Study on risk assessment of expressway nighttime maintenance construction: A Dynamic Bayesian Network model

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Abstract. There are many risk factors and large uncertainties in expressway nighttime maintenance construction (ENMC), and the state of risk factors will change dynamically with time. In this study, a Dynamic Bayesian Network (DBN) model was proposed to investigate the dynamic characteristics of the time-varying probability of traffic accidents during expressway maintenance at night. Combined with Leaky Noisy-or gate extended model, the calculation method of conditional probability is determined. By setting evidences for DBN reasoning, the time series change curve of the probability of traffic accidents and other risk factors are obtained. The results show that DBN can be applied to risk assessment of ENMC.

1 Introduction

Accident statistical analysis and research showed that the accident rate and fatality rate of nighttime maintenance construction operations are much higher than that of day maintenance construction [1]. In order to analyze the risk of expressway construction work area, Kairan Zhang et al. [2], Yingfeng Li et al. [3], Xianghai Meng et al. [4], Sze and Soong [5], and Higa et al. [6] identified operation-related risk factors. Xinxin Wei et al. [7] analyzed accidents under different illumination conditions. The severity was studied. Biao Wu et al. [8] conducted risk assessment on risk factors in the work area; Jikun Liu et al. [9] proposed a LECT evaluation method that can identify key risk factors in the operation process; Rahman et al. [10] studied the effect of dynamic information signs on controlling the speed of the driver. The current researchers mainly focus on the identification and evaluation of risk factors in the daytime maintenance of expressways or the construction operations of new construction, renovation and expansion. However, ENMC's quantitative risk analysis is still lack of systematic research. DBN is a higher efficient approach to risk analysis [11]. Therefore, it is a very important way to quantitatively analyze the risks of ENMC through the DBN method.

2 Dynamic Bayesian Network

A DBN is a Bayesian network extended with additional mechanisms that are capable of modeling influences over time [12]. Hidden Markov model is considered the simplest DBN [13]. Due to the system change characteristics of the DBN, directly perform analysis and modeling is hard to obtain. Therefore, in order to

minimize the difficulty of usage, the two hypotheses are proposed as follow:

- (1) Markov hypothesis: the future state is only related to the present and has nothing to do with the past.
- (2) Static hypothesis: adjacent random processes within a finite time are stable and consistent at any time t .

The general structure of the DBN is shown in Fig.1.

Fig.1 The general structural of the DBN

3 Methodology

3.1 Defining the risk factors used in the ENMC model

According to literature review, our study is to investigate the ENMC workplace, including conduct lots of surveys with relevant personnel. The Operational risk factors were identified through a combination of literature review, on-site investigation and personnel interviews. The risk factors are divided into 5 categories: Driver(D), environment(E), Highway(H), Vehicle(V), and Workzone(W), and corresponding secondary indicators are shown in Table 1.

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Table 1. Description of risk factor

No.	Risk factor	Description
1	D	D1 Driving experience
2		D2 Night line of sight
3		D3 over-speed driving
4		D4 Fatigue driving
5		D5 Dangerous driving
6		D6 Aggressive driving
7		D7 Driving error
8	E	E1 temperature
9		E2 Light
10		E3 weather
11		E4 Traffic volume
12		E5 Traffic composition
13		E6 Indicator visibility
14	H	H1 Speed limit
15		H2 Number of lanes
16		H3 Road conditions
17		H4 Geometric Features
18		H5 Maintenance location
19	W	W1 Operator fatigue
20		W2 Unsafe behavior of workers
21		W3 Job skills and knowledge mastery level
22		W4 Pre-job education and training and clarification
23		W5 Illegal command
24		W6 Operation error
25		W7 Guardianship error
26		W8 Work area settings
27		W9 Work area lighting
28		W10 Traffic safety facilities
29		W11 Construction time
30	V	V1 Vehicle Type
31		V2 Overload or overrun
32		V3 Brake failure of vehicle
33		V4 Tire burst or drop
34		V5 The vehicle is out of control
35		V6 Construction vehicle breakdown
36		V7 Construction vehicles enter and exit the work area

3.2 Defining the structure of the ENMC model

As a modeling tool dedicated to the construction and analysis of graphical decision-making theory models [14], the professional analysis software GeNIe3.0 (academic version) can be used to build a probability assessment models and data inference.

Input the basic data into the Bayesian network constructed by the GeNIe, performing DBN inference, and selecting the prior probability of key time nodes for real-time updating. The dynamic reasoning results are revised and integrated through machine learning to realize the mutual complementation of mathematical theories and expert knowledge, thereby further improving the scientificity and rationality of the evaluation results.

According to the risk events and secondary indicators identified in Table 1, the DBN model shown in Figure 2 is constructed. Where R represents the risk of traffic accidents in the workplace.

During the site investigation, we found that the time of ENMC is a total of 9 hours usually from 9:00 PM to 6:00 AM the next day, so the DBN constructed in this study can establish an hourly time point to the event node, A total of 10 time steps to represent the changing events evolution mechanism (The temporal plate division can be adjusted according to the actual situation of each place). The proposed model can be seemed as a tool to calculate the traffic accident risk of ENMC. The time dependence of nodes and arcs in the model can be adjusted according to the conditions of a specific area. This model is designed to support time-related operational decision-making to reduce the value of the node R(risk of traffic accidents in the work area), such as adjusting traffic volume and selecting vehicle speed limits. For example, in this study, we assumed that ENMC is in progressing, and the time-series changes of traffic volume and operation area in the area are constantly observed during the operation. The correlation among those indicators can be reflected by pointed arrows in the GENIE3.0. The directed arc segment "1" on each parent node indicates that the time interval between adjacent time slices is 1 hour. We can clearly displays those indicators and its sub-indicators by different colours as shows in Fig.2.

Fig. 2 DBN model structure of ENMC

3.3 Conditional probability table

By experts scoring to the probability of each time state, the prior probability, conditional probability and original transition probability of all the parent nodes of an event are obtained. To standardize the probabilistic expression during scoring and make the scoring data easy to refer to and distinguish, the 7-level risk probability expression method proposed from the United Nations Intergovernmental Panel on Climate Change (IPCC) is adopted to our study[16]. Considering the statistical data of expressway traffic accidents studied from a China expressway management company, the probabilities of traffic accidents are ranking in 10^{-5} to 10^{-4} . In the study, all of values of those probabilities are multiplied by 10^{-4} for sake of take the risk analysis into the most dangerous place. In next stage, based on the relevant data by the expert survey method, the conditional probability table of the entire network is calculated according to the noisy-or-gate model[17]. The prior probability, conditional probability and original transition probability are input to GENIE3.0 for DBN inference. Because of space limits of this paper, only node E5 can be regarded as an example to present the conditional probability table, as shown in Fig.3. Y represents the occurrence or development of the risk factor in the wrong direction, while N is the opposite of Y.

	E2	E3	E4	Y	N
Y	0.391304	0.382352	0.2356842	0.137096	
N	0.608695	0.617647	0.763157	0.862903	

Fig. 3 Conditional probability table for the variable E5

4 Scenario analysis and evaluate of DBN model

In this study, four nodes E4, D, W1 and V2 are used for evidence setting. Fig.4 shows the evidence settings for the four nodes. These evidences are not set randomly, which should be according to the actual characteristics of the expressway at night. For example, in the case of E4 (traffic volume), when the traffic is heavy from 9:00 PM to 12:00 PM, we can select "Y" to indicate the occurrence of risk event. From 0:00 AM to 5:00AM, we can choose "N" when the traffic volume decreases. When the traffic volume increases after 5:00 AM, we can choose "Y". The other three "Evidence" settings also follow the above logic, so these four evidences can be established.

Dynamic Evidence: E4

Time	Evidence
0	Y
1	Y
2	Y
3	N
4	N
5	N
6	N
7	N
8	Y
9	Y

Dynamic Evidence: W1

Time	Evidence
0	N
1	N
2	N
3	N
4	Y
5	Y
6	Y
7	Y
8	Y
9	Y

Dynamic Evidence: D

Time	Evidence
0	N
1	N
2	N
3	Y
4	Y
5	Y
6	Y
7	N
8	N
9	N

Dynamic Evidence: V2

Time	Evidence
0	N
1	N
2	N
3	N
4	Y
5	Y
6	Y
7	Y
8	N
9	N

Fig. 4 Evidence setting

Input the evidence into the DBN model to perform DBN forward inference, and the results are shown in Fig.5, Fig.6 and Table 2. Among them, R in Table 2 and Fig.5 represents the probability of a traffic accident in a hazard state at ENMC.

Fig. 5 DBN model with evidence input

Table 2. Dynamic reasoning results

Node	T=0	T=1	T=2	T=3	T=4	T=5	T=6	T=7	T=8	T=9
E1	0.17	0.20	0.20	0.17	0.17	0.17	0.17	0.17	0.20	0.20
E2	0.18	0.31	0.31	0.14	0.14	0.14	0.14	0.14	0.31	0.31
E3	0.19	0.33	0.33	0.15	0.15	0.15	0.15	0.15	0.33	0.33
E4	1	1	1	0	0	0	0	0	1	1
E5	0.21	0.36	0.36	0.15	0.15	0.15	0.15	0.15	0.36	0.36
E6	0.19	0.24	0.24	0.18	0.18	0.18	0.18	0.18	0.24	0.24
E	0.16	0.27	0.27	0.06	0.06	0.06	0.06	0.06	0.27	0.27
H1	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
H2	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
H3	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
H4	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
H5	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
H	0.09	0.11	0.11	0.08	0.08	0.08	0.08	0.08	0.11	0.11
eD1	0.16	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
D2	0.08	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
D3	0.15	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
D4	0.17	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
D5	0.06	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
D6	0.15	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
D7	0.17	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
D	0	0	0	1	1	1	1	0	0	0
V1	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
V2	0.23	0.24	0.24	1	1	0.24	0.24	0.24	0.24	0.24
V3	0.13	0.13	0.13	0.18	0.18	0.13	0.13	0.13	0.13	0.13
V4	0.19	0.20	0.20	0.36	0.36	0.20	0.20	0.20	0.20	0.20
V5	0.15	0.15	0.15	0.32	0.32	0.15	0.15	0.15	0.15	0.15
V6	0.11	0.11	0.11	0.33	0.33	0.11	0.11	0.11	0.11	0.11
V7	0.08	0.09	0.09	0.21	0.21	0.09	0.09	0.09	0.09	0.09
V	0.27	0.22	0.22	0.24	0.29	0.28	0.28	0.28	0.29	0.29
W1	0	0	0	0	1	1	1	1	1	1
W2	0.08	0.09	0.09	0.09	0.14	0.14	0.14	0.14	0.14	0.14
W3	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
W4	0.16	0.15	0.15	0.15	0.36	0.36	0.36	0.36	0.36	0.36
W5	0.12	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
W6	0.08	0.08	0.08	0.08	0.10	0.10	0.10	0.10	0.10	0.10
W7	0.10	0.11	0.11	0.11	0.15	0.15	0.15	0.15	0.15	0.15
W8	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
W9	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
W10	0.07	0.08	0.08	0.08	0.10	0.10	0.10	0.10	0.10	0.10
W11	0.11	0.12	0.12	0.12	0.23	0.23	0.23	0.23	0.23	0.23
W	0.13	0.18	0.18	0.14	0.34	0.34	0.34	0.34	0.38	0.38
R	0.13	0.08	0.08	0.21	0.24	0.24	0.24	0.12	0.14	0.14

We can see from Fig.5 that the probability of risk factor D1 is the only node exceeding 50%, Node E4 and W1 are affected by the evidence input, and they are actually 7% and 17% respectively when no evidence is input, indicating that the node D1 is the most significant risk in the driver dimension factor with 54%. The most noteworthy of the other four dimensions are H2 (21%) , V2 (24%) , E5 (15%) and W4 (17%) .

Among the five first-level indicators, except for the decline in the probability of nodes H and E, the other three have a significant increase. The changing trends of all the first-level indicators are H (-3%), D (+8%), V (+13%), W (14%) and E (-7%). The risk of R in the hazard state has risen from 11% to 21%. The other remaining nodes' probability has changed not over 5%.

Fig. 6 Time steps variable curves of probability of risk factors

It can be seen from Table 2 and Figure 5 that after setting the evidence node, the secondary indicators in the E dimension are obviously affected by E4, and the trend is opposite to E4. The secondary indicators in the H and D dimensions are less affected, and the probability of occurrence only increases slightly when the time steps are 0~1. The change trend of the second-level indicator probability in the W dimension is consistent with the W1 evidence setting, indicating that W1 is positively correlated with other second-level indicators. The change trend of R presents a W shape, and the probability has gone through two processes of first falling and then rising, demonstrating that the four evidence nodes have a significant impact on R.

5 Conclusions

The risk factors of EMNC operations are uncertain and are prone to dynamic changes over time. In this paper, we had proposed a DBN to investigate the dynamic characteristics of the time-varying probability of traffic accidents during expressway maintenance at night. The results show that node D1 (driver skill) is the most significant factor for node R (traffic accident). The DBN is capable of simulating temporal relationships in ENMC. Besides, a Chinese related company has also participated in the data collecting and provided historic statistical probability in traffic accidents. Combined with Leaky Noisy-or gate extended model, the calculation method of conditional probability is determined. By setting evidences for DBN reasoning, the time series change curve of the probability of traffic accidents and other risk factors are obtained.

In the case of setting evidence, risk can also be quantified. These quantitative risk assessments provide a basis to dynamic risk management and control on the workplace along with improve the accuracy of risk estimation. The results show that DBN can be applied to risk assessment of ENMC and other critical process construction work systems.

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