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A Bayesian Network for the Transportation Accidents of Hazardous Materials Handling Time Assessment

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Abstract

To improve the efficiency of emergency rescue in transportation accidents of hazardous materials(HAZMAT), a Bayesian network(BN) was developed in this paper to estimate the accident handling time. Also, based on this BN, the difficulty of handling every types of accidents can be quantified. According to theoretical analysis and literature review, 7 nodes (season, time, type of road, type of HAZMAT, the former accident, the secondary accident and handling time) are used to set up the BN. The value of mutual information was calculated to refine the BN. A database of 902 transportation accident of HAZMAT cases was built up for Bayesian parameter learning. Based on the parameter learning of BN, the results were summarized as follow: (1) The BN could be used to estimate the probabilities of handling time in different periods which include '0 to 2 hours', '2 to 4 hours', '4 hours and more'. (2) The difficulty of each type of accident can be ordered as follow: rollover> rear-end> internal fault≈ impact> falling> tire fault> vehicle body fire. Leakage>combustion explosion.

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Keywords: hazardous materials transportation accidents, Bayesian network, accident handling time, emergency rescue

1. Introduction

In recent years,the road transportation volume of HAZMAT ranges from 0.1 billion tons to 0.2 billion tons annually in China [1]. With the increase of the HAZMAT freight amount, there were the hazmat road transportation accidents frequently, which caused great damage to the national economy, peoples' life property and the environment resources. Because of the physic-chemical characters of HAZMAT (such as explosion, combustion, poison, corrosion, combustion supporting), a more serious secondary accident is often derived from the former accident which poses a great threat to pedestrians, residents, ecological environment, buildings and vehicles. It is significant to seek a mathematic model for estimating the accident handling time. Only in this way, can the traffic situation be controlled timely. Also, according to the estimate of the accidents handling time, once an accident happened, an emergency response plan can be formulated appropriately.

The following scholars have studied the causes and the consequences of the accident. A. Ronza [2] used transportation accident databases to investigate ignition and explosion probabilities of flammable spills by event trees; C. Samuel [3] presented a temporal trend study of HAZMAT incidents occurring through the transportation of flammable liquids; Bahareh Inanloo [4] weighed exposure health risks, proximity to vulnerable areas, delay costs and trucking expenses of HAZMAT cargo routing by Python programming. Although there has been many studies on road transportation accidents of HAZMAT, the disposal of these accidents was always neglected.

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Moreover, with the advantage of causal analysis, Bayesian network is widely used in the case study of accidents in transporting hazardous meterials. L.J. Zhao [5], developed a Bayesian network of 8 nodes(road condition, weather, management, human, HAZMAT packing and loading, transportation vehicle) which based on a database of 94 cases transportation accidents of HAZMAT. T. Zhu et al [1]. studied 162 accidents that occurred during the transportation of HAZMAT and concluded that the following major factors were responsible for the accidents: such as road condition, weather, management, human, HAZMAT packing and loading, transportation vehicle, the number of deaths and the number of injured. X. Wang [6] concluded the following factors: human, type of tank, weather, road condition. However, the related research was mainly to analyze the cause of the accident, the vital factors such as handling time, type of the former accident and the secondary accident were always neglected.

In this respect, 902 transportation accidents of HAZMAT were studied from the beginning of 2013 to 2016 in this paper. A new BN was developed for estimating accident handling time and assessing the difficulty of each types of accidents.

2. Bayesian network and NETICA

Bayesian network is a graph model for describing the probabilistic correlation between variables. It is one of the most effective theoretical models in uncertain knowledge representation and reasoning field [7]. With the development of Bayesian statistics, it has been widely used. Also, BN is gaining more and more experts and scholars' recognition.

2.1. Directed acyclic graph

Based on literatures material, risk analysis methods such as fault tree [7] and bow tie [8] are applied to construct BN. By using these methods, the structure of BN is simplified. However, the directed edges in levels can only be neglected. BN constructed by directed acyclic graph can avoid the above-mentioned problems. The directed edge between two nodes (from the parent node to its offspring nodes) represent the causal relationship of them, each node corresponds to a conditional probability [9]. A typical DAG was shown in Fig. 1.

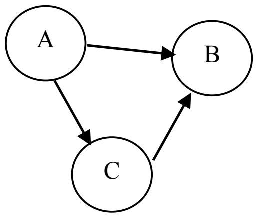

Fig. 1. Directed acyclic graph

2.2. A brief introduction of NETICA

At present, many software platforms are available to construct BN, such as BN Toolkit, BayesBuider, JavaBayes, Hugin expert. Compared with other software, NETICA is such popular for its GUI and practicability. It is a powerful, easy-to-use, complete program for working with belief networks and influence diagrams. It has an intuitive and smooth user interface for drawing the networks, and the relationships between variables may be entered as individual probabilities, in the form of equations.

3. Develop a Bayesian network for transportation accidents of HAZMAT assessment

3.1. Define the variables and develop preliminary Bayesian network

According to theoretical analysis and literature review, the following factors were concluded: Weather condition, Management, Type of road, Road condition, Skill, Health, Safety awareness of driver, HAZMAT packing and loading, Transportation vehicle. However, once a transportation accident of HAZMAT occurred, the accident investigation has not yet been carried out, so after answered the emergency call, only 6 nodes (season, time, the type of road, the type of HAZMAT, the former accident, the secondary accident) can be obtained. Therefore, the 7 nodes (season, time, the type of road, the type of HAZMAT, the former accident, the secondary accident and handling time) are used to construct the BN and they can be divided into 3 levels:

1) The first level

There are 4 nodes involved in this level which are season, time, the type of road, the type of HAZMAT. These nodes have an indirect effect on accident handling time, also, they can be confirmed before the transportation. More details were shown in table 1.

Table 1. Nodes in the first level

Nodes	Description	Value set
Season（S）	The season when the accident occurred.	Spring, fall（0）；Summer（1）；Winter(2) (According to temperature difference)
Time（T）	When the accident happened.	Day（0）；Night（1）(According to visibility difference)
Type of road（R）	Type of road	Highway（0）；National road（1）；Provincial road（2）；County and township road（3）；Urban road（4）.
Type of HAZMAT（H）	According to the flash point of HAZMAT	>60℃（0）；28~60℃（1）；<28℃（2）；Compressed gas or liquefied gas（3）.

2) The second level

During the processing of a transportation accident of HAZMAT, the former accident often caused the secondary accidents (such as leakage, combustion and explosion). More details were shown in table 2.

Table 2. Nodes in second level

Nodes	Description	Value set
Former accident（A_1）	Former accident	Rollover（0）；Vehicle body fire（1）；Tire fault（2）；Internal fault（3）；Impact（4）；Rear-end（5）；Falling（6）
Secondary accident（A_2）	Secondary accident	Leakage（0）；Combustion explosion（1）；None（2）

3) The third level

There are different methods to quantify the consequence of transportation accidents of HAZMAT. The number of injured, economic loss, the degree of environment pollution can be used for the quantitative analysis of consequence. Accident handling time are chosen, because this factor can characterize not only the influence between the type of accident and handling time, but also the handling difficulty of each type of accidents. More details were shown in table 3.

Table 3. Handling time

Nodes	Value set	Description
Handling time（D）	0~2h (0)	Not difficult to handle
	2~4h (1)	Difficult to handle
	>4h (2)	Very difficult to handle

In application, BN based on casual relationship can always be simple and clear [11]. To reduce the number of relationships, we adopted certain simplifying assumption that processing time only result from parent direct factors [5]. According to the levels divided above, a preliminary BN can be built up as Fig 2.

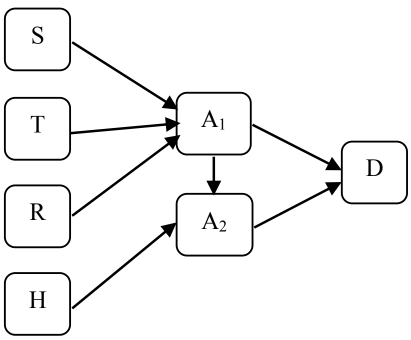

Fig. 2. The preliminary Bayesian network

3.2. The reasonableness verification of Bayesian network

In order to reduce the subjectivity of the preliminary BN, the values of mutual information are calculated for improving the BN. In probability theory and information theory, the mutual information of two random variables is a measure of the mutual dependence between the two variables. Mutual information is defined as follow:

Formally, the mutual information of two discrete random variables X and Y can be defined as Eq. (1):

$$I(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y)\log\frac{p(x,y)}{p(x)p(y)} \tag{1}$$

Where p(x, y) is the joint probability function of X and Y, and p(y) are the marginal probability distribution functions of X and Y. By using this method, we can find the causal relationships among all the factors, and refine the preliminary Bayesian network.

The calculation results of mutual information are summarized in the table 4.

Table 4. the value of mutual information

	S	T	R	H	A_1	A_2	D
S		0.00043	0.00129	0.00211	**0.00490**	0.00132	0.00277
T	0.00043		0.00161	0.00061	**0.00414**	0.00201	0.00362
R	0.00129	0.00161		0.00558	**0.02315**	0.00156	0.00693
H	0.00211	0.00061	**0.00558**		**0.00522**	**0.01462**	0.00471
A_1	0.00490	0.00414	0.02315	0.00522		**0.02840**	**0.01576**
A_2	0.00132	0.00201	0.00156	0.01462	0.02840		**0.00676**
D	0.00277	0.00362	0.00693	0.00471	0.01576	0.00676	

According to Table 4, combined with actual situation, a threshold can be given to judge the casual relationship of two nodes. Let the threshold be 0.004. In Bayesian network, if I(X;Y)< 0.004, the casual relationship between X, Y can be neglected. Otherwise, a new directed edge must be appended between X, Y. The refined Bayesian network was shown in Fig 3.

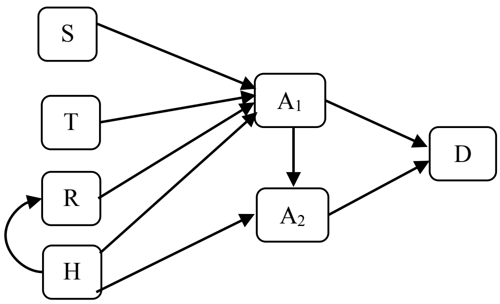

Fig. 3. The refined Bayesian network

4. Parameter learning of Bayesian Networks

4.1. Data sources

In this paper, 902 transportation accidents of HAZMAT were studied from the beginning of 2013 to 2016 which are obtained from the State Administration of Work Safety's website, China Chemical Safety Association website and Chemical Accident Information website. According to the factors mentioned in chapter 3.1, a database for parameter learning was set up. More details were shown in table 5.

Table 5. Database for parameter learning

No	S	T	R	H	A_1	A_2	D
1	2	0	0	0	0	0	0
2	2	1	1	3	5	1	2
3	2	0	0	2	0	1	2
4	2	0	0	1	6	0	2
5	2	0	0	0	0	0	0
...	...	...	...	...	...	...	...
899	2	0	3	2	0	0	2
900	2	0	1	2	0	0	2
901	2	0	0	1	2	0	1
902	2	1	3	2	0	0	2

4.2. Parameter learning of the Bayesian network

1) The estimate of accident handling time and a case test

By using NETICA, a Bayesian network was constructed, as it is shown in Fig 4.

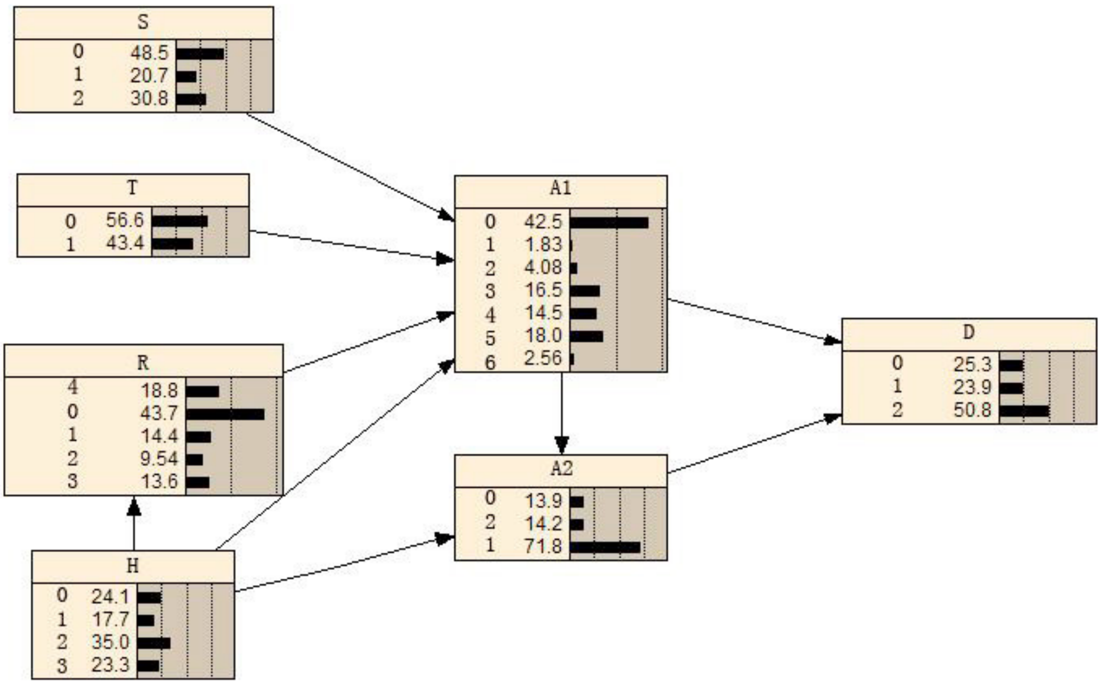

Fig. 4. Bayesian network constructed by NETICA

Suppose that 'The type of road' is 'Highway'(R=0), the Statistical probability and Posterior probability of node 'H' was shown in Table 6.

Table 6. The statistical probability and posterior probability of 'D'(R=0)

P \ D	0~2h（0）	2~4h（1）	>4h（2）
Statistical probability	0.249	0.231	0.520
Posterior probability	0.263	0.247	0.490

According to Table 6, when D=0,the statistical probability is 0.249 while posterior probability is 0.263. The following conclusions can be obtained that the probability of accident handling time is 0~2h improved.

A case test was given as follow: On the 2nd of April, a tank truck rear-ended at 7:50pm on urban road in Jurong city, Jiangsu province. These keywords can be obtained: ‘spring’, ‘night’, ‘urban road’, ‘rear-end’, ‘leakage’. According to these keywords, the 5 nodes could be confirmed: S=0, T=1, R=4, A1=0, A2=1. The Statistical probability and Posterior probability of node ‘H’ was shown in Table 7.

Table 7. The statistical probability and posterior probability of ‘D’ in the case

P \ D	0~2h（0）	2~4h（1）	>4h（2）
Statistical probability	0.249	0.231	0.520
Posterior probability	0.181	0.190	0.629

The calculation results are showed in Table 7, that the probability of handling time in ‘>4h’ is maximum (0.629). It is far over the statistical probability (0.520). Therefore, the handling time of this accident is most likely to be ‘>4h’ and the other possibilities could be ignored. The actual handling time of this accident was 8 hours, which is corresponding to the estimate.

2) Assessment of accident handling difficulty

Based on Bayesian network, we can measure the difficulty of handling various types of accidents by observing the probability changes of node A1and A2 as well as setting different conditions----assuming the handling time > 4h (P(P=2)). To check more details please refer to table 8 and 9.

Table 8. The statistical probability and posterior probability of ‘A_1’

	Former accident（A_1）						
	Roll over（0）	Vehicle body fire（1）	tire failure（2）	Internal fault（3）	Vehicle body fire（4）	Rear-end（5）	（6）
Statistical probability	0.442	0.017	0.041	0.150	0.143	0.184	0.023
Posterior probability	0.500	0.008	0.026	0.129	0.124	0.179	0.033

Table 9. The statistical probability and posterior probability of ‘A_2’

	Secondary accident（A_2）		
	Leakage（0）	Combustion explosion（1）	None（2）
Statistical probability	0.744	0.123	0.133
Posterior probability	0.789	0.105	0.106

Table 8 and 9 showed that, among all kinds of former accidents, the probabilities with handling time> 4 hours can be sorted in a decrease turn as followed: P(A1=0)> P(A1=5)> P(A1=3)≈ P（A1=4）> P（A1=6）> P（A1=2）> P（A1=1），it illustrated that when a rollover accidents occurred, the handling process will consume a lot of time and also brings great difficulty. Among all kinds of secondary accidents, the ones with handling time> 4 hours can be sorted in a decrease turn as followed: P（A1=0）> P（A1=1）, it reveals the truth that when a leakage accident occurred, it usually means the handling process is very difficult to handle.

5. Conclusion

Based on the statistics of all 902 accidents occurred during 2013-2016 and analyzing the data with the method of Bayesian network, we can get such conclusions:

1) Comparing with fault tree and bow tie model etc, Bayesian network can better illustrate the casual relationships of all nodes in detail.

2) With the help of Bayesian network, an estimate of the handling time of transportation accidents of HAZMAT can be obtained. We can use this model to predict the probability of totally handling the accident within 0-2h, 2-4h and more than 4 h with the preliminary information from alarm calls.
3) The posterior probability of adjusting node D via Bayesian network is 1, it can help us ration the difficulty of handling different kinds of former accidents and secondary accidents. The result is as followed: rollover> rear-end> internal fault ≈ impact> falling> tire fault> vehicle body fire. Leakage>combustion explosion.

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