Research on Risk Assessment of Truck Rear-end Accident Based on Bayesian Network Model

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Abstract:

In order to minimize the occurrence of truck rear-end accidents and reduce the severity of accidents. Based on the in-depth investigation data of truck traffic accidents, this paper studies and determines risk factors set of truck rear-end accidents from four aspects: driver, vehicle, road and environment. Based on Bayesian theory, Bayesian network model was constructed by using Netica software. The Bayesian network structure was established by using data fusion method, and Expectation-Maximization algorithm that could process missing data was adopted to train the parameter in Netica. The model verification has been shown that the model was effective and can be used for the risk analysis and assessment of truck rear-end accidents. Bayesian network model in this paper has been used to quantitatively analyze the sensitivity of each risk factor and the significant risk factors of different risk levels in truck rear-end accidents have been put forward. The research results in this paper have been of important reference value for the formulation of prevention measures for truck rear-end accidents.

Keywords: *Truck, Rear-end accident, Bayesian network model, Quantitative analysis, Risk assessment.*

I. INTRODUCTION

In recent years, with the rapid development of China's logistics industry, the road transportation industry has become increasingly busy, and the number of road traffic accidents caused by trucks has increased year by year. According to the National Road Transportation Safety Development Report, there were 26,715 operational trucks traffic accidents in 2016, resulting in 14,256 deaths and a direct economic loss of approximately 300 million yuan. The traffic safety situation of truck is very severe[1]. Truck rear-end accidents account for a high proportion in traffic accidents in China, and more than 90% of trucks are flat headed at present[2]. Once truck rear-end accidents occur, the loss consequences are quite serious. Therefore, it is of great significance to study the risk factors of truck rear-end accidents and evaluate the risk level of the accident scientifically, so as to effectively prevent or reduce the rear-end accidents and improve the road transportation environment.

At present, domestic and foreign experts have conducted research on the influencing factors and severity of truck rear-end accidents, and have made some achievements. Quan Yuan[3] used a binary logistic regression model to establish the relationship between the severity of personal injury and influencing factors in the truck rear-end accidents. Yong Peng[4] established an ordered logistic regression model based on the truck accident data of expressway, and determined the influencing factors of the injury severity of rear truck drivers and co-drivers. Yong Jo[5] proposed a method to predict the collision risk level by using the WIM (dynamic weighing system) data of heavy trucks, and studied the possibility and potential risk of heavy truck rear-end collision accidents on expressways. Champahom Thanapong[6] constructed a hierarchical logistic model for the severity of rear-end accidents using the traffic accident data of Thailand, and studied the important risk factors of rear-end accidents on urban and rural roads. Qiang Luo[7] comprehensively considered the risk factors of response time and road adhesion coefficient, and studied the relationship between each risk factor and the minimum following distance using a comprehensive weighted analysis method and a neural network model. Based on the comprehensive consideration of road traffic safety risk factors, Xin Zou[8] uses Bayesian network theory to study the risk factors of road traffic accidents, and quantitatively predicts the probability of road traffic accidents. Yaping Li[9] used single-factor analysis of variance to analyze rear-end risk between professional and non-professional drivers, established a rear-end accident risk assessment model for drivers. Chaoyong Sun[10] established a fault tree model of influence of human factors on automobile rear-end accidents, applied the down-line method to find the shortest set of the fault tree, and found the most important human factors from probability and critical importance. According to the mechanism of road traffic accidents, Yadong Yang[11] introduced the catastrophe theory to analyze the risk factors, and constructed the coattail catastrophe model, which verified the feasibility of the model in the accident analysis. Taking the data of U.S. highway rear-end accidents as research samples, Benmin Liu[12] established a Binary classification model of vehicle rear-end accidents based on SVM, and studied the key influencing factors of Multiple rear-end collision. Peng Wang[13] screened the road traffic accident data of North Carolina and analyzed the severity of rear-end accident and important influencing factors by using ordered probit model.

The above research work is mostly based on single-factor analysis or multi-factor analysis of representation, ignoring that the occurrence of rear-end accident is the result of multiple risk factors interacting and acting together. Based on the theory of traffic accident causes, this paper comprehensively considers the operational safety risk factors of trucks, and uses Bayesian network (Netica) to build a risk assessment model of truck rear-end accidents. Quantitative analysis of the sensitivity of the risk factors of truck rear-end accidents, evaluation and judgment of significant risk factors, provides an important reference for formulating effective accident prevention countermeasures.

II. MATERIALS AND METHODS

2.1 Accident Data Source

In this paper, the case of truck rear-end accidents used come from National Automobile Accident In-depth Investigation System (NAIS) - Shandong Work Station. At present, there are more than 1,000

in-depth investigation accident cases in the workstation database, among which more than 200 truck accident cases.

2.1.1 Principles for selecting accident samples

In order to meet the research needs of the thesis, the screening conditions for accident samples are as follows:

(1) Number of accident participants: In order to facilitate research and analysis, the number of accident participants is strictly defined as two.

(2) Types of accident vehicles: The types of accident vehicles are all trucks (light trucks, medium trucks, heavy trucks, alticulated vehicles), and the sample of accidents does not include minivans.

(3) Casualties of accident participants: at least one of the participants in the accident has ordinary or above injuries (AIS $\geq$ 3).

(4) Integrity of accident sample data information: the selected accident sample data information must be complete to ensure that the analysis conditions are met.

2.1.2 Statistical analysis of accident data

According to the selection conditions of the above accident samples, a total of 95 cases of truck rear-end accidents were screened from the NAIS accident case database for research and analysis, of which 85 accident cases were randomly selected for parameter learning of the Bayesian network model, and the remaining 10 accidents cases are used for model verification.

According to the data statistical analysis of 95 selected accident cases, Fig 1 shows the proportion of accident vehicle types, and Fig 2 shows the casualties of accident participants. As can be seen from Figure 1, there are 95 alticulated vehicles in the type of accident vehicles, accounting for 50% of the total number of accident vehicles; followed by 47 heavy trucks, accounting for 24.7% of the total number of accident vehicles; only 9 dangerous goods transportation vehicles, accounting for about 4.7%. As can be seen from Fig 2, a total of 257 people participated in the accident, of which 82 people died, accounting for 32% of the total number of casualties; only 5 people were slightly injured, accounting for about 2%. According to the statistical analysis of accident data, it can be seen that alticulated vehicles and heavy vehicles account for a relatively high proportion of truck rear-end accidents, and the consequences of accidents caused by such vehicles are more serious.
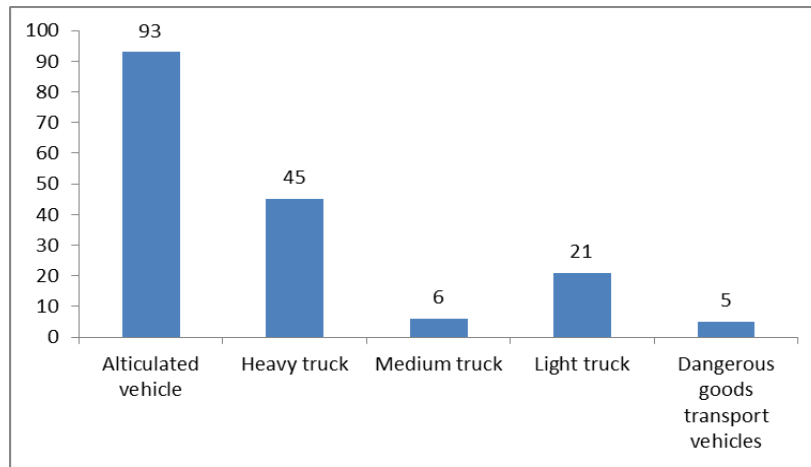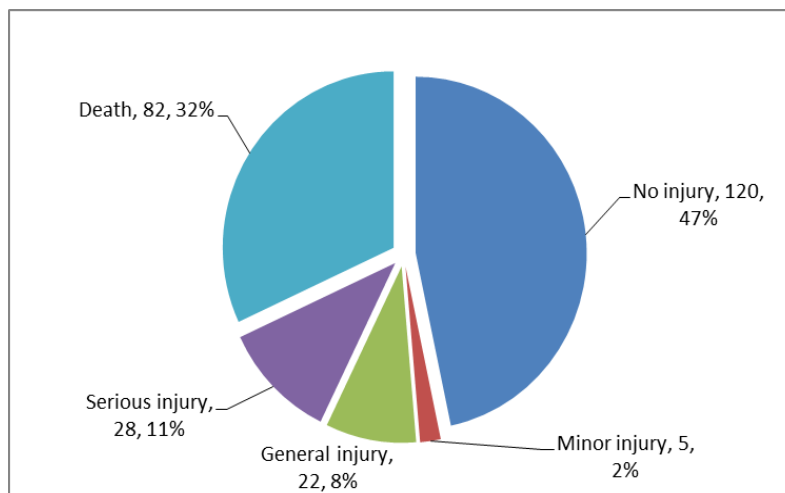
Fig 1: proportion of accident vehicle types

Fig 2: proportion of casualties in accidents

2.2 Construction and Verification of Bayesian Network Model

Bayesian network, also known as belief network, is a directed acyclic network topology graph composed of node sets and directed edges. Each node represents a variable state, while directed edges represent the dependency between variables. The conditional probability Table (CPT) is used to describe the correlation strength or confidence coefficient between variables [14].

Bayesian network model construction mainly includes two processes: structure learning and parameter learning. Structure learning is to determine the dependence or independent relationship between the factor variables (nodes) related to the research object and the nodes, and to construct a directed acyclic network structure, which is the basis of Bayesian network learning. Parameter learning is based on the constructed Bayesian network structure, using the accident sample data to learn the conditional probability table (CPT) of each node in the Bayesian network model. Due to the timeliness and uncertainty of road traffic accident

trace evidence, as well as the subjective and objective influencing factors of accident data collection, there are often cases of missing accident data. In Bayesian network analysis software-Netica, the EM algorithm can perform maximum likelihood estimation on unknown parameters in the incomplete data sets, thus ensuring the relative integrity of the data set. This paper uses the method of combining expert experience and machine learning to construct Bayesian network structure, and uses EM algorithm to learn the parameters of Bayesian network structure, aiming to improve the accuracy of the model.

2.2.1 Model building

2.2.1.1 Node variable definition

Based on the theoretical research on the causes of traffic accidents, through statistical analysis of the selected accident sample data, 19 risk factors were selected as evidence nodes, namely driver age $X1$, driving age $X2$, fatigue driving $X3$, distracted attention $X4$, unsafe Driving distance $X5$, illegal parking $X6$, not set safety warning device $X7$, speeding $X8$, overload driving $X9$, illegal loading $X10$, low speed driving $X11$, rear reflective signs $X12$, road grade $X13$, road alignment $X14$, road surface status $X15$, Lighting condition $X16$, weather condition $X17$, traffic environment $X18$ and accident occurrence time $X19$, the definition of each risk factor attribute is shown in TABLEI. At the same time, driver factor $Y1$, vehicle factor $Y2$, road factor $Y3$ and environment factor $Y4$ are regarded as the intermediate nodes of Bayesian network model. Each intermediate node is divided into three risk levels: "1" represents less risk, "2" represents general risk, and "3" represents greater risk. The target node "T" (the rear-end accident severity level) is divided into three levels according to the casualties of the accident participants: "1" represents low severity, "2" represents general severity, "3" represents high severity. The classification principle is shown in TABLE II.

TABLE I. Definitions of evidence node variables and attributes

NODE VARIABLE CODE	NODE VARIABLE ATTRIBUTE RANGE
X1	1: 21~30 years old; 2: 31~40 years old; 3: 41~50 years old; 4: 51~60 years old
X2	1: 1~5; 2: 6~10; 3: More than 10 years
X3	Y: Yes; N: No
X4	Y: Yes; N: No
X5	Y: Yes; N: No
X6	Y: Yes; N: No
X7	Y: Yes; N: No
X8	Y: Yes; N: No
X9	Y: Yes; N: No
X10	Y: Yes; N: No
X11	Y: Yes; N: No
X12	Y: Yes; N: No

X13	1: Expressway; 2: National highway; 3: Provincial Highway; 4: County Highway
X14	1: Straight; 2: General slope
X15	1: Dry; 2: Damp
X16	1: Day; 2: No street lighting at night; 3: Street lighting at night
X17	1: Sunny; 2: Cloudy; 3: Rainy; 4: Foggy
X18	1: Good; 2: Crowd
X19	1: 0~6; 2: 7~12; 3: 13~18; 4: 19~24

TABLE II. Principles of accident severity division

SEVERITY LEVEL	DIVISION PRINCIPLE
1	Seriously injured 1 ~ 2 people or slightly injured more than 3 people
2	1 person died, or more than 2 people were seriously injured
3	Two or more people were dead

To meet the requirements of the Netica software platform, compile the statistical data of 85 accident samples into an accident sample data set (as shown in TABLE III), and set it to Case File Format, using the string "// ~- > [CASE-1]-> ~ " means. In the process of accident data statistics, the unavailable index data is replaced with "*", which means that the data is missing. TABLE III is the incomplete risk factor data set with a missing rate of 1%.

TABLE III. Principles of accident severity division

//~->[CASE-1]->~											
IDnum	X1	X2	X3	X4	X5	X6	X7	X8	…	X18	X19	T
1	3	4	N	N	Y	Y	N	N	…	1	1	2
2	3	4	Y	Y	Y	N	N	N	…	1	1	2
3	3	3	N	Y	Y	Y	N	N	…	1	1	2
4	1	1	N	Y	Y	N	N	*	…	1	1	2
5	2	3	N	Y	N	N	Y	N	…	1	1	1
6	2	3	N	Y	Y	N	N	N	…	1	1	2
7	3	3	N	N	Y	N	N	N	…	1	2	1
8	2	3	Y	Y	Y	N	N	N	…	1	1	3
…	…	…	…	…	…	…	…	…	…	…	…	…
85	3	4	N	Y	Y	N	N	N	N	1	3	1

2.2.1.2 Bayesian network structure learning

According to the expert experience knowledge, the node variables and network structure of Bayesian

network are determined. The accident sample data set in TABLE Ⅲ is used to learn and optimize the network structure in the Netica software platform. The completed Bayesian network structure is shown in Fig 3. Bayesian network does not perform data parameter learning, and the reliability grids in node variables are equal in Fig 3.
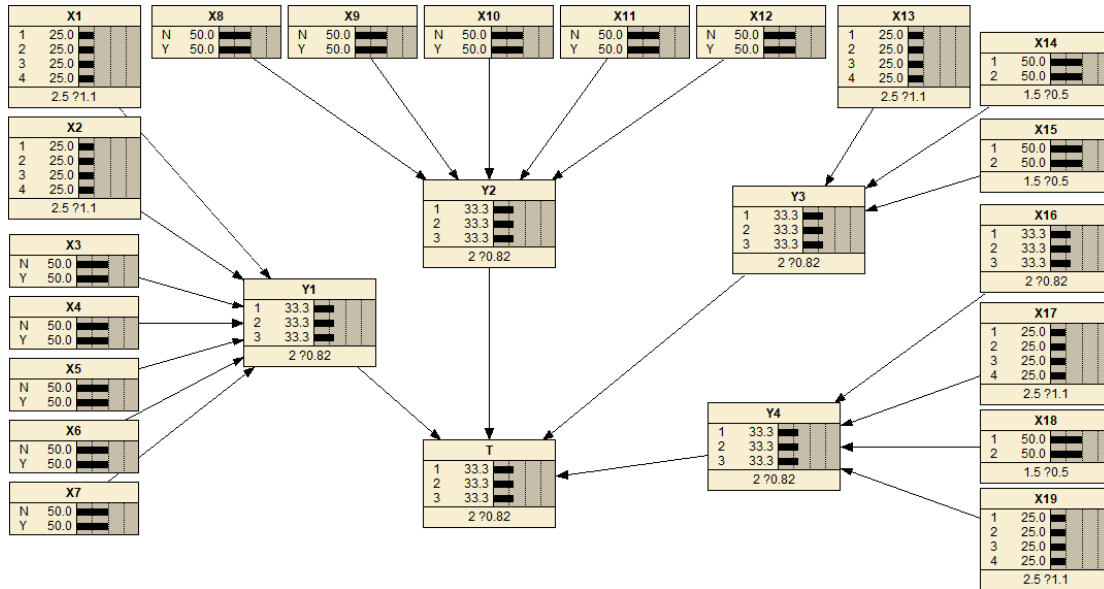

Fig 3: Bayesian network structure model (untrained)

2.2.1.3 Bayesian network parameter learning

For the constructed Bayesian network structure model, the EM algorithm is used to learn the parameters of the model, and the conditional probability distribution of each node is obtained. After the parameter learning, the reliability grid of each node in the Bayesian network model changes, as shown in Fig 4.
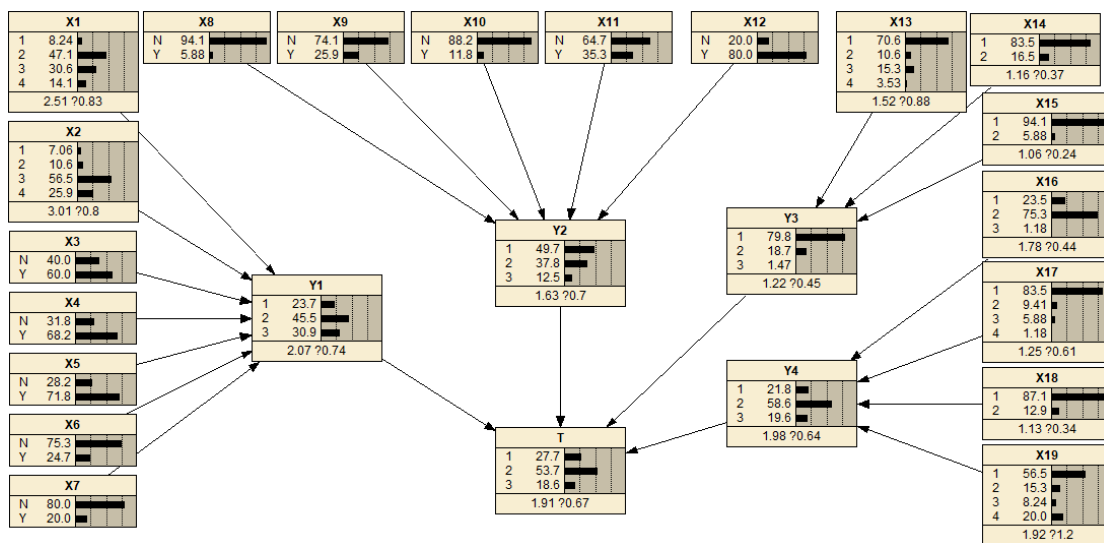

Fig 4: Bayesian network model (trained)

2.2.2 Model validation

The validity of the established Bayesian network model is verified by using 10 accident samples randomly selected. The accident sample data set used for verification is shown in TABLE IV. Considering that the change of evidence nodes will not have any impact on the intermediate nodes after the intermediate nodes are determined, the model validation process needs to be carried out in sections.

The model verification process is carried out according to the following steps: First, input the evidence node data in the verification sample into the model, and observe whether the intermediate node calculation data value after the model update matches the verification sample intermediate node data value. Then input the verification sample intermediate node data into the model, observe whether the calculated data value of the target node after the model update matches the data value of the target node of the verification sample.

Input the values of evidence nodes X1 ~ X19 in TABLE Ⅳ into the Bayesian network model in Fig 4, and automatically update the probability of Bayesian network nodes. The output result of the updated model is shown in Fig 5.

TABLE IV. Validation sample dataset

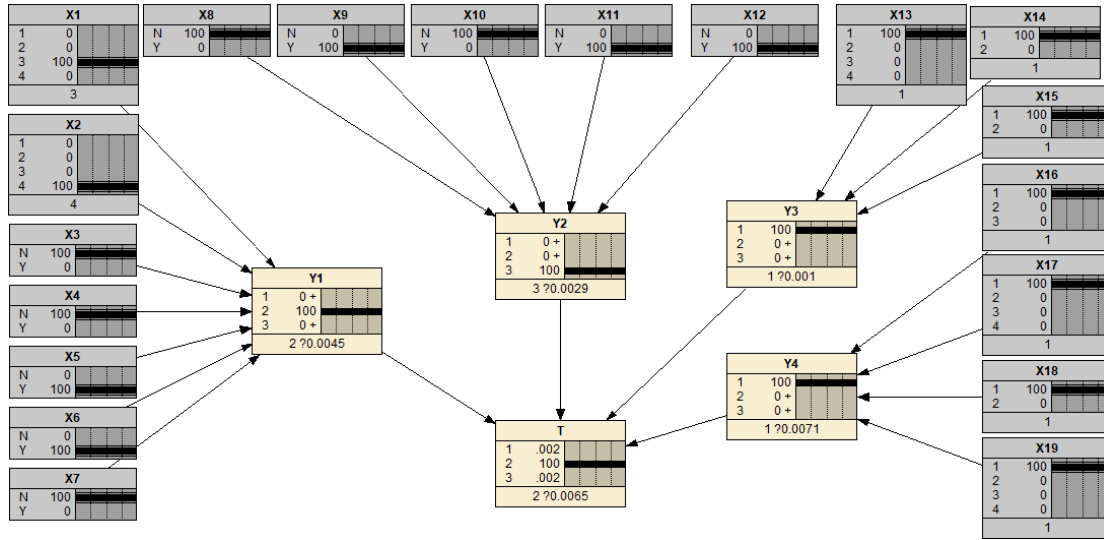| NODE	NODE ATTRIBUTES	NODE	NODE ATTRIBUTES	NODE	NODE ATTRIBUTES
X1	3	X9	Y	X17	1
X2	4	X10	N	X18	1
X3	N	X11	Y	X19	1
X4	N	X12	Y	Y1	2
X5	Y	X13	1	Y2	3
X6	Y	X14	1	Y3	1
X7	N	X15	1	Y4	1
X8	N	X16	1	T	2

Fig 5: Bayesian network model (numerical input of evidence nodes)

It can be seen from Fig 5 that the calculated data values of the four intermediate node variables Y1, Y2, Y3 and Y4 are consistent with the data values of the intermediate nodes in the validation sample in TABLE Ⅳ. Continue to verify the target node, input the data value of the intermediate node in TABLE Ⅳ into the Bayesian network model in Fig 4, and automatically update the Bayesian network model. The output result of the updated model is shown in Fig 6.
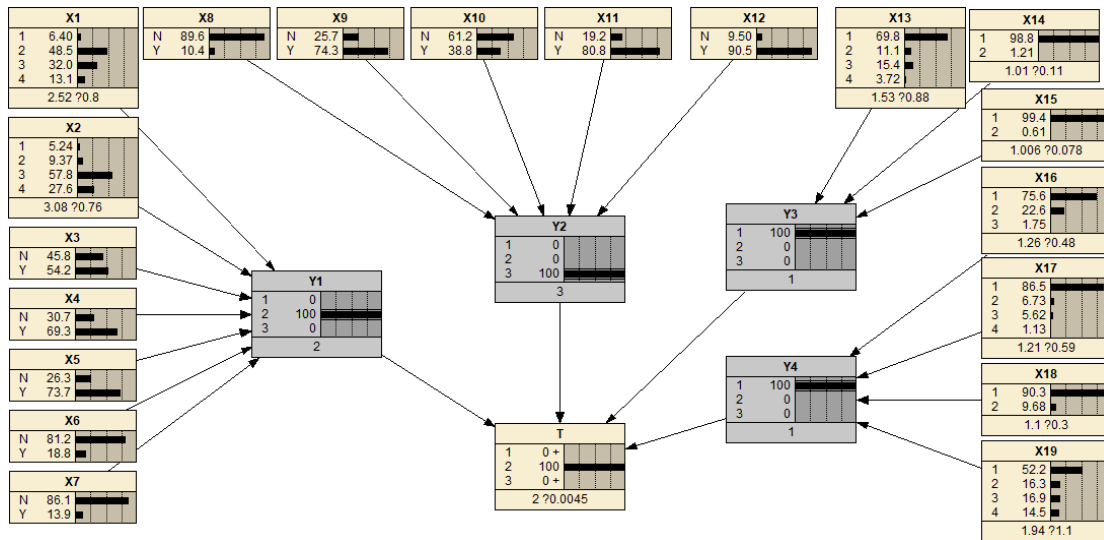

Fig 6: Bayesian network model (numerical input of intermediate nodes)

It can be seen from Fig 6 that the calculated data value of the target node of the Bayesian network model is consistent with the data value of the target node of the validation sample in TABLE IV. According to the above procedures, the model validation was carried out for the remaining 9 accident

sample data one by one, and the model validity was represented by the consistency P, and the validation results are shown in TABLE V.

TABLE V. Validation sample dataset

GOODNESS of FIT(*P*)	*P*=100%	*P*=80%	*P*<80%
Number of samples	8	2	0

According to the above verification results, under the condition of the existing accident sample size, the Bayesian network model constructed in this paper has a high consistency (more than 80%), and this model can be used for quantitative analysis and assessment of the risk of truck rear-end accidents.

III. RESULTS AND DISCUSSION

By using the bidirectional inference technology of Bayesian network model, the posterior probability of each risk factor is deduced reversely when the target node state is determined. The sensitivity of each risk factor of truck rear-end accident can be quantitatively analyzed, and the significant risk factors of different risk levels of truck rear-end accident can be proposed.

3.1 Quantitative Analysis of the Sensitivity of Accident Risk Factors

Based on the sample data of truck rear-end accidents, the sensitivity of accident risk factors is quantitatively analyzed by Bayesian network model. First, input the data value of the target node in the Netica software (T = 3, probability p = 100%), then perform the automatic update function in the Netica software to update the whole model probability, and the posterior probability output results of each risk factor after the update are shown in Fig 7.
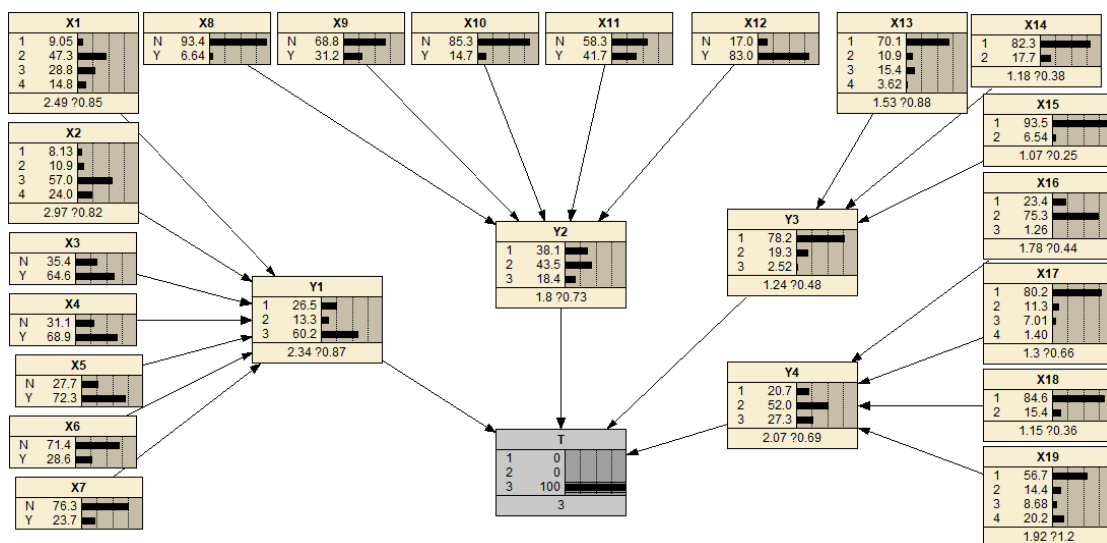

Fig 7: Bayesian network model posterior probability (T=3, P=100%)

According to the output of Bayesian network model, the sensitivity of each intermediate node variable is analyzed quantitatively. Compare the posterior probability of each intermediate node variable in Fig 7 with the prior probability in Fig 4, calculate the sensitivity of each intermediate node variable, and sort the intermediate node variables according to the maximum sensitivity in the variable attribute of each node, and the results are shown in TABLE VI.

TABLE VI. Sensitivity ranking of intermediate node variables

	Y1			**Y2**			**Y3**			**Y4**		
SEVERITY LEVEL	1	2	3	1	2	3	1	2	3	1	2	3
PRIORI PROBABILITY	23.7	45.5	30.9	49.7	37.8	12.5	79.8	18.7	1.47	21.8	58.6	19.6
POSTERIOR PROBABILITY	26.5	13.3	60.2	38.1	43.5	18.4	78.2	19.3	2.52	20.7	52.2	27.3
SENSITIVITY	2.8	-32.2	29.3	-11.6	5.7	5.9	-1.6	0.6	1.05	-1.1	-6.4	7.7
SORT	1			3			4			2		

According to the analysis in TABLE VI, when the target node state "T = 3", the posterior probability of Y1 (driver factor) is the highest (60.2%) and its sensitivity is the highest (29.3%). The posterior probability of Y3 (road factor) is the lowest (2.52%) and its sensitivity is the lowest (1.05%). It can be seen that when the severity of truck rear-end accident is level "3", the driver factor is the most sensitive among the intermediate node variables, and the road factor is the least sensitive. The sensitivity ranking results of the risk factors are Y1 > Y4 > Y2 > Y3.

3.2 Significance Assessment of Accident Risk Factors

According to the output results of Bayesian network model (shown in Fig 7), the sensitivity of various risk factors of drivers is quantitatively analyzed, and the ranking results are shown in TABLE VII. According to the analysis in TABLE VII, the posterior probability of factor X3 (fatigue driving) is 64.6%, and its sensitivity is the highest (4.6%). Therefore, it can be considered that fatigue driving is the most sensitive significant risk factor among driver risk factors.

TABLE VII. Sensitivity ranking of driver risk factors

FACTOR	**X1**				**X2**				**X3**	**X4**	**X5**	**X6**	**X7**
SEVERITY LEVEL	1	2	3	4	1	2	3	4					
PRIORI PROBABILITY	8.24	47.1	30.6	14.1	7.06	10.6	56.5	25.9	60	68.2	71.8	24.7	20
POSTERIOR PROBABILITY	9.05	47.3	28.2	14.8	8.13	10.9	57	24	64.6	68.9	72.3	28.6	23.7
SENSITIVITY	0.81	0.2	2.4	0.7	1.07	0.3	0.5	-1.9	4.6	0.7	0.5	3.9	3.7
SORT	4				5				1	6	7	2	3

According to the above quantitative analysis method, the sensitivity of each risk factor of vehicle can be determined, and the ranking result is X11 > X9 > X12 > X10 > X8. It is determined that X11 (Low speed driving) is the most sensitive significant risk factor of vehicle factors. The quantitative analysis of other risk factors can be determined by the above methods: among the road risk factors, factor X14 (road alignment is general slope) has the highest sensitivity; among the environmental factors, factor X18 (traffic environment congestion) has the highest sensitivity.

Based on the above analysis, it can be seen that when the severity of truck rear-end accident is level "3", the driver risk factor is the most sensitive significant risk factor among the intermediate nodes, and the combination of significant risk factors is "driver fatigue driving + vehicle driving at low speed + road alignment is general slope + traffic environment congestion". Therefore, in order to effectively prevent or reduce the truck rear-end accidents, the driver's unsafe factors should be taken into consideration when formulating preventive measures of truck rear-end accidents, and the targeted accident risk control measures should be implemented according to the combination of significant risk factors obtained from the study.

In the same way, when the severity of the truck rear-end accident is level"2", the posterior probability output results of each risk factor are obtained by using the Bayesian network model quantitative analysis, as shown in Fig 8. The environmental factor is the most sensitive risk factors among intermediate nodes, and the combination of significant risk factors is "driver distracted attention + vehicle low speed driving + road surface condition drying + accident time at 0-6am". When the severity of the truck rear-end accident is level "1", the posterior probability output results of each risk factor are shown in Fig 9. The vehicle factor is the most sensitive risk factor among the intermediate nodes, and the combination of significant risk factors is "unsafe driving distance + rear reflective sign is unqualified + road alignment is general slope + lighting condition is daytime".

Therefore, in order to effectively prevent or reduce truck rear-end accidents, the most sensitive risk factors should be taken into account according to the different levels of accident severity, and accident prevention countermeasures and risk control measures should be formulated according to the significant risk factor combination obtained through quantitative analysis.
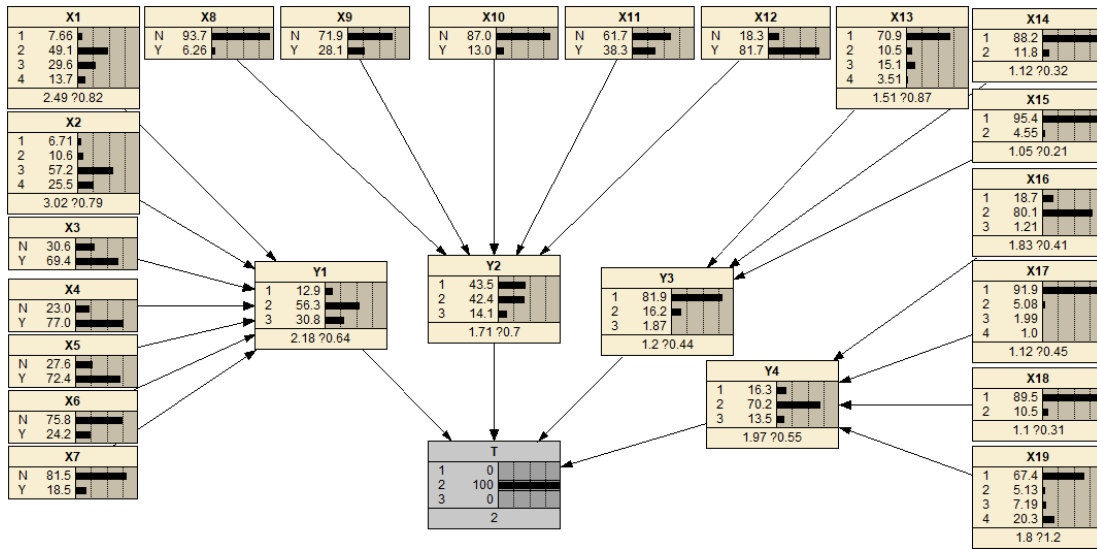
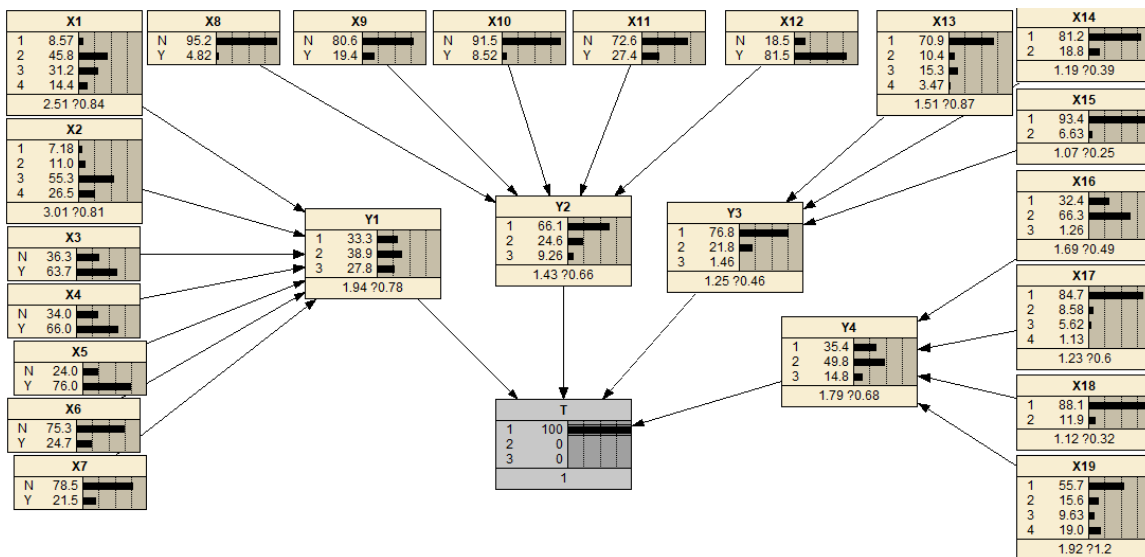Fig 8: Bayesian network model posterior probability (T=2, P=100%)

Fig 9: Bayesian network model posterior probability (T=1, P=100%)

IV. CONCLUSION

Based on the traffic accident cause theory, expert experience and previous research results, the risk factors set of truck rear-end accident is determined from four aspects of driver, vehicle, road and environment by using the in-depth investigation data of truck accidents. Based on the Bayesian theory, the Bayesian network model was constructed using Netica software. The Bayesian network structure learning was completed by integrating expert knowledge and machine learning and parameter learning was performed using the EM algorithm, and the validity of the model was verified. The model verification shows that the model has a high consistency (more than 80%) and can be used for the risk analysis and assessment of truck rear-end accidents.

The quantitative analysis and assessment of the truck rear-end accident risk is carried out by using the constructed Bayesian network model. The results show that: when the severity of truck rear-end accident is level "3", the driver risk factor is the most sensitive significant risk factor among the intermediate nodes, and the combination of significant risk factors is "driver fatigue driving + vehicle driving at low speed + road alignment is general slope + traffic environment congestion". When the severity of the truck rear-end accident is level "2", the environmental factor is the most sensitive risk factors among intermediate nodes, and the combination of significant risk factors is "driver distracted attention + vehicle low speed driving + road surface condition drying + accident time at 0-6 am". When the severity of the truck rear-end accident is level "1", the vehicle factor is the most sensitive risk factor among the intermediate nodes, and the combination of significant risk factors is "unsafe driving distance + rear reflective sign is unqualified + road alignment is general slope + lighting condition is daytime". The research results of this paper can provide an important decision-making basis for formulating risk control and accident prevention measures for truck rear-end accident. It is of great significance to effectively prevent or reduce truck rear-end accidents and improve the safety level of road transportation.

In this paper, the static Bayesian network model is used. Later research will build dynamic Bayesian network model, consider the influence of time factor on variables, improve the model accuracy, and carry out the research of dynamic risk assessment and real-time control.

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