Research on Urban Public Safety Management Method Based on Bayesian Network

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ABSTRACT

With the development of economy and the improvement of living standards, there are many problems in urban public safety management, and the hidden danger of fire is one of the prominent problems. Aiming at this problem, this paper uses Bayesian network to establish a prediction model of urban public security risk evolution trend, and applies the model to real life to verify that it has the characteristics of accurately predicting risk evolution trend, which can be used in daily real life. At the same time, using the methods of literature review, case study and expert interview, this paper analyzes the situational factors that affect urban risk from the aspects of disaster causing factors, disaster bearing carriers, disaster pregnant environment and disaster response in the development of public security management.

Keywords: *City; Public Safety management; Bayesian network; Evolution trend.*

1. INTRODUCTION

Public safety management can be understood as various management measures taken to ensure the public safety of urban grass-roots society.

(1) Scope and content of public safety management. According to the connotation of public safety, the public safety management of grass-roots society can be roughly divided into four categories: grass-roots social security management, traffic safety management, life safety management and production safety management. In the form of safety management, publicity and safety education are typical, such as traffic safety education, life safety education, etc [1]. In the long-term development and practice, various types of safety management have formed their own specific safety service content. Public security management. Public security service mainly refers to various public security management activities, involving crime prevention and strike, population management, dangerous goods management and public order management. ② Traffic safety management. In addition to traditional forms such as publicity and safety education, in recent years [2].

Driving effect prediction management, pedestrian safety skill training and other new forms. [3] Life safety management. Life safety management covers a wide range, including all aspects of basic social residents' clothing, food, housing and transportation, such as health safety services, fire safety services, disaster prevention and reduction services, emergency medical services, etc. Production safety management. It mainly refers to the development of a series of measures to ensure the personal safety and normal life of grassroots social residents, mainly including operation equipment and vehicle management, operation personnel management, production responsibility implementation management, etc [4].

(2) Public security service supply mode. How to optimize service supply based on service demand is a key issue in public security service decision-making research. Existing studies have carried out research in the following aspects. Stakeholder relationship of service supply. In public security services, stakeholders mainly include grass-roots governments, superior managers, grass-roots social residents and organizations related to public security services [5]. Some scholars have established an evolutionary game model between the service subject and other service institutions in the production safety service, and found that the service behavior of the service subject is related to the self supply capacity. Other scholars have proposed community cooperation, partnership and other cooperation models from the perspective of inter community cooperation.

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2. EVOLUTIONARY RISK ANALYSIS MODEL BASED ON BAYESIAN NETWORK

With the vigorous development of big data, the number of variables in complex systems is huge, and the interrelationships are intricate, and these relationships are usually nonlinear. It becomes very difficult to learn and describe uncertain knowledge from a large amount of data. In order to solve this problem, artificial intelligence and data mining have become the focus of attention of researchers. Bayesian networks stand out from the many models and are widely used because they have significant advantages over other models:

(1) Bayesian network is intuitive and easy to understand, easy to explain and understand. The topology of Bayesian network is a directed acyclic graph, which can intuitively and qualitatively reflect the dependencies between nodes. And the existence of conditional probability table enables the degree of dependence to be described quantitatively. For the above reasons, compared to other models, it is more intuitive and easy to understand.

(2) The mathematical background of the Bayesian network is solid and very rigorous. Compared with other models, Bayesian network is based on knowledge inference based on graph theory and probability theory. It has a solid mathematical theoretical foundation, and the reasoning is rigorous and reliable.

(3) Bayesian network has certain flexibility. Bayesian networks can be directly learned based on data, but with prior knowledge, Bayesian networks can also be established based on prior knowledge. When the prior knowledge and data are combined to use the learning Bayesian network, the scoring function can be adjusted to realize the adjustment of the proportion of the prior knowledge and data in the learning process.

(4) The Bayesian network can describe the dependencies between variables more accurately. The conditional probability table of Bayesian network can accurately and quantitatively describe the degree of dependence between variables, which makes up for the lack of qualitative description of directed acyclic graphs.

Based on the above advantages, Bayesian network can well describe the probabilistic dependence between variables, so it is widely used in data mining, pattern recognition, medical diagnosis, troubleshooting and many other fields. So many application scenarios also bring new requirements for causal discovery based on Bayesian network. Bayesian network learning includes two aspects: parameter learning and network structure learning. Parameter learning is to obtain the optimal parameters of the network through learning under the premise of known network structure; structure learning needs to determine the topology of the network through scoring function or conditional independence test, and then further parameter learning.

The construction of Bayesian network model mainly includes: determining each node of the topological network, analyzing the directed relationship between nodes, and determining the probability distribution of nodes with the help of probability formula. The specific process of Bayesian network model construction is as follows:

(1) Determining nodes and value ranges in the network

Firstly, the relevant factors of the problem are transformed into random variables, that is, the corresponding Bayesian network nodes, which mainly include input nodes and output nodes. Then, according to the actual situation of the research problem, the corresponding value range and value type of each node are determined through case analysis, expert interview and other methods.

(2) Constructing Bayesian network structure

The causal logic relationship between nodes is analyzed, which is represented by a directed arrow, from the input node to the output node, and then connected to draw a directed acyclic model diagram. On this basis, the Bayesian network structure is constructed.

(3) Bayesian network parameter calculation

Determine the probability of each variable node in Bayesian network, including prior probability, conditional probability and full probability, which are collectively referred to as Bayesian network parameter calculation. This paper mainly analyzes it through expert judgment method. First, according to the experts' understanding and experience accumulation of the research problem, the prior probability of the root node and the conditional probability of each node are determined, and then the preliminary correction is made. Then, combined with the Bayesian network structure and Bayesian network parameters, the probability of each node and the posterior probability of the Bayesian network are calculated.

Step1: A priori probability. Also known as edge probability, it generally refers to the follow-up probability of root node events expressed in P (AI), and the prior probability is generally obtained by experts' practical experience or statistical historical data.

Conditional probability indicates the probability that event B still occurs when event AI has occurred.

$$P(B|A_i) = \frac{P(B \cap A_i)}{P(A_i)} \tag{1}$$

(2) Total probability

The probability of the output node is obtained through the full probability calculation formula, which

corresponds to the essence of Bayesian network, that is, the derivation of the result from the cause, and the derivation from the root node to the leaf node.

$$P(B) = P\ (BA_1) + P\ (BA_2) + \cdots P\ (BA_N) = \sum_{i=1}^{N} P(B|A_i)P(A_i) \quad (2)$$

(3) Bayes formula

It refers to the probability of occurrence of a cause corresponding to an event with a known result, that is, the probability of occurrence of an evolution path is calculated.

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B)} \quad (3)$$

According to the analysis of scenario evolution law and scenario information elements, the variables of evolution and development in this paper are: fire scenario state (s), disaster response (R) and response objective (T). After the occurrence of safety management problems, under the action of disaster resistance response taken by each emergency response subject, the scenario status is constantly evolving. The scenario network relationship based on this is shown in Figure 1:

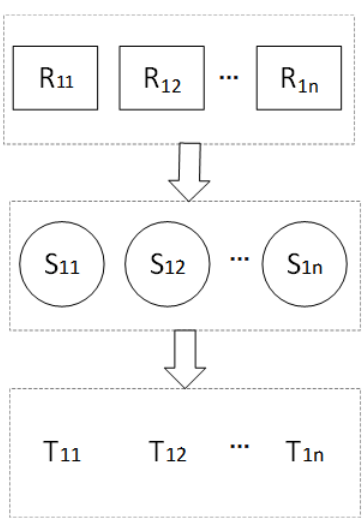

Figure 1 evolution diagram of management problems

3. EFFECT ANALYSIS

In this paper, the probability of each node of the network, including the prior probability of the root node and the conditional probability of the scenario state s, is determined by means of expert scoring. By inviting 4 authoritative experts to score the evolution scenario, due to the great subjectivity of expert scoring, the expert prediction probability is connected with the triangular fuzzy number by using the triangular fuzzy theory, and seven language variables "VH", "H", "sh", "m", "SL", "L" and "VL" (representing very high, high, slightly high, medium, slightly low, low and very low respectively) are introduced. The corresponding relationship with the triangular fuzzy number is shown in table 1.

Table 1 fuzzy semantic value transformation

Serial number	value	fuzzy number
1	VH	(0.9 , 1.0 , 1.0)
2	H	(0.7 , 0.9 , 1.0)
3	SH	(0.5 , 0.7 , 0.9)
4	M	(0.3 , 0.5 , 0.7)
5	SL	(0.1 , 0.3 , 0.5)
6	L	(0 , 0.1 , 0.3)
7	SL	(0 , 0 , 0.1)

According to the above figure, the expert's scoring of each node is transformed into a fuzzy probability expressed by triangular fuzzy numbers. For example, the probability that node Xi is in J can be expressed as: in order to reduce the experts' limitations due to personal subjectivity and knowledge understanding, the fuzzy probability of four experts is averaged by formula (4), and then the accurate probability of the node is calculated. Generally, the "mean area" method is used to solve the fuzzy probability, That is, the fuzzy probability is transformed into the exact probability by using formula (5) to obtain the node probability.

$$\tilde{P}'_{ij} = \frac{\tilde{P}_{ij}^{1}+\tilde{P}_{ij}^{2}+\tilde{P}_{ij}^{3}+\tilde{P}_{ij}^{4}}{4} \quad (4)$$

$$P'_{ij} = \frac{a'_{ij}+2m'_{ij}+b'_{ij}}{4} \quad (5)$$

This paper mainly relies on Bayesian correlation formula and Bayesian software genie to complete the calculation of each node.

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B)} \quad (6)$$

$P(A|B)$ is a posteriori probability, $P(A)$ is a priori probability, $P(A)$ is a conditional probability, and $P(B)$ is a full probability. The full probability formula is:

$$P(B) = \sum_{i=1}^{N} P(B|A_i)P(A_i) \quad (7)$$

Build a typical risk scenario evolution network diagram (s represents different fault problems), as shown in Figure 2.

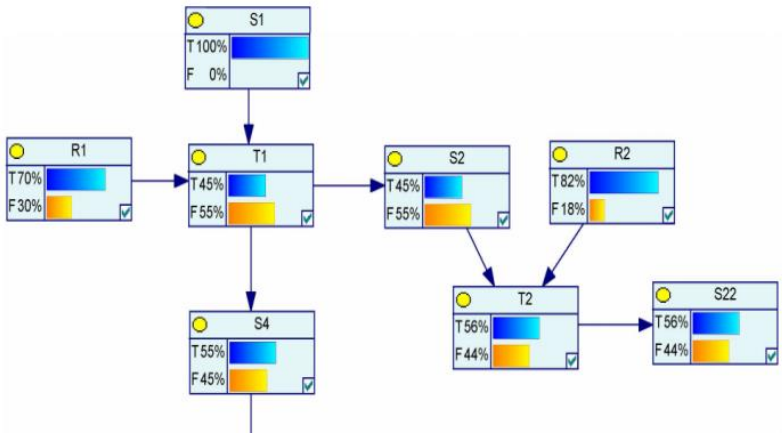

Figure 2 evolution trend analysis

4. CONCLUSIONS

The focus of urban public security work is at the grass-roots level. The grass-roots society (including streets, communities, residents, merchants, non-governmental organizations, non-governmental organizations, enterprises and institutions and other related social subjects) is the foundation for ensuring urban public security. With the continuous introduction of multi-source big data into public security scenarios, the data chain relationship is becoming more and more complex, making the grass-roots social big data governance a complex system engineering, and its analysis effect may be affected by various uncertain factors, including the targeted public security scenarios, diversified big data governance issues, adopted governance practices and internal and external governance environment. For the complex problem scenarios facing the big data governance of the grass-roots society, whether it is the identification and analysis of the governance problem scenarios, or the formulation and evaluation of the problem response schemes, intelligent analysis methods are required to support the rational and efficient integration of governance data, information and knowledge distributed in fragments.

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