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Effectiveness of Port State Control Inspection using Bayesian Network Modelling

ABSTRACT
As a key factor in ship safety, the effectiveness of the Port State Control (PSC) is very important. This study investigates the effect of the PSC inspection on ship accident and its impacts on the ship safety level in the next inspection, together with the ship inherent attributes and the time interval between inspections. The ship safety level is judged by the number of defects found in the PSC inspection and the risk of ship accident in this study. The Bayesian Network (BN) model is employed and the Bayesian Search algorithm is used to learn the structural networks using the data from various data sources. In addition, the safety level of ships at different time is also introduced into the model as latent variables. The results suggest that the safety level in the first inspection has a significant impact on the inspection time interval and the safety level of the next inspection. It is optimal to select vessels with a medium inspection time interval for inspection to improve ship safety quality effectively. This model can not only help to detect and monitor the dynamic changes in the effectiveness of PSC inspection, but also improve the PSC inspection system to provide guidance for stakeholders.
Keywords: Port State Control, Ship safety, Ship accident, Effectiveness, Bayesian Network

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1 INTRODUCTION

As the most economical way of transportation, shipping is indispensable for the international trade. With the development of global economy and the utilization of e-commerce and digitization, the demand for shipping service is expected to be further developed. The United Nations Conference on Trade and Development (UNCTAD) projected that the world seaborne trade volume will expand at a 3.8 percent compound annual growth rate between 2018 and 2023 (UNCTAD 2018). However, shipping accidents occur frequently, and it is likely to cause huge property and life losses and environment pollution once ship accident occurs. For example, the Maersk Honam, a container ship, caught fire in the Arabian Sea *en route* to the Mediterranean on March 6, 2018, killed five seafarers and destroyed thousands of containerized cargo, which caused huge losses (THELOADSTAR 2018). Therefore, how to reduce shipping risks and avoid ship accidents becomes increasingly important.

To prevent ship accident, various maritime regulatory conventions have been put forward, such as the International Convention for the Safety of Life at Sea (SOLAS) 74, and the Convention on the Prevention of Marine Pollution (MARPOL) 73/78 (Akyuz 2015). In addition, two important measures have also been implemented, namely, flag state control (FSC) and port state control (PSC) (Fan, Luo, and Yin 2014). However, the ship accident rate has not been effectively controlled through the FSC. This is because many flag states, such as open registers, are not able to control the ships under their flags (Li and Wonham 1999).

Controls implemented by flag states and ship classification societies have failed to effectively reduce the number of sub-standard ships from the world merchant fleet, and it has been a concern to the International Maritime Organization (IMO) and port authorities around the world (Chen et al. 2017). As a result, PSC authorities began to be considered as an important measure to improve the ship safety level. The IMO regulates safety and environmental issues through the Memoranda of Understanding (MoU) and regional PSC authorities (Akyuz and Celik 2014). It mainly endows the governments of port states the right to inspect the foreign flagged ships visiting its ports according to the relevant international conventions (Li and Zheng 2008), and ensures that the ships' condition, equipment and crew comply with the requirements laid down in international conventions (Ravira and Piniella 2016). When ship or staffing conditions are not up to the standard of the applicable convention, the ship will be detained until the defects are rectified (Marten 2017).

As PSC inspection is regarded as an important measure to improve ship safety and reduce ship accidents, its effectiveness is particularly important. There are many factors that affect the effectiveness of PSC inspection, such as the evaluation of performance of flag states and identifying priority ships for inspection (Kara and Oksas 2015). What's more, different backgrounds of inspectors can also lead to inconsistency in the inspection procedures (Graziano et al. 2018), so the effectiveness of PSC is hard to be guaranteed. These factors are only considered for some certain conditions from inspection authorities. However, as an objective factor, the time interval from the last inspection will also affect the effectiveness of the PSC inspection for the ship. PSC inspections may reduce the risk of ship accident, but it is worth mentioning that as time goes on, the effect of PSC inspection on the safety level will not remain unchanged, ship experts generally agree that the effects of all inspections disappear after a year (Heij, Bijwaard, and Knapp 2011). Therefore, how the effect of the PSC inspection on ships changes over time should be considered to determine an appropriate time interval for re-inspection on ships. Identifying appropriate inspection interval can help save inspection cost and improve inspection efficiency.

There are numerous studies on the relationship between PSC and ship accidents. However, there is no conclusion about the effect of the interval time between two inspections on the effectiveness of PSC inspection in existing studies. Therefore, this study adopts the Bayesian Network (BN) model to discuss the effectiveness of the PSC inspection using data containing vessels' two adjacent inspections and it introduces two latent variables into the model measure the safety level of the ships at different time. The Analysis of Variation (ANOVA) is employed in the sensitivity analysis of the model. This study is mainly discussed from the following aspects:

(1) How does the ship safety level change the accident rate?
(2) How does the safety level of the inspected ships change at the next inspection?
(3) What role does the interval time between two consecutive inspections play?

The rest of this study is arranged as follows: Section 2 reviews the related literature. In section 3, data collection and state description are shown. Section 4 is about the model, in which the model is constructed and the results of the model are discussed and analyzed. Finally, the conclusions are presented in Section 5.

2 LITERATURE REVIEW

PSC inspection has long been regarded as an important measure to reduce ship accidents and improve maritime safety (Fu et al. 2020, Fan et al. 2019, Hänninen and Kujala 2014, Heij, Bijwaard, and Knapp 2011, Knapp and Franses 2007, Yang, Yang, and Teixeira 2020) and TABLE 1 summarizes these studies. Besides, Li, Yin, and Fan (2014) developed a safety index for port authorities to determine whether an on board inspection is needed. The deficiencies of ships found in the PSC inspection may directly affect ships' safety and the ships will be detained by port states until the deficiencies are rectified. Based on detention data in port states in the Asia-Pacific Region, Chen et al. (2019) analyzed the main factors which affect ship detention using grey rational analysis (GRA) model with improved entropy weight, which offered decision-making support on maritime safety policy. Combing the PSC deficiency with the accident data, Hänninen, Banda, and Kujala (2014) established a safety management model to identify room for safety improvement. These studies mainly focused on the impact of PSC inspection on ship safety. In order to effectively help inspectors discover ship deficiencies, more and more studies have been conducted on the relationship between defects and PSC inspection. Chung et al. (2020) found some useful association rules among PSC inspection deficiencies by using the Apriori algorithm. Yang, Yang, and Yin (2018) discussed the effects of number of deficiencies on PSC inspection and ship detention. In these studies, the relationship between two inspections has not been discussed.

TABLE 1 Studies of PSC inspection on maritime safety.

Author	Method	Influencing factors	Main findings
Fu et al. (2020)	Improved Apriori algorithm	Ship deficiencies from PSC inspection; Ship characteristic indicators	Ship type, age, deadweight and GT are closely related to ship deficiency identification.
Yang, Yang, and Teixeira (2020)	BN model with TAN learning	Inspection time; Port of inspection; Inspection date; Ship characteristic indicators	Inspection characteristics and ship characteristics all impact ships' detention especially after the implementation of the new inspection regime
Fan et al. (2019)	BN model with the GTT and BS algorithms	17 deficiency items; Ship characteristic indicators	Ship deficiencies and Ship characteristics have significant impacts on ship accident.
Hänninen and Kujala (2014)	BN model with a constraint-based learning algorithm NPC and score-based algorithm repeated hill-climbing	The deficiencies; Inspection type; Accident involvement; Ship characteristic indicators	PSC inspection type, ship type and the number of structural conditions related deficiencies provide the most information about accident involvement.
Heij, Bijwaard, and Knapp (2011)	Hazard rade model	Arrivals; Inspections; Number of deficiencies; Casualties	Ship inspections can improve maritime safety and future casualty risk is meaningful for safety inspection in PSC.
Knapp and Franses (2007)	Binary logistic regression	Ship characteristic indicators; PSC	Inspections can effectively reduce the probability of

	inspections; Detention; Casualties	casualty, especially for the very serious casualties.

PSC: port state control; GT: gross tonnage; BN: Bayesian network; GTT: Greedy thick thinning; BS: Bayesian search; NPC: Non-deterministic Polynomial Complete problem; TAN: Tree Augmented Naïve.

From the perspective of methodology used, BN is a common method in the research of shipping risk and maritime safety, which has been and will continue to be an appropriate approach (Zhang and Thai 2016) in this area. Hänninen (2014) also claimed that Bayesian Network is an attractive modeling tool and there are many advantages, such as suitability for complex system modeling, coping with uncertainty, relaxation of causality, versatility and capability of dynamic modeling. Hyun-Joong et al. (2018) proposed the development of risk model based on BNs for risk assessment. Due to the powerfulness of BN to express probability relations, its application is more convenient to analyze the effect of PSC inspection on ship accidents. Furthermore, it also has been utilized to evaluate ship detention and PSC efficiency (Hänninen, Banda, and Kujala 2014). Yang, Yang, and Yin (2018) proposed a data-driven BN based approach for PSC inspection. Considering time based on BN, the Dynamic Bayesian Network (DBN) is developed, and Ventikos, Sotiralis, and Drakakis (2018) employed it to analyze ship inspection and predict the probability of ship damage.

Many researchers have also attached great importance to the efficiency and effectiveness of PSC inspection (Li and Zheng 2008, Cariou, Mejia, and Wolff 2008). Considering the effectiveness of PSC inspection, it is necessary to discuss the impact of PSC inspection on ship accident. Knapp and Franses (2007) explored that PSC inspection is effective especially for very serious casualties and they believed that there is further room for improvement in this category. Fan et al. (2019) tried to identify the key deficiency items and analyzed the structural connections between key items with other inspection items in detail, which can improve port state inspection efficiency. It is also helpful to identify the association rules among ship deficiencies under different ship characteristics to improve the inspection efficiency (Chung et al. 2020). Since the implementation of New Inspection Regime (NIR) of PSC, its effectiveness has also been concerned (Xiao et al. 2020, Yang, Yang, and Teixeira 2020).

Different with previous studies focusing on the impact of PSC inspection deficiencies on ship accidents, this study tries to investigate the dynamics of two consecutive inspections to verify the effectiveness of PSC inspection. By developing a BN model, the relationship between the ship safety levels of two concessive inspections and the ship accident is established to analyze whether the inspection would improve ship safety level and reduce accident rate. Most importantly, this study takes into account the effect of the time interval between two inspections on the next inspection.

3 DATA DESCRIPTION

The data used in this study are mainly from three sources: the PSC inspection database from Tokyo Memorandum of Understanding (Tokyo MoU) (TokyoMoU 2018), the information about nearly 150,000 ships from Lloyd’s register of shipping (LR), and the

Marine Casualties and Incidents from International Maritime Organization (IMO 2018). The PSC inspection database comprises 572,196 inspection cases in the Tokyo MoU from January 2000 to July 2018. In addition, the information of incidents covers more than 7000 incident cases in the Marine Casualties and Incidents from January 2000 to December 2018, containing information related to marine casualties and incidents. However, the "accident" mentioned in this study only includes serious and very serious items.

During the above inspection period, one ship may be inspected several times. However, as this study intends to analyze the effect of an inspection on the next inspection, those ships that have been inspected only once during the study period and other invalid data are excluded. In addition, if the interval time between two inspections is too long, the impact of one inspection on the next is negligible. Therefore, we only select the last two consecutive inspections for each ship before July 2018 that are not separated more than a year. The last inspection is defined as the second inspection, and the adjacent inspection before it is the first inspection. The ship information under PSC inspection, including accident, flag, ship type, ship size (gross tonnage, GT), IACS (whether certified by an International Association of Classification Society or not), ship age at inspection, and 17 defect items for PSC inspection, are collected. After all these analyses and data cleaning, the final data of this study consists of 25,596 ships.

TABLE 2 and 3 describe the states of all variables used in the BN model and the variables are selected by referring to relevant literatures (Fan et al. 2019, Hänninen and Kujala 2014) when constructing the model. Two latent variables, representing the results of two inspections, are introduced to simplify the model. Different flags are classified into two categories according to their registration system: open flag (Open) and closed flag (Close). There are seven types of ships, which are passenger, offshore, general, tanker, container, bulker and others. The offshore are ships that generally serve specifically operational purpose activities in the high sea. Variable IACS describes a ship's classification society. State Yes means the ship is certified by an IACS member and State No represents a non-IACS member. Following Fan et al. (2019), a ship is defined as small when its gross tonnage is no more than 20,000 tons, middle when it is between 20,000 and 40,000 tons, and large when it is more than 40,000 tons. Similarly, for the ship age, based on the second inspection, it is New if a ship's age is no greater than 10, Middle if it is more than 10 and less than or equal to 20, and Old if it is more than 20. The remaining nodes, 17 defect items and accident, have both Yes and No states representing whether the defects or accident occurred. The accident rate is denoted as the proportion of vessels involved in accidents. Since the data only includes those vessels that have been inspected by the Tokyo MoU at least twice within a year, the accident rate is different with previous studies.

The effectiveness of PSC inspection is defined as whether the ship's safety level is improved after the first inspection. It is believed that the time interval from the last inspection will affect the long-term effectiveness of inspection, so the Time_Interval variable is introduced in this study. Under the new inspection regime of Tokyo MoU, the information of inspection of different risk ships is described. For high risk ships, they must be inspected when more than 4 months have elapsed since the last inspection. For a standard risk ship, it must be inspected only if it has been more than 8 months since the last inspection. However, low risk ships may be inspected if it has been no more than 18 months after the last inspection. Therefore, in order to test the effectiveness of PSC inspection, we further specified three states for the Time_Interval variable—Short: the time interval is less than or equal to 120 days; Middle: from 120 days to 240 days; and Long: more than 240 days.

TABLE 2 Variables in the main model.

Variables	Variable States	Percentage of States
Flag	Close	29%
	Open	71%
IACS	No	19%
	Yes	81%
Age	New: <=10	43%
	Middle: 10<Age<=20	29%
	Old: >20	28%
GT	Small: <=20000	48%
	Middle: 20000<GT<=40000	27%
	Large: >40000	25%
Type	Passenger	1%
	Offshore	2%
	General	18%
	Tanker	18%
	Container	20%
	Bulker	35%
	Others	6%
Time_Interval	Short: <=120 days	54%
	Middle: 120<Days<=240	27%
	Long: >240 days	19%
Safety_level_1	State 0	75%
	State 1	25%
Safety_level_2	State 0	32%
	State 1	68%
Accident	No	93%
	Yes	7%

TABLE 3 Defect items in the sub-models.

Variables	Variable States	Percentage of States			
		First Inspection		Second Inspection	
		No	Yes	No	Yes
Certificate_Documentation_1/2	No/Yes	77%	23%	79%	21%
Structural_Conditions_1/2	No/Yes	90%	10%	90%	10%
Water_Weathertight_Conditions_1/2	No/Yes	83%	17%	84%	16%
Emergence_Systems_1/2	No/Yes	86%	14%	87%	13%

Radio_Communications_1/2	No/Yes	91%	9%	92%	8%
Cargo_Operations_Including_Equipment_1/2	No/Yes	98%	2%	98%	2%
Fire_Safety_1/2	No/Yes	69%	31%	71%	29%
Alarms_1/2	No/Yes	98%	2%	98%	2%
Working_and_Living_Conditions_1/2	No/Yes	89%	11%	90%	10%
Safety_of_Navigation_1/2	No/Yes	70%	30%	72%	28%
Life_Saving_Appliances_1/2	No/Yes	73%	27%	75%	25%
Dangerous_Goods_1/2	No/Yes	99%	1%	99%	1%
Propulsion_and_Auxiliary_Machinery_1/2	No/Yes	87%	13%	88%	12%
Pollution_Prevention_1/2	No/Yes	83%	17%	84%	16%
ISM_1/2	No/Yes	92%	8%	93%	7%
Labor_Conditions_1/2	No/Yes	93%	7%	94%	6%
Other_1/2	No/Yes	97%	3%	97%	3%

Note: "_1/2" represents the variables in the first or second inspection.

4 MODEL CONSTRUCTION AND DISCUSSION

4.1 Model Construction

BN is a probabilistic graph model consisting of nodes which represent the random variables, and arrows with direction between the nodes that represent the direct dependencies of the nodes (Fan et al. 2019). It is a non-circular model in which there is no loops for any nodes (Hänninen 2014) and can be used to describe the dependence and probability distributions between nodes both qualitatively and quantitatively. However, the causes of maritime accidents are quite complex. When there are multiple factors, only relying on expert knowledge for analysis is relatively low feasible. The BN model can address this issue using structural learning algorithms based on the individual observations. Bayesian network structures can be constructed based on empirical information or data learning from actual observations and this study adopts the way of data learning to build the model structure. The connecting structure among the notes can be analyzed and learned using various algorithms after importing data. Since there are no big differences between those learning methods, this study uses the Bayesian Search (BS) algorithm. The BS learning algorithm is one of the earliest and most popular algorithms. It basically follows a random restart of the climbing procedure (Druzdzel 1999) and it can find the dependencies between variables and automatically establish the relationships based on the data imported. After the model is established, we can discuss the probability relationship between variables by setting different evidence nodes.

Comparing with other methods, the BN model can combine existing data with expert knowledge and get corresponding models to express the relationship between various factors (Heckerman 1999). For the qualitative part, the model can intuitively express relationship between various factors. For each node in the model, the probabilities of several states will be reflected and they will be affected by nodes connected to it, which shows the quantitative analysis ability of the BN model. In addition, the BN model can be used for prediction because it can calculate the prior probability of each node based on original data and posterior probability of nodes can be calculated based on the interaction between related nodes. Taking advantage of this feature, it is more convenient and effective to discuss the effect of time interval on the effectiveness of PSC inspection in this study. This also makes it easier to predict ship accident rates from different factors.

According to above introduction, the BS learning algorithm is adopted in learning the structure among all the variables considered in this study. After obtaining the initial structural model, we adjust the model partially according to the actual influence relationship and research needs, and finally get the final model. Figure 1 is the main model of this study, where the two inspections are represented by sub-models. Inspection_1 represents the first inspection and Inspection_2 represents the second inspection. Figure 2 and Figure 3 illustrate the sub-models of the first inspection and the second inspection respectively. In addition, two latent variables Safety_level_1 and Safety_level_2 are added into the model as child nodes of the two inspections respectively to replace the ship safety level of that inspection. According to the learning results in Figure 2 and 3, the key nodes of deficiencies, Safety_of_Navigation and ISM, are directly connected to the corresponding latent variable nodes in the main model. The key nodes suggest that when these key defect items have no deficiencies, there is no need to inspect other items connecting to them. However, when these key defect items have deficiencies, other items that are strongly related to the key nodes should be considered (Fan et al. 2019).

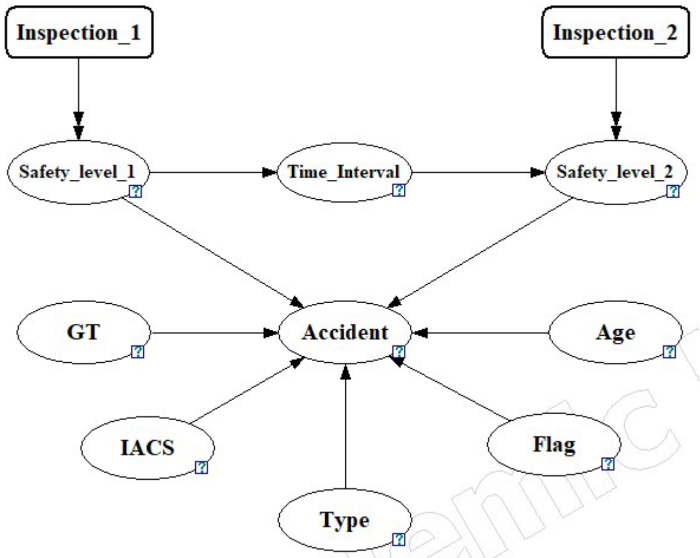

Figure 1 The main model.

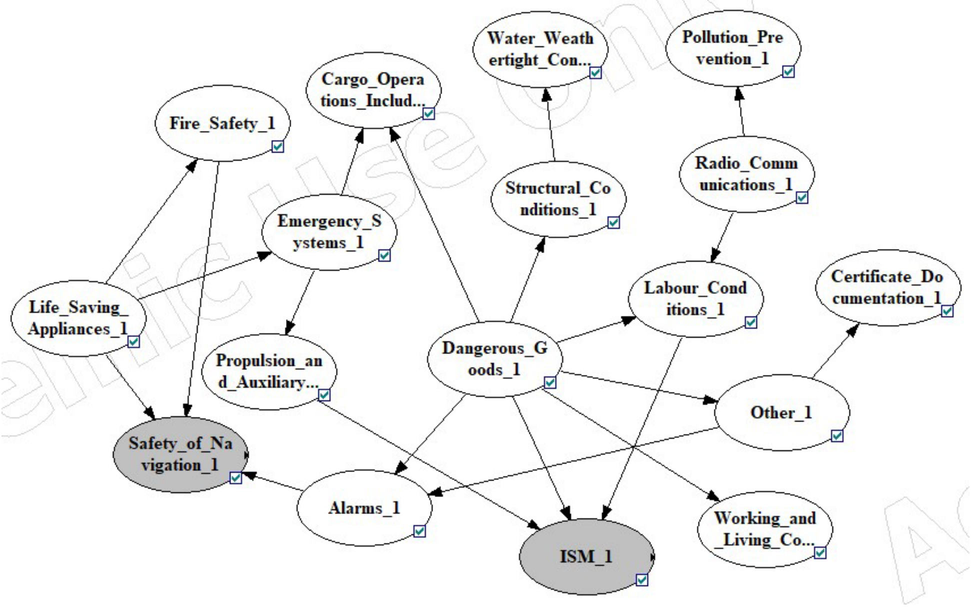

Figure 2 The sub-model of the first inspection.

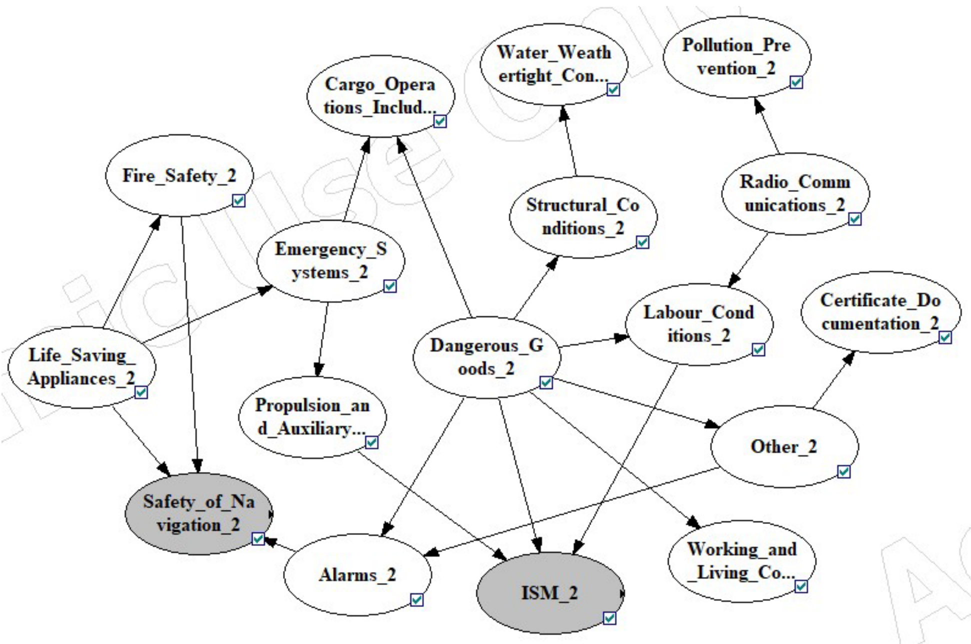

Figure 3 The sub-model of the second inspection.

Both Safety_level_1 and Safety_level_2 contain two states, representing the high and low safety level of the ships. However, these two Safety_level variables are latent variables, the states of which are directly generated by the BS learning process, so the meaning of their states needs to be discussed.

The prior probability of the variables manifests the initial probability distribution of each state. The learning results show that the prior probabilities of State 0 and State 1 of Safety_level_1 are 75% and 25% respectively, while those of Safety_level_2 are 32% and 68% respectively. We believe that a ship's safety level will be low when there are defects. As TABLE 4 shows, compared to the marginal probability of 25% in State 1 of Safety_level_1, its probability is 78% when two key defects occur. Similarly, compared to the marginal probability of 32% in State 0 of Safety_level_2, its probability is 56% when two key defects occur. Therefore, both State 1 of Safety_level_1 and State 0 of Safety_level_2 represent a low safety level, which has been indicated in the table. This also suggests that with the increase of the number of defects, the safety level decreases.

To further verify the above discussion of the states, TABLE 5 illustrates the effects of the safety level variables on accidents. It is obvious that the accident probability increases from 6% to 10% when the Safety_level_1 variable changes from State 0 to State 1. It confirms that State 1 of Safety_level_1 represents a low safety level. Similarly, State 0 represents a low safety level for the Safety_level_2 variable.

TABLE 4 The effect of the key nodes on Ship Safety Level.

Key Nodes (State =Yes)	**Safety_level_1**		**Key Nodes (State =Yes)**	**Safety_level_2**	
	State 0 (high)	State 1 (low)		State 0 (low)	State 1 (high)
Safety_of_Navigation_1	75%	25%	**Safety_of_Navigation_2**	41%	59%
ISM_1	27%	73%	**ISM_2**	66%	34%
Both[a]	22%	78%	**Both[a]**	56%	44%

Note: [a] Both of the two key nodes have defects.

TABLE 5 The effect of Ship Safety Level on Accident.

Nodes and states		**Safety_level_1**		**Safety_level_2**	
		State 0 (high)	State 1 (low)	State 0 (low)	State 1 (high)
Accident	No (93%)	94%	90%	91%	94%
	Yes (7%)	6%	10%	9%	6%

4.2 Model Validation

K-fold cross-validation is a tool to evaluate the predictive performance of a model. It first divides all the data into K subsamples, one of which is not repeatedly selected as the test set and the other k-1 samples are used for training. After repeated K times, the results are averaged to produce a single evaluation value.

According to Rodríguez, Pérez, and Lozano (2010), we select K-fold cross-validation with K=10 for the model of this study and use the Receiver Operating Characteristic (ROC) curve to depict the results. Ultimately, the Area Under the ROC Curve (AUC) is used to express the quality of the model. The AUC value is equivalent to the probability that a randomly chosen positive example is ranked higher than a randomly chosen negative example (Fawcett 2005), where *positive* means the sample is correct and *negative* means the sample is incorrect.

When the AUC value is larger than 0.5, the model is considered to have a certain predictive value (Ling, Jin, and Zhang 2003). As shown in Figure 4, the AUC values are both larger than 0.5 when Accident=No and Accident=Yes. Therefore, this BN model can be used to represent and predict ship accident well.

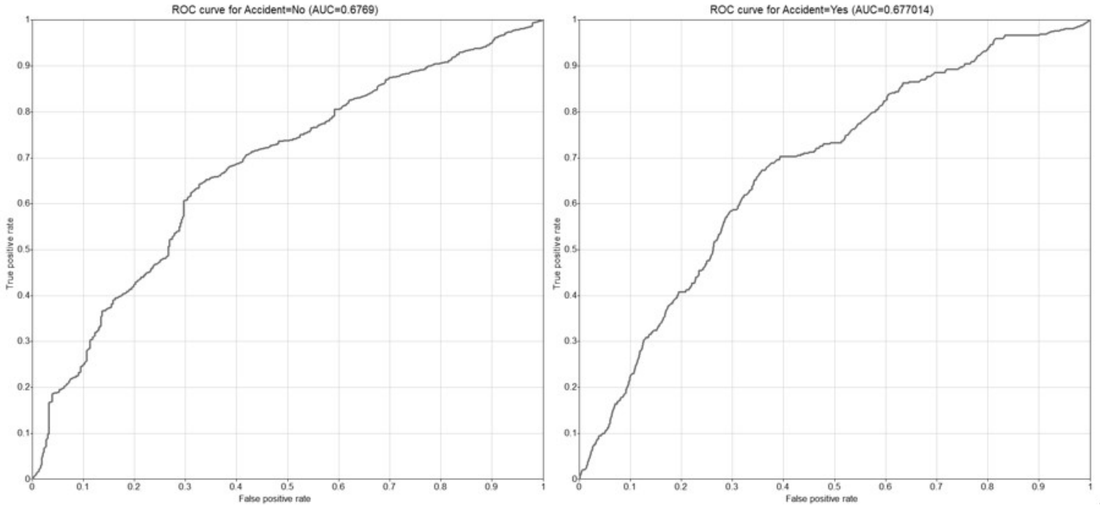

Figure 4 ROC curves for Accident=No and Yes.

4.3 Sensitivity Analysis

In order to verify the model and ensure the accuracy of the results, sensitivity analysis of the model has been conducted in TABLE 6. The prior probability of the ship accident is 7%. We calculate the posterior probability of accidents for different states of each variable and the rate of change between them. An ANOVA (Analysis of Variation) test is then conducted to test whether the posterior probabilities are significantly different for different states of the variable.

According to the result in TABLE 6, when the Flag node changes from close to open, the posterior probability of accident changes from 9% to 6%, so it indicates that the accident rate of the ships flying closed flags is 50% higher than those flying open flags. The F test of ANOVA suggests that this difference is significant at 1% significance level. Generally speaking, the accident rate of ships flying open flag is higher (Fan, Luo, and Yin 2014, Li et al. 2014), but the ships in the sample selected for this study have been inspected at least twice within a year and considered to be at a higher risk. Therefore, this result can be used to represent the state distribution of the sample.

The posterior probabilities of accident of IACS member ships and non-IACS member ships are 5% and 16% respectively. The accident rate of the ships classified by a non-IACS member is 220% higher than that of the ships classified by an IACS society. The F test is significant at 1% significance level. This suggests that the IACS variable has a high sensitivity in predicting the ship accident probability.

In addition, a low safety level at the first inspection increases the posterior probability of accident to 10%, and a high safety level decreases it to 6%. The change rate of these two posterior probabilities is 67%. Similarly, the F test suggests the significant difference between the posterior probabilities of the states. This indicates a high variance of effects of this variable on ship accident. Similarly, the posterior probabilities of accident of Safety_level_2 in low and high states are 9% and 6% respectively, with a relatively high variance of 50%.

The sensitivity of ship age and ship size also needs to be analyzed. As shown in TABLE 6, if the ship age is middle, the posterior probabilities of accident is 8%, while if the ship is new or old, it is 7%. The rate of change of the posterior probabilities is 14% and the F test suggests the significant difference among them. From the perspective of ship size, the accident rate of large ships is the highest and that of small ships is the lowest, at 13% and 4% respectively. Both the change rate and the F test suggest the high sensitivity of this variable in the model.

The last column of TABLE 6 is the sensitivity analysis of ship type on accident. The rate of change of the posterior probabilities, i.e., 733%, and the significant F test suggest a considerably high sensitivity of the variable states.

The above sensitivity analysis of the variables on accident suggests a good nodes selection and a high validity of the model, while it also shows that ship inherent attributes and ship safety levels have significant influence on the accident rate. Therefore, the following parts discuss the results of this model in detail.

TABLE 6 Sensitivity analysis of variables in the Model.

Variables	States	Posterior probability of accident	
Flag	Close	9%	
	Open	6%	
Rate of change		**50%**	
F Value[a]	**19.196**	**P Value**	**0.000**
IACS	No	16%	
	Yes	5%	
Rate of change		**220%**	
F Value[a]	**192.074**	**P Value**	**0.000**
Safety_ level_1	high	6%	
	low	10%	
Rate of change		**67%**	
F Value[a]	**106.864**	**P Value**	**0.000**
Safety_ level_2	low	9%	
	high	6%	
Rate of change		**50%**	
F Value[a]	**60.494**	**P Value**	**0.000**

Variables	States	Posterior probability of accident	
Age	New	7%	
	Middle	8%	
	Old	7%	
Rate of change[b]		**14%**	
F Value[a]	**41.983**	**P Value**	**0.000**
GT	Small	4%	
	Middle	8%	
	Large	13%	
Rate of change[b]		**225%**	
F Value[a]	**39.090**	**P Value**	**0.000**

Variables	States	Posterior probability of accident	
Type	Passenger	25%	
	Offshore	23%	
	General	16%	
	Tanker	4%	
	Container	5%	
	Bulker	3%	
	Others	8%	
Rate of change[b]		**733%**	
F Value[a]	**18.230**	**P Value**	**0.000**

Note: [a] It is the F value from the ANOVA test. [b] It is the rate of change between the biggest posterior probability and the smallest one.

4.4 Model Results and Discussion

4.4.1 Relationship between various factors and accident

In order to further understand the influence of various factors on ship accident, the probability changes of all the nodes with the change of the accident state are reported in Figure 5.

As shown in Figure 5, the probability of new ships drops from 43% to 40% when there is an accident compared to no accident. This indicates that the older the ship, the more deficiencies there may be (Cariou, Mejia, and Wolff 2009), so the ship is more prone to accidents. The probability of ships flying open flags reduces from 72% to 65%, the reason of which has been explained in above sensitivity analysis. The proportion of large ships increases from 24% to 44%. Our explanation for this is that the larger the ship, the more difficult it is to be controlled and the more likely it is to cause accidents. The percentage of non-IACS ships increases significantly, from 17% to 41%, because we generally believe that non-IACS ships are of lower quality.

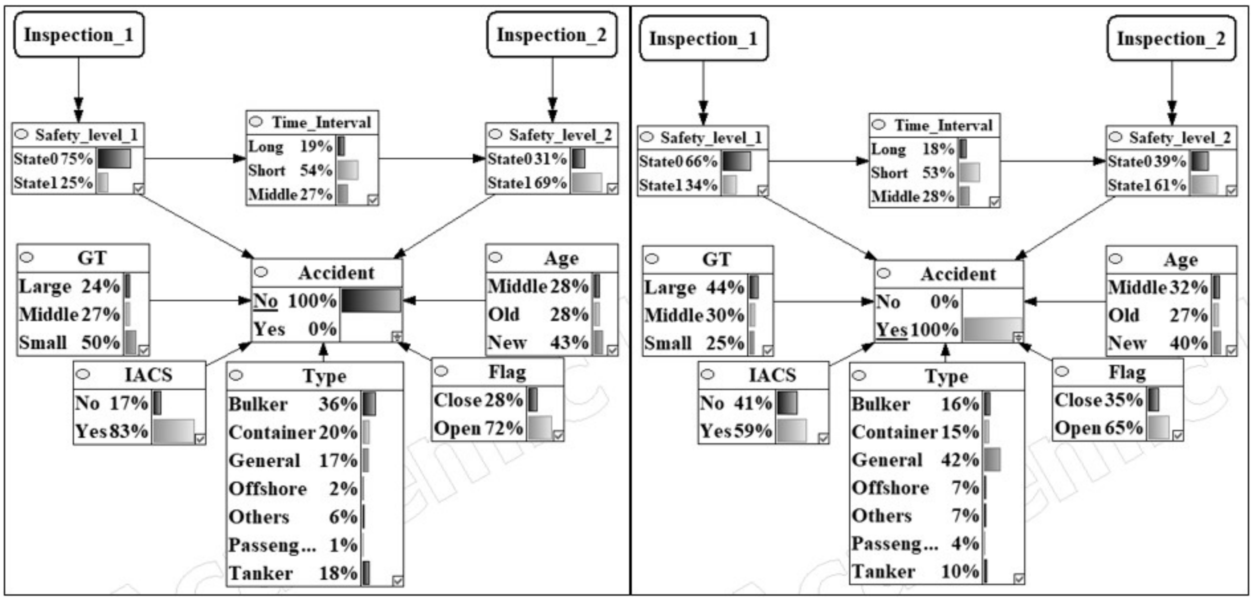

Figure 5 Comparison of the posterior probabilities distribution when there are No and Yes accidents.

In addition, when the state of accident changes from No to Yes, the probability of the low safety level of the ships inspected increases correspondingly. The probability of State 1 (low) of Safety_level_1 increases from 25% to 34% and the probability of State 0 (low) of Safety_level_2 increases from 31% to 39%, which demonstrate that the lower the safety level of ships, the more prone to accidents.

4.4.2 Relationship between the first and the second inspections

In addition to verifying the impact of the two inspections on ship accident, the effectiveness of the PSC inspection is also analyzed by discussing the effect of the first inspection on the next inspection. It is reflected in the probability relationship between the first ship safety level and the second. Meanwhile, as the effects of inspection on ships change over time, the time interval between two inspections should be considered. Therefore, the relationship between inspection time interval and two inspections need to be discussed from two different aspects:

1) The effects of the first inspection on the time interval and the second inspection

TABLE 7 illustrates the effects of the first inspection on the time interval and the second inspection. When the ship safety level is high during the first inspection, the probability of a short time interval changes from 54% to 49%, indicating that the port state will extend the inspection interval for ships with high safety level. However, when the ship safety level is low during the first inspection, the probability of a short time interval changes from 54% to 69%, indicating that port states are more likely to inspect ships with low safety level more frequently.

Moreover, the safety level of the first inspection also affects the safety level of the second inspection. When a ship has a high safety level in the first inspection, the probability of high safety level varies very little in the second inspection, slightly reducing from 68% to 67%, but it is still higher than the probability of low safety level. However, the safety level of ships with low safety level in the first inspection increases the probability of high safety level in the second inspection from 68% to 73%.

This can be explained from the perspectives of ship owners and port states. If the PSC inspection finds severe defects in a ship, i.e., a low safety level, the port state authority will force the ship owner to repair ship deficiencies, and the ship owner will take the initiative to improve the ship safety level in order to avoid trouble or detention. Since the ship owners will waste time and pay a certain amount of money once detained, and may bear the compensation for the delayed delivery of the goods, the ship owners will improve the ship safety level in order to avoid these problems. On the contrary, if the safety level is high during the first inspection, the ship owner may cut down the investment in ships in order to reduce the cost and other reasons, so that ship safety level may be reduced in the next inspection. However, most of ship owners still do their best to maintain a high safety level to avoid ship accidents, so the probability of high safety level is higher than that of low safety level generally.

TABLE 7 The effects of the first inspection on time interval and the second inspection.

Evidence		Time_Interval			Safety_level_2	
		Short	Middle	Long	State 0 (low)	State 1 (high)
Prior probability		54%	27%	19%	32%	68%
Safety_level_1	State 0 (high)	49%	31%	20%	33%	67%
	State 1 (low)	69%	16%	15%	27%	73%

2) The effect of the time interval on the second inspection

The direct effect of the inspection time interval on the second inspection is shown in TABLE 8. When Short is evidenced in the Time_Interval node, the probability of high safety level in the second inspection increases from 68% to 82%. This is because the inspection was only past for a short time and most of the deficiencies have been repaired, so the ship has a high safety level. When Middle is evidenced, the probability of low safety level increases to 58%. With the increase of the time interval, the ship may begin to have new defects, which makes the safety level decrease. As the inspection interval becomes longer, the probability of high safety level increases again. As time goes on, the ship owners may conduct self-inspection and repair some defects to avoid ship accident, so ship safety level will be improved. These results indicate that it will be more optimal to select vessels with a medium (more than 120 days and less than or equal to 240 days) inspection time interval to inspect. This could help improve ship safety level more effectively and improve utilization of resources for inspection organizations.

TABLE 8 The effect of the time interval on the second inspection.

Nodes and states		Safety_level_2	
		State 0 (low)	State 1 (high)
Prior probability		32%	68%
Time_Interval	Short	18%	82%
	Middle	58%	42%
	Long	32%	68%

Considering above analyses, the safety level in the first inspection significantly affects the inspection time interval and the safety level in the second inspection. If the ship safety level is higher in the first inspection, the second inspection usually may not be conducted in a short time. When it comes to the second inspection, the safety level will not change much or is likely to drop slightly, because ship owners may reduce the input of some items in order to reduce cost. Furthermore, if the safety level in the first inspection is low, ship owners will try their best to improve ship safety level in order not to be detained. So, ship safety level will increase in the next inspection. Finally, when the interval time is short, most of deficiencies have been repaired, so the ship safety level is generally higher during the second inspection. As time goes on, new problems begin to appear and the safety level decreases. However, as the time interval continues to increase, ship owners will also take the initiative to check and repair ship defects to avoid accidents and elevate ship safety level. Through these analyses, the effectiveness of PSC inspection is verified, which can improve safety level of ships and reduce accident rate to a certain extent. Besides, the time interval between two inspections also plays an important role in PSC inspection.

5 CONCLUSIONS

This study employs the BN model to analyze the relationship between ship inherent attributes, the results of two consecutive inspections and ship accidents. Different from previous studies on the direct relationship between ship inherent attributes, deficiencies and ship accidents, this study uses data with two inspections within one year to build a BN model, and only observes accidents that occur after inspections, which more accurately and effectively illustrates the impact of the PSC inspection on ship accident. To summarize, no matter of the risk levels for the inspected ships, it is most effective when the time interval between the two inspections is medium, namely 120 days to 240 days.

From a theoretical perspective, this study is an interesting and meaningful attempt for the research on PSC inspection. It introduces the BN model with latent variables which are Safety_level_1 and Safety_level_2 representing the results of PSC inspections and the risks of ship accidents. This makes the model simpler and clearer, as well as easier to analyze. The sensitivity analysis of this model adopts the ANOVA, which also provides an idea for other sensitivity analysis. In addition, through the analysis of time interval, this study discusses the dynamic changes of the ship safety level after PSC inspections.

The result of this study has certain guiding significance to the practical operation of PSC inspections. On one hand, excessive PSC inspections may harm the competitiveness of the port and increase the burden of ship owners. According to results of this study, ports can analyze the last inspection result and inspection date of each ship and evaluate the safety level of the ship. Therefore, ships that may be at high risk can be effectively selected for inspection, which is also helpful for improving global shipping safety. In order to avoid economic losses caused by being detained, ship owners should try their best to reduce ship defects and make ships maintain a high safety level. On the other hand, a loose inspection policy is not helpful to stimulate ship owners to implement high intensive maintenance effort (Yang et al. 2018). If a ship's safety level is estimated to be low, key inspection items can be appropriately inspected. Then further inspections can be determined according to the inspection results of the key items. These operations will greatly save the PSC inspection time and improve the inspection efficiency. In general, this study not only helps port authorities to optimize inspection system, but also saves the inspection cost.

There are still some limitations in this study. First, this study only analyzes the ships inspected by the Tokyo MoU. Due to different characteristics and development degrees of each region, there are different PSC modes, including different inspection methods and targets. Besides, some organizations may have data on other types of inspections, such as inspections conducted by class societies. Therefore, inspections in other areas can be added in future studies. Second, both crew and environment may have impacts on ship navigation, and then affect ship accidents. However, because of their uncertainties, this study does not consider crew and environment factors.

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