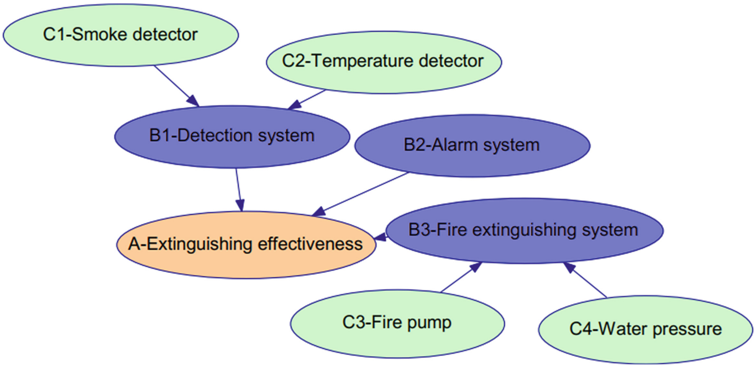

Fig. 2. The reasoning network structure of Extinguishing effectiveness.

In this way, the marginal probability of available Extinguishing effectiveness could be calculated by Eq. (3), based on the reasoning network structure. Where 1 means Available and 0 means Unavailable.

$$\begin{aligned} P(A=1) &= P[(B1=1)\cap(B2=1)\cap(B3=1)] \\ &= P[(C1=1)\cup(C2=1)]\cdot P(B2)\cdot P[(C3=1)\cap(C4=1)] \\ &= [1-P(C1=0)\cdot P(C2=0)]\cdot P(B2=1)\cdot P(C3=1)\cdot P(C4=1) \\ &= (1-0.10\times 0.10)\times 0.95\times 0.98\times 0.98 = 0.9033\approx 0.90 \end{aligned} \tag{3}$$

Likewise, the conditional probability of unavailable Temperature detector with unavailable Extinguishing effectiveness could also be calculated by Eq. (4). Where 1 means Available and 0 means Unavailable.

$$\begin{aligned} P(C2=0|A=0) &= \frac{P(A=0|C2=0)\cdot P(C2=0)}{P(A=0)} \\ &= \frac{[1-P(C1=1)\cdot P(B2=1)\cdot P(C3=1)\cdot P(C4=1)]\cdot P(C2=0)}{1-P(A=0)} \\ &= \frac{(1-0.90\times 0.95\times 0.98\times 0.98)\times 0.10}{1-0.90} = 0.1789\approx 0.18 \end{aligned} \tag{4}$$

3.4 Results and Discussion

To verify the results above, the interaction among the nodes is drawn in GeNIe (Decision Systems Laboratory 2008), thus the directed acyclic BBN model could be formed and presented. The prior probability distribution of the scenario could be revealed as shown in Fig. 3. The posterior probability distribution with unavailable Extinguishing effectiveness could be illustrated in Fig. 4.

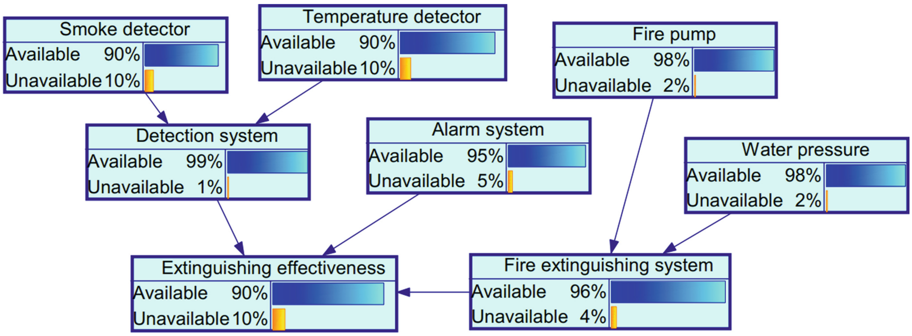

Fig. 3. The prior probability distribution of the scenario.

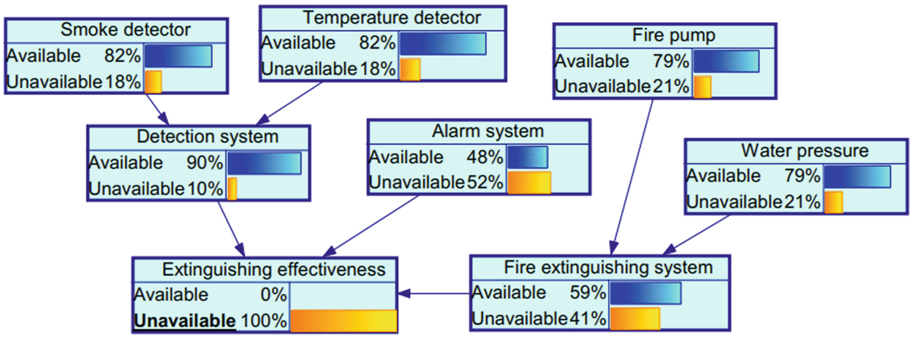

Fig. 4. The posterior probability distribution with unavailable Extinguishing effectiveness.

In addition, Behaviour Sensitivity Test (BST) could confirm whether the model correctly predicts the behavior of the system modeling, based on the measurement of Parameter Sensitivity Analysis (PSA). With the sensitivity analysis tool of GeNIe, the target node is set to Extinguishing effectiveness, the visual result of the PSA is presented

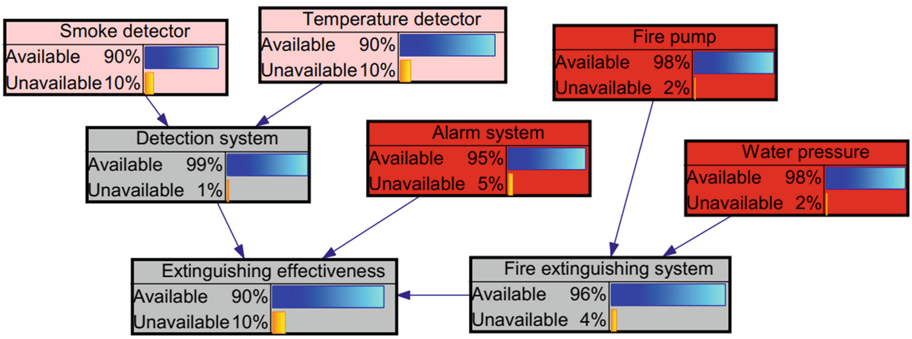

Fig. 5. Variable sensitivity analysis of the model by setting the Extinguishing effectiveness as the target node.

in Fig. 5. It is obvious that the nodes are sensitive to the target node in different degrees, which provides certain confidence to that the model is working as intended.

4 Conclusions

Fires become one of the common challenges faced by smart cities. To evaluate fire risk dynamically, an integrated approach to quantitative risk assessment for urban fires based on BBNs was proposed. Fire RAFs are identified based on the fire history statistics of Futian District in Shenzhen City over the past 11 years. Then the various variables and the interaction among the variables were combined in the BBN model structure constructed for predicting the consequence of urban fires. With the approach applied to Extinguishing effectiveness as a case study, the BBN calculation model was expounded therein.

In general, BBNs show good adaptation of modeling and evaluating urban fire risk, which could be used to provide effective decision-making support for government and fire department. The BBN model could be improved continuously when new knowledge becomes available due to its advantage of flexibility. With more and more fire RAFs considered in the BBN model, the CPTs would be updated, thus more convincing assessment could be obtained based on the more accurate results.

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