Model and Algorithm Design for Cargo Shipping Safety Based on Fuzzy-Precise Bayesian Network

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Abstract—The shippers have the requests for the accessibility and economics of logistics on the premise of cargo safety, and the cargo shipping safety is an important part of logistics safety. Thus, it is quite essential to monitor the cargo shipping safety. The data is difficult to obtain in the research for cargo shipping safety, thus it cannot cover all states of influencing factors during modeling process of Bayesian network. In order to solve this problem, the computation process of Bayesian network was improved in this paper, and the Fuzzy-precise Bayesian network was obtained. The Fuzzy-precise Bayesian network was applied to monitor cargo shipping safety. According to the multi-field coupling theory, the index system influencing the cargo shipping safety was established, the GeNIe software was used to conduct the inference of Bayesian network. The inference model was utilized for conducting the safety monitoring of specific cargo on a bulk cargo ship of a company in Hainan province, and the effectiveness and availability of this model was examined. This paper provides guidance for safety production of enterprises’ cargo shipping.

Index Terms—Bayesian Network; Cargo Safety; Shipping; Safety Monitoring

I. INTRODUCTION

Over 80% international cargo transport is by water for its low cost, large capacity and long distance. The rotation volume of goods transport of China by water reached to 8,652,073 million tons in 2013, and there is an increase of 16.6% compared with that in 2012. The most important thing during shipping process is to ensure the cargo safety on basis of cargo accessibility. However, many factors in the logistics process have influence on cargo safety, thus making the cargo shipping safety is difficult to be predicted and controlled. At present, there are lots of studies about safety of cargo movement, most of the research work focus on safety of dangerous goods, but little research has been done in this area of general cargo. The research of Zhao has shown that factors affecting the transportation accidents of dangerous goods, such as human factor, transportation facilities and packing of harmful substance. Clark and Besterfield-Sacre reported the data-driven models on dangerous goods for strategic decision making in other domains involving risk. Shao et al. designed an application to monitor the transportation safety of asphalt based on Bayesian network model. The cargo safety based on characteristics of transport agent and cargo was studied by improved the computing method of Bayesian Network in this paper, and the “fuzzy-precise Bayesian Network” was established to evaluate cargo shipping safety [5-6].

Bayesian Network, also known as Belief Network, was developed from the Bayes method that proposed by Judea Peral in 1988. Bayesian Network is an inference network model based on the uncertainty and variability of probability and applicable to explore various uncertainty and probability problems. When Bayesian Network was used in decision-making events involving various control factors, it can make correct inferences from incomplete, ambiguous or uncertain knowledge or information. It has been widely used in fault diagnosis, data mining, medical diagnosis and traffic safety in considering of its unique uncertainty, knowledge representation form, strong probability expressive ability and the incremental learning of comprehensive priori knowledge. In particular, Bayesian Network has achieved outstanding success in traffic safety field, such as cause analysis of traffic disasters, early-warning of traffic safety and traffic safety evaluation.

The main theoretical basis of Bayesian network is the Bayes formula, or known as the posterior probability formula. Suppose the prior probability is \( p(B_i) \) and \( p(A_i|B_j) \) \( (i = 1,2\cdots n, j = 1,2,m) \) is known, then the posterior probability calculated from the Bayes formula [8-9].

\[
p(B_j|A_i) = \frac{p(B_j)p(A_i|B_j)}{\sum_{i=1}^{n} p(B_j)p(A_i|B_j)}
\]

(1)

Given Bayes formula, then the probability analysis of any node of Bayesian network can be conducted in accordance with characteristic of Bayesian network inference. If the prior probability of the father node is given, then the posterior probability of the child node can be calculated. Similarly, if the posterior probability of the child node is given, the prior probability of the father

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node can also be calculated. For example, if the node \( E_i \)
 is observed in the state of \( e_{j0} \), then the posterior

\[
p(E_i = e_{j0} | E_j = e_{j0}) = \sum_{E_{k1}, ..., E_{kn}} p(E_{k1}, ..., E_{kn} | E_i = e_{j0})
\]

where, \( E_k \) is corresponding to the nodes in the
Bayesian Network, \( N \) is the number of nodes in a
Bayesian Network, \( e_i \in \Omega_k \) is used to characterize
the state of node \( E_k \), and \( \Omega_k \) is the state space of node
\( E_k \).

Bayesian Network is very suitable to be applied to
security evaluation, and both subjective Bayesian
Network and objective Bayesian Network are applicable
to security evaluation. Subjective Bayesian Network uses
the Bayesian Network model to predict the probability of
accident occurrence based on expert’s subjective
estimation result when appropriate objective data are
unavailable. The subjective Bayesian Network also can
be called as fuzzy Bayesian Network because it predicts
the probability of even occurrence through fuzzy set
theory. Objective Bayesian Network makes network
inferences on the probability of the happened accident
occurrence based on collected abundant relevant node
data. When using Bayesian Network to evaluate cargo
shipping safety, objective data are difficult to be collected
because of various influencing factors and incomplete
records of shipping enterprises and owners of cargo.
Although the author has collected some objective data
about the cargo shipping safety, these data cannot cover
all influencing factors. Therefore, the established
Bayesian Network model failed to predict the probability
of accident occurrence under all conditions and presented
many unreasonable predictions. In this paper, the
Bayesian Network was improved on basis of studying the
results more intuitively when there’s no specific data is
available. The subjective Bayesian Network also can
be transferred into level-based values, that are, determining
the weight of influencing indexes and complete
records of shipping enterprises and owners of cargo.
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about the cargo shipping safety, these data cannot cover
all influencing factors. Therefore, the established
Bayesian Network model failed to predict the probability
of accident occurrence under all conditions and presented
many unreasonable predictions. In this paper, the
Bayesian Network was improved on basis of studying the
results more intuitively when there’s no specific data is
available. The subjective Bayesian Network also can
be transferred into level-based values, that are, determining
the weight of influencing indexes and complete
records of shipping enterprises and owners of cargo.

### III. Proposed Scheme

#### A. Fuzzy-precise Bayesian Network

In this paper, a fuzzy-precise Bayesian Network was
established by combing the objective Bayesian Network
and fuzzy Bayesian Network, which was used to monitor
cargo shipping safety. Fig. 2 shows its calculation flow
chart. The established fuzzy-precise Bayesian Network
mainly accomplishes Bayesian Network computation
tasks when no adequate historical data are available
[16-17].

Fuzzy set theory is essential to perfect the data
structure of the fuzzy-precise Bayesian Network. Fuzzy
set, the set of specific-property objects with ambiguous
limits or boundaries, can represent expert’s evaluation
results more intuitively when there’s no specific data is
available. The fuzzy language description, corresponding
fuzzy number and \( \lambda \)-cut set are listed in Table II.

Generally speaking, it has to take the evaluation results
of several experts into account when quantify the
probability of occurrence of a certain accident. Therefore,
the evaluation results of several experts were integrated
by using the arithmetic method in this paper. The
comprehensive evaluation of \( n \) experts can be expressed
as (3).

\[
P(i) = \frac{1}{n} \sum_{i} f_{i} \quad i = 1, 2, \cdots, m
\]

where \( f_{i} \) the fuzzy probability of occurrence of \( i^{th} \)
accident is, \( f_{i}\) is the fuzzy number of \( i^{th} \) expert to the \( i^{th} \)
accident, and \( m \) is the amount of accidents.

The fuzzy evaluation results of several experts were
processed by integral method in this paper. Suppose \( P \) is
the fuzzy number of L-R type, the ambiguity resolution
of \( P \) is:

\[
I(P) = (1 - \varepsilon) I_{L}(P) + \varepsilon I_{U}(P)
\]

where \( \varepsilon \in [0, 1] \) is the optimistic coefficient. when \( \varepsilon = 0 \)
and \( \varepsilon = 1 \), \( I(P) \) are the upper and lower limits of the
ambiguity resolution of $P$, when $e=0.5$, $I(P)$ is the representative value of ambiguity resolution of $P$. $I_R(P)$ and $I_L(P)$ are the integral values of the right and left inverse membership functions of the fuzzy number. For the triangle fuzzy number, $I_R(P)$ and $I_L(P)$ can be expressed by $\lambda$-cut set:

$$I_R(P) = [\lambda+0.1, -\lambda+0.3]$$

$$I_L(P) = [0.1\lambda+0.7, -0.1\lambda+0.9]$$

Figure 1. Topological structure of cargo safety monitoring during shipping

<table>
<thead>
<tr>
<th>Target Layer</th>
<th>System Layer</th>
<th>Criterion Layer</th>
<th>Factor Layer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crew $D_1$</td>
<td>Character Trait $Y_{11}$</td>
<td>Psychological Quality $y_1$</td>
<td>Safety Awareness $y_2$</td>
</tr>
<tr>
<td></td>
<td>Personal Ability $Y_{12}$</td>
<td>Operational Capacity $y_3$</td>
<td>Working Years $y_4$</td>
</tr>
<tr>
<td></td>
<td>Physiological Conditions $Y_{13}$</td>
<td>Age $y_5$</td>
<td>Health Condition $y_6$</td>
</tr>
<tr>
<td></td>
<td>Enthusiasm $Y_{14}$</td>
<td>Degree of Enthusiasm for Work $y_7$</td>
<td>Stability of Ship Structure $y_8$</td>
</tr>
<tr>
<td></td>
<td>Hull Structure $Y_{21}$</td>
<td>Hull Strength $y_{10}$</td>
<td>Requirements of Cargo for Hull $y_{11}$</td>
</tr>
<tr>
<td>Vessel $D_2$</td>
<td>Ship Equipment $Y_{22}$</td>
<td>Communication Signal Appliance $y_{12}$</td>
<td>Lashing Equipment $y_{13}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Fire Extinguishing System $y_{14}$</td>
<td>Requirements of Cargo for Ship Equipment $y_{15}$</td>
</tr>
<tr>
<td>Environment $D_3$</td>
<td>Hydrologic Condition $Y_{31}$</td>
<td>Wave Height $y_{16}$</td>
<td>Visibility $y_{17}$</td>
</tr>
<tr>
<td></td>
<td>Weather Condition $Y_{32}$</td>
<td>Air Humidity $y_{18}$</td>
<td>Temperature $y_{19}$</td>
</tr>
<tr>
<td>Management $D_4$</td>
<td>Application of Cargo Stowing Software $Y_{41}$</td>
<td>Degree of Application of Cargo Stowing Software $y_{20}$</td>
<td>Degree of Application of Cargo Stowing Software $y_{21}$</td>
</tr>
<tr>
<td></td>
<td>Regulations of Cargo Shipped Management $Y_{42}$</td>
<td>Soundness of Regulations of Cargo Shipped Management $y_{21}$</td>
<td>Soundness of Regulations of Cargo Shipped Management $y_{22}$</td>
</tr>
<tr>
<td>Features of Cargo $D_5$</td>
<td>Shipping Time $Y_{51}$</td>
<td>Safety Degree of Shipping Time $y_{22}$</td>
<td>Safety Degree of Cargo Loading Place $y_{23}$</td>
</tr>
<tr>
<td></td>
<td>Cargo Loading Place $Y_{53}$</td>
<td>Safety Degree of Cargo Loading Place $y_{23}$</td>
<td>Physical and Chemical Features of Cargo $y_{24}$</td>
</tr>
<tr>
<td></td>
<td>Features of Cargo $Y_{54}$</td>
<td>Degree of Packaging Meeting Requirements $y_{24}$</td>
<td>Degree of Packaging Meeting Requirements $y_{25}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Language description</th>
<th>Fuzzy number</th>
<th>$\lambda$-cut set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very high (VH)</td>
<td>$f_{vH} = (0.8, 0.9, 1.0)$</td>
<td>$f_{vL} = [0.1\lambda+0.8, -0.1\lambda+0.1] $</td>
</tr>
<tr>
<td>High (H)</td>
<td>$f_H = (0.7, 0.8, 0.9)$</td>
<td>$f_{H} = [0.1\lambda+0.7, -0.1\lambda+0.9]$</td>
</tr>
<tr>
<td>Fairly high (FH)</td>
<td>$f_{FH} = (0.5, 0.6, 0.7, 0.8)$</td>
<td>$f_{FH} = [0.1\lambda+0.5, -0.1\lambda+0.8]$</td>
</tr>
<tr>
<td>Moderate (M)</td>
<td>$f_{M} = (0.4, 0.5, 0.6)$</td>
<td>$f_{M} = [0.1\lambda+0.4, -0.1\lambda+0.6]$</td>
</tr>
<tr>
<td>Fairly low (FL)</td>
<td>$f_{FL} = (0.2, 0.3, 0.4, 0.5)$</td>
<td>$f_{FL} = [0.1\lambda+0.2, -0.1\lambda+0.5]$</td>
</tr>
<tr>
<td>Low (L)</td>
<td>$f_L = (0.1, 0.2, 0.3)$</td>
<td>$f_{L} = [0.1\lambda+0.1, -0.1\lambda+0.3]$</td>
</tr>
<tr>
<td>Very low (VL)</td>
<td>$f_{vL} = (0.0, 0.1, 0.2)$</td>
<td>$f_{vL} = [0.1\lambda+0.0, -0.1\lambda+0.2]$</td>
</tr>
</tbody>
</table>
\( I_R (P) = \frac{1}{2} \left[ \sum_{i=0}^{0.9} \lambda_i (p) \Delta \lambda + \sum_{i=0}^{0.9} \lambda_i (p) \Delta \lambda \right] \) \hspace{1cm} \text{(5)}

\( I_L (P) = \frac{1}{2} \left[ \sum_{i=0}^{0.9} \lambda_i (p) \Delta \lambda + \sum_{i=0}^{0.9} \lambda_i (p) \Delta \lambda \right] \) \hspace{1cm} \text{(6)}

where \( \lambda_u (P) \) and \( \lambda_l (P) \) are the upper and lower limits of the \( \lambda \)-cut set of \( P \). \( \lambda = 0, 0.1, 0.2, \ldots, 1; \Delta \lambda = 0.1 \).

It is difficult to obtain the joint probability distribution of intermediate node and target node just based on historical data. In general, the maximum posterior estimation is used to calculate the joint probability distribution of intermediate node and target node.
Suppose we need to estimate the unobserved population parameter $\theta$ on the basis of observed data $X$, let $f$ denote sampling distribution of $X$, thus $f(x|\theta)$ is the probability of $X$ when the population parameter is $\theta$. The function $\theta \propto f(x|\theta)$ is likelihood function, and the estimation of the function $\hat{\theta}(x) = \arg\max_\theta f(x|\theta)$ is the maximum likelihood estimation of $\theta$.

It is assumed that $g$ is the prior distribution of $\theta$, and $\theta$ is the random variable in Bayesian statistics, then the posterior distribution of $\theta$ is:

$$
\hat{\theta}_M(X) = \arg\max_\theta \frac{f(x|\theta)g(\theta)}{\int_\Theta f(x|\theta)g(\theta)\,d\theta}
$$

(7)

where $\Theta$ is definitional domain of $g$. The objective function of maximum posterior estimation can be gotten by (8):

$$
\hat{\theta}_M(X) = \arg\max_\theta \frac{f(x|\theta)g(\theta)}{\int_\Theta f(x|\theta)g(\theta)\,d\theta}
$$

(8)

B. Bayesian Network of Cargo Shipping Safety Based on Historical Data

The historical sample data are mainly related with cargo accident risks on 27 cargo ships (including 19 bulk cargo ships, three container ships, four tank ships and one chemical tanker) of a shipping company of Hainan province in 2012 and 2013. The relevant data of 884 batches was collected, and 843 data was effective. Since these data couldn’t cover all nodes’ conditions, they shall be reasoned by Bayesian Network firstly to identify influencing factors of cargo safety of evidence nodes. Then, the marginal probability of the evidence nodes as well as the conditional probabilities of intermediate nodes and target nodes that influence the cargo shipping safety can be acquired.

During the Bayesian Network inference process, the software of GeNiE for Bayesian Network modeling was used in this paper. The GeNiE was developed by the decision-making system laboratory of University of Pittsburgh provides development environment for imaging decision-making theoretical model, and can be used for project study or even business field. It not only has visual windows, but also can make accurate and approximate inferences as well as parameter and structural learning, thus establishing static and dynamic Bayesian Network models. The cleared historical data was input into the established GeNiE Bayesian Network model to calculate the marginal probability and conditional probability of the Bayesian Network, and the cargo shipping safety was evaluated (Fig. 3).

Fig. 3 presents a generally high cargo shipping safety. The probability of cargo shipping safety is 0.71, while the probability of cargo shipping risk is 0.29.

### TABLE III. MARGINAL PROBABILITY OF EVIDENCE NODES

<table>
<thead>
<tr>
<th>Degree of Enthusiasm for Work $y_8$</th>
<th>Level 1</th>
<th>2</th>
<th>3</th>
<th>Marginal probability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age $y_5$</td>
<td>Level 1</td>
<td>2</td>
<td>3</td>
<td>Marginal probability</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree of Fatigue $y_7$</td>
<td>Level 1</td>
<td>2</td>
<td>3</td>
<td>Marginal probability</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree of Enthusiasm for Work $y_6$</td>
<td>Level 1</td>
<td>2</td>
<td>3</td>
<td>Marginal probability</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### TABLE IV. CONDITIONAL PROBABILITY OF INTERMEDIATE NODE (PERSONALITY CHARACTERISTICS)

<table>
<thead>
<tr>
<th>Indexes related with “personality characteristics”</th>
<th>Evaluation level of “personality characteristics”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Psychological quality</td>
<td>Safety awareness</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>0.87</td>
</tr>
<tr>
<td>3</td>
<td>0.63</td>
</tr>
<tr>
<td>4</td>
<td>0.37</td>
</tr>
</tbody>
</table>

### TABLE V. MARGINAL PROBABILITY OF MANAGEMENT’S EVIDENCE NODES CALCULATED FROM FUZZY SET

<table>
<thead>
<tr>
<th>Application of Cargo Stowing Software $y_{20}$</th>
<th>Level 1</th>
<th>2</th>
<th>Marginal probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soundness of Regulations of Cargo Shipped Management $y_{21}$</td>
<td>Level 1</td>
<td>2</td>
<td>Marginal probability</td>
</tr>
</tbody>
</table>

### TABLE VI. CONDITIONAL PROBABILITY OF THE INTERMEDIATE NODE (PERSONALITY OF CHARACTERISTICS) BEYOND THE HISTORICAL DATA

<table>
<thead>
<tr>
<th>Indexes related with “personality characteristics”</th>
<th>Evaluation level of “personality characteristics”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Psychological quality</td>
<td>Safety awareness</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>0.43</td>
</tr>
<tr>
<td>4</td>
<td>0.57</td>
</tr>
</tbody>
</table>

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TABLE VII. PROBABILITY OF CARGO SHIPPING SAFETY AND ITS SUB-INDEXES

<table>
<thead>
<tr>
<th>Node</th>
<th>Probability of safety</th>
<th>Probability of accident occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cargo safety risks during shipping D</td>
<td>0.7298</td>
<td>0.2702</td>
</tr>
<tr>
<td>Crew D1</td>
<td>0.8181</td>
<td>0.1819</td>
</tr>
<tr>
<td>Vessel D2</td>
<td>0.7224</td>
<td>0.2776</td>
</tr>
<tr>
<td>Environment D3</td>
<td>0.7304</td>
<td>0.2696</td>
</tr>
<tr>
<td>Management D4</td>
<td>0.7369</td>
<td>0.2631</td>
</tr>
<tr>
<td>Psychophysical characteristics of passengers D5</td>
<td>0.8117</td>
<td>0.1883</td>
</tr>
</tbody>
</table>

TABLE VIII. NODE STATES OF THE TESTING BULK CARGO SHIP CARRIED WHITE SUGAR

<table>
<thead>
<tr>
<th>Seaman evidence node</th>
<th>State</th>
<th>y2</th>
<th>y1</th>
<th>y3</th>
<th>y4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vessel evidence node</td>
<td>State</td>
<td>y11</td>
<td>y12</td>
<td>y13</td>
<td>y14</td>
</tr>
<tr>
<td>Environment evidence node</td>
<td>State</td>
<td>y16</td>
<td>y17</td>
<td>y18</td>
<td>y19</td>
</tr>
<tr>
<td>Management evidence node</td>
<td>State</td>
<td>y22</td>
<td>y23</td>
<td>y24</td>
<td>y25</td>
</tr>
<tr>
<td>Evidence node of the cargo’s characteristics</td>
<td>State</td>
<td>y27</td>
<td>y28</td>
<td>y29</td>
<td>y30</td>
</tr>
</tbody>
</table>

TABLE IX. SAFETY PROBABILITY OF CARGO

<table>
<thead>
<tr>
<th>Node</th>
<th>Probability of safety</th>
<th>Probability of accident occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cargo safety risks during shipping D</td>
<td>0.7867</td>
<td>0.2133</td>
</tr>
<tr>
<td>Crew D1</td>
<td>0.9592</td>
<td>0.0408</td>
</tr>
<tr>
<td>Vessel D2</td>
<td>0.7780</td>
<td>0.2220</td>
</tr>
<tr>
<td>Environment D3</td>
<td>0.5502</td>
<td>0.4498</td>
</tr>
<tr>
<td>Management D4</td>
<td>0.9000</td>
<td>0.1000</td>
</tr>
<tr>
<td>Psychophysical characteristics of passengers D5</td>
<td>0.7057</td>
<td>0.2943</td>
</tr>
</tbody>
</table>

The marginal probability of evidence nodes of influencing factors on cargo safety was calculated (Table III). The conditional probabilities of evidence nodes were calculated based on maximum posterior estimation (Table IV). It is concluded that there are five influencing factors involved in the marginal probability and 19 influencing factors involved in the conditional probability. Not all conditional probabilities were introduced in this paper due to the limited article length.

C. Determination of Marginal Probability and Conditional Probability of Cargo Safety Nodes Based on Fuzzy Set Theory

The collected historical data only involves limited cargo ships, a small navigation geographic reach and only one company’s management system, thus resulting in the poor accuracy of marginal probability concerning ship, environment and management. Therefore, these absent and unreal data have to be revised by using Delphi method and fuzzy set theory. On the contrary, the marginal probability concerning characteristics of seamen and cargoes is believed reliable since the historical data involves adequate samples with certain representativeness. But the historical data size is too small to cover all conditions of evidence nodes, indicating the incompleteness of conditional probability and poor accuracy of cargo shipping safety calculated from the established Bayesian Network. Therefore, the conditional probability of nodes beyond the historical data shall be estimated.

10 experts (three researchers of passenger ships, two managers of passenger ship and six senior captains) was invited to correct the unreal marginal probability (Table V) by using fuzzy language and predict conditional probability (Table VI) of nodes beyond the collected historical data.

D. Bayesian Network inference of cargo shipping safety under complete data

Based on the established hierarchical structure of the Bayesian Network, and calculated marginal probability and conditional probability of evidence nodes, the cargo shipping safety can be reasoned by using the joint probability distribution. The probability of “cargo shipping safety” of target nodes was calculated directly by GeNIE (Table VII).

IV. PERFORMANCE ANALYSIS

To test the feasibility and validity of the research result, the empirical study was conducted, and the established model was used on a bulk cargo ship of a shipping company in Hainan province to monitor the cargo safety. The bulk cargo ship carried 14,000 tons of white sugar from the Yangpo Port of Hainan province to Qingdao Port of Shandong province on June 12th, 2013. Parameters of the testing ship are as follows: length was 199.99 m, draught of the ship was 12.5 m, and its weight and deadweight was 33,511 tons and 5,5000 tons, respectively. The ship was carrying a crew of 26, including eight senior officers. The weather condition was as following: a cloudy day with showers, North wind 4-5 mph, 1.2 m high waves, and visibility within 1200km, temperature 24-28°C and air humidity 78%. The white sugar was packed by polyethylene plastic woven bags.

The monitoring data were converted into status value of evidence nodes of the Bayesian Network according to the evaluation standard. Unmonitored node states were
defaulted to normal. The status values of different evidence nodes are listed in Table VIII.

The evidence states of white sugar on the bulk cargo ship were inputted into the Fuzzy-precise Bayesian network model established by GeNIe to calculate the joint probability of root nodes (Table IX). The table IX shows that the probability of cargo safety was 0.7867, and probability of accident occurrence was 0.2133 of the empirical status of each node. The probability of accident occurrence in table VII was 0.2702 under normal circumstances. The probability of accident occurrence was decreased in table IX since the safe conditions of crew, ship and management was better than the general conditions. But there had an impact on cargo safety due to the higher wave height and air humidity. Meanwhile, the package of cargo was simple, and the water proofing property was poor, thus also caused a certain threat to the cargo safety. The bulk cargo ship drove 173 nautical miles on that day, it docked in Zhanjiang Port of Guangdong province to load other goods, and the segment from Yangpo Port to Zhanjiang Port was near the Qiongzhou strait. The actually check revealed that cargo damage was happened, and the white sugar close to the ship's rail occurred wet with water. Mainly because there has a shower in Qiongzhou strait, and the rainfall was large, which resulted in a small amount of water on the ship. Meanwhile, the polyethylene plastic woven bags were used to pack the white sugar, and its function of waterproof was poor. But, the white sugar in overall was safety since it did not meet other risks. The safety probability that calculated by the Fuzzy-precise Bayesian Network was coincided with the actual transportation result. Moreover, there were certain risks during transportation of the white sugar, and the risk was relatively little. The damage of the white sugar could be reduced or eliminated, if the crew could take preventive actions in advance based on the safety probability of cargo.

V. CONCLUSIONS

The unsafe condition, for example damage and shortage of cargo, are frequently occurred during shipping, and these accidents are caused by various factors, thus making it difficult to predict cargo shipping safety. The “Fuzzy-precise Bayesian Network” theory was used to establish a model for monitoring cargo shipping safety. The Fuzzy-precise Bayesian Network was obtained by improving the computation process of Bayesian Network. It can offset the poor performance of Bayesian Network caused by the difficult data acquisition and failure to cover all influencing factors of cargo shipping safety. A model used to monitor cargo shipping safety was established based on the Bayesian Network inference from the established influencing index system and its topological structure, historical data and prior probability on basis of fuzzy set theory. This monitoring model was verified the validity through an empirical study and can be used to predict cargo safety in a certain period of coming shipping.

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