DEVELOPMENT OF MACHINE LEARNING AND DATA MINING MODELS FOR PORT STATE CONTROL INSPECTION

YAN Ran
MPhil

Supervised by: Dr. Shuaian (Hans) Wang

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Certificate of Originality

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________YAN Ran________(Name of student)

Abstract

This thesis aims to address two critical issues faced in port state control (PSC) inspection in maritime transportation by using machine learning and data mining models: ship selection for inspection before conducting PSC inspections and deciding onboard inspection sequence during PSC inspections. In this first study, a data-driven Bayesian network classifier named Tree Augmented Naive Bayes (TAN) classifier is developed to identify high-risk foreign vessels coming to the port state authorities. By using data of 250 PSC inspection records from Hong Kong port in 2017, we construct the structure and quantitative parts of the TAN classifier. Then the proposed classifier is validated by another 50 PSC inspection records from the same port. The results show that, compared with the Ship Risk Profile selection scheme that is currently implemented in practice, the TAN classifier can discover 130% more deficiencies on average. Several analyses of the variables (features) included in the model are also conducted. The proposed classifier can help the PSC authorities to better identify substandard ships as well as to allocate inspection resources. The second study proposes two innovative and highly-efficient PSC inspection schemes describing specific PSC inspection sequences for the inspectors' reference when time and resources are limited, especially when there are difficulties in estimating the possible deficiencies in advance. Both schemes take the occurrence probability, inspection cost, and ignoring loss of each deficiency item into account. More specifically, the first inspection scheme is based on the occurrence probabilities of the deficiency items in the whole data set, while the second scheme further considers the correlations among the deficiency items extracted by association rules. The results of numerical experiments show that the efficiency of the two proposed inspection schemes is 1.5 times higher than that of the currently used inspection scheme. In addition, the second inspection scheme performs better than the first inspection scheme, especially when inspecting ships with no less than 5 deficiency items using limited inspection resources.

Key words: Maritime transportation, port state control (PSC) inspection, Bayesian network (BN), TAN classifier, association rule

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List of Abbreviations

- Bayesian network (BN)
- Conditional probability table (CPT)
- European Maritime Safety Agency (EMSA)
- Gross tonnage (GT)
- High risk ship (HRS)
- International Labour Organization (ILO)
- International Maritime Organization (IMO)
- International Safety Management (ISM)
- Low risk ship (LRS)
- Memorandum of Understanding (MoU)
- New Inspection Regime (NIR)
- Port state control (PSC)
- Port state control officer (PSCO)
- Recognized organization (RO)
- Ship risk profile (SRP)
- Standard risk ship (SRS)
- Tree Augmented Naive Bayes (TAN)
- United Nations Conference on Trade and Development (UNCTAD)

Chapter 1: Introduction

1.1 BACKGROUND

Maritime transportation plays a pivotal role in the economic development and globalization. According to UNCTAD (2017), over 80% of global trade by volume and more than 70% of its value are carried on board ships and handled by seaports worldwide. Maritime transport is relatively safe, but once a maritime accident occurs, the costs and loss can be huge to both the shipping industry and society (Chauvin et al., 2013). It is reported by European Maritime Safety Agency (EMSA) that from 2011 to 2017, there were a total of 20,616 maritime casualties and incidents with 23,264 ships involved. Due to the accidents, 6,812 people were injured and 683 died (EMSA, 2018). As the consequences of maritime accidents are unbearable to ships, human beings, and cargos, marine safety is gaining increasing attention in recent years. Meanwhile, reducing environment pollutions related to international shipping is receiving wide notice in recent decades (IMO, 2011). To reduce maritime risks and protect the marine environment, various international rules have been formulated under the auspices of the International Maritime Organization (IMO) and International Labour Organization (ILO), such as the International Convention for the Safety of Life at Sea (SOLAS), the International Convention for the Prevention of Pollution from Ships (MARPOL), the International Convention on Standards of Training, the International Convention on Certification and Watchkeeping for Seafarers (STCW), the International Convention on Tonnage Measurement of Ships, and the International Convention on Load Lines (CLL) (IMO, 2017; Knapp and Franses, 2007a).

Ships that cannot comply with these conventions are called substandard ships (Li and Zheng, 2008). In the maritime industry, flag states, which are deemed as the nationality of a vessel and under whose laws the vessel is registered, are seen as the first line of defence against substandard ships (Knapp and Velden, 2009; Cariou et al., 2007). However, it is widely believed that many flag states are unable to perform well their mandated duties of ensuring that ships flying their flags are fully compliant with the international rules, as these ships may visit their flag state ports only irregularly. The situation can be worse in the open registry countries, as these flag states often have insufficient or substandard regulations and those regulations are poorly enforced (Li and Wonham, 1999). As a result, port state control (PSC), which is an internationally agreed regime to inspect foreign ships coming to the port state, was first proposed in 1982. It acts as the "second line of defence" and "last safety net" to eliminate substandard vessels, and is a complement instead of a substitute, to consolidate the safety net of the former maritime safety administration by the flag state (Cariou et al., 2008; Li and Zheng, 2008).

The Memorandum of Understanding (MoU) on PSC, which is an organization consisting of several PSC member authorities in a certain region, was first established in Europe in 1982 (often referred to as the "Paris MoU"), and by the end of 2018, nine MoUs on PSC have been signed around the world. The reason for the development of regional cooperation for the PSC by forming MoUs are to ensure the exchange of information between states on the safety records of ships, to prevent multiple inspections of ships in the same region over the period of time, and to eliminate the negative actions that reduce the commercial activities of neighbouring ports within the same region. When a ship visits the foreign ports within a certain MoU, the port should decide whether to inspect the ship according to the requirements of the corresponding MoU (Graziano et al., 2018). The goal of the MoUs on PSC is the same: to verify that the incoming ships meet the requirements of the international agreements through a harmonized system of port state control which allows for information sharing (Kasoulides, 1993; Paris MoU, 2019). In each MoU, the member authorities are responsible for inspecting incoming foreign ships and should adopt the same set of inspection rules. In 2016, the number of inspections conducted by the nine PSC MoUs was 63,805 in total (Indian Ocean MoU, 2017; Caribbean MoU, 2017; Abuja MoU, 2017; Black Sea MoU, 2017; Viña del Mar Agreement, 2017; Tokyo MoU, 2017a; Mediterranean MoU, 2017; Riyadh MoU, 2017; Paris MoU, 2017), while the total number of merchant vessels in the whole world was 96,161 (UNCTAD, 2017). During a PSC inspection, conditions on board that are not in compliance with the requirements are recorded as deficiencies and are required to be rectified. The PSC authorities also have the right to detain a ship until the deficiencies are rectified if those deficiencies might pose a danger to the crew and the marine environment (Tokyo MoU, 2017a). After the inspection, a report on the inspected ship, including ship information (e.g., ship name, ship flag, and ship company) and inspection information (e.g., inspection date, inspection authority, the types and total number of deficiencies detected, and ship detention information), is generated and kept in the database of the corresponding MoU.

A general inspection process is shown in Figure 1-1. When foreign ships come to the port state, the port state authority first selects the ships to be inspected based on some criteria. After that, available PSC officers (PSCOs), who are properly qualified persons and are authorized to carry out PSC inspection, are assigned to get onboard and inspect these ships. After getting onboard, the first impressions of the ship left to the PSCO are obtained by walking around the ship to check its overall condition. A general PSC inspection can contain an initial inspection and a more-detailed inspection. In initial inspection, the PSCO first checks the required certificates and documentary, and then walks around the ship to assess its comprehensive condition. If little wrong is found, the inspection can be quickly finished. On the contrary, if clear grounds are identified, i.e. the condition of the ship or its equipment does not correspond substantially with the particulars of the certificates, a more detailed inspection will be conducted. A more detailed inspection is an in-depth inspection covering the ship's construction, equipment, manning, living and working conditions and compliance with onboard operational procedures. After an inspection, the inspection results, including ship deficiencies and detention, together with ship information are recorded in the corresponding database.

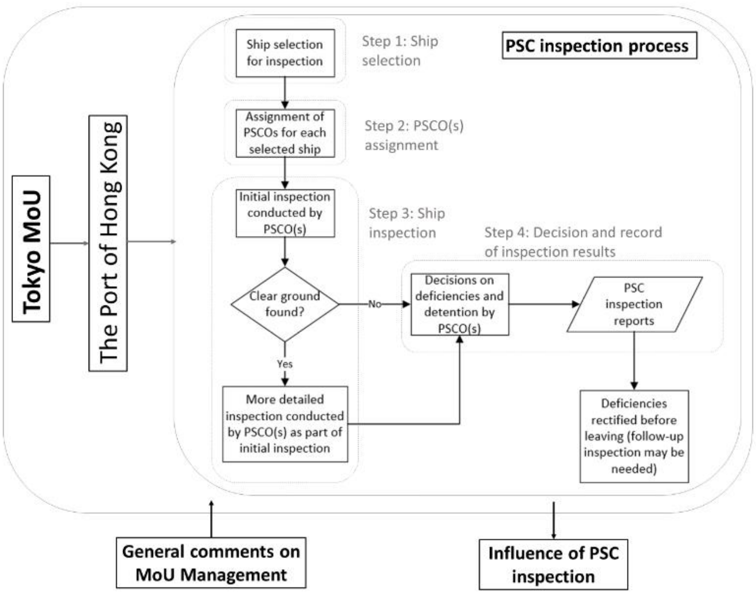


Figure 1-1: General process of a PSC inspection

This thesis aims to improve PSC inspection efficiency by considering two critical and practical issues in PSC inspection: ship selection for inspection (i.e. step 1) and ship onboard inspection sequence by using machine learning and data mining technics (i.e. step 3). Ship selection is a pre-determinant action and foundation of efficient and effective PSC inspection, as only a small ratio of ships can be inspected due to high inspection costs and limited inspection resources. However, the currently implemented ship selection schemes adopts a simple weighted sum model to classify the incoming ships, and the weight of each parameter is determined simply by expert judgement. In addition, it does not take the dependencies between different parameters into account. Moreover, even if each incoming ship is given a risk profile, there is no further information about the risk level of the ships in the same risk profiles. Therefore, Chapter 3 aims to propose a data-driven Bayesian network classifier called a Tree Augmented Naive Bayes (TAN) classifier as a new scheme to select ships for PSC inspection by using real inspection records at the Hong Kong port. To the best of our knowledge, there is no official documents of PSC inspection and current literature that offer detailed onboard inspection sequence for the PSCOs' reference when conducting PSC inspection. As a result, the inspected areas of a ship and to what extent they will be inspected are highly dependent on PSCOs' expert judgments, which may lead to inefficiency. Therefore, Chapter 4 presents two innovative and highly-efficient PSC inspection schemes for specific onboard inspection sequence based on the occurrence probability and the association rules of the deficiency items.

1.2 THESIS OUTLINE

The remainder of the thesis is organized as follows. Chapter 2 gives a comprehensive literature review of the studies on PSC inspection. Chapter 3 presents a detailed introduction of the concepts of Bayesian network and TAN classifier. Then, a TAN classifier is developed for ship selection at the Hong Kong port, and its performance is validated. Chapter 4 gives a detailed introduction of association rule mining using Apriori algorithm. Then, large itemsets and association rules are generated among the deficiency items in real inspection records at the Hong Kong port. Comparisons between the current inspection scheme and the newly proposed inspection schemes are conducted. Chapter 5 concludes the thesis.

Chapter 2: Literature Review[1]

The literature review chapter divides the studies on PSC inspection into four categories: studies on factors influencing PSC inspection results, studies on ship selection scheme, studies on the effects of PSC inspection, and studies on suggestions to improve PSC inspection. Moreover, we consider ship factors and non-ship factors that influence PSC inspection results, and the effects on maritime safety and inspected ships of PSC inspection.

2.1 FACTORS INFLUENCING THE RESULTS OF PSC INSPECTION

The results of the PSC inspection include detection of ship deficiencies and decision on ship detention. Much of the current literature considers the factors that may affect the PSC inspection results. Some of those factors are ship factors, including ship generic factors (e.g., ship age, ship type, ship size, the performance of ship flag, and ship company) and ship inspection factors (e.g., the number of previous detentions and the number of outstanding deficiencies). A small number of studies focus on non-ship factors, including the impact of PSC inspection time, inspection area and the background of the PSC inspectors. In some papers, the abovementioned factors are analyzed simultaneously.

2.1.1 Ship factors influencing PSC inspection results

Some papers are focused on generic factors. Cariou et al. (2007) reported that ship age at inspection, ship type, and ship flag are the dominant predictors of ship deficiencies by using Poisson models. Cariou et al. (2009) then further identified that determinants of ship deficiency number and probability of detention were ship age (40%), ship recognized organization (31%) and place of inspection (17%). Recently, Yang et.al (2018a) identified the factors that were most influential to ship detention were the number of deficiencies, type of PSC inspection, ship recognized organization and ship age by using a data-driven Bayesian network.

More detailed ship factors are also identified in the literature. Cariou and Wolff (2015) presented a quantile regression model and concluded that bulk vessels, dry

1 Yan, R., Wang S. 2019. Ship inspection by port state control—review of current research. Smart Transportation Systems 2019, 233–241. Springer, Singapore.

cargos, and reefer ships, as well as older ships were associated with a higher number of deficiencies and probability of detention. Tsou (2018) used association rule mining techniques in big data analysis to examine the relationships between deficiencies and the contribution of target factors to deficiencies and concluded ship attributes that might lead to high detention rate. Chung et al., (2019) also adopted association rule learning method and identified association rules among PSC deficiencies in terms of specific ship characters.

2.1.2 Non-ship factors influencing PSC inspection

Regarding non-ship factors, Knapp and Franses were the pioneers who used the econometric methods to analyze the influencing factors. They claimed that certain types of deficiencies were more frequently identified in some regimes and various backgrounds of inspectors would lead to differences among the regions (Knapp and Franses, 2007a). Some other studies also found that PSC inspection regimes, the professional profile of PSC inspectors, PSC inspection team composition, and inspectors' background would influence the results of PSC inspection, including the deficiencies recorded, the total number of deficiencies identified, and the decision of detention (Knapp and van de Velden, 2009; Ravira and Piniella, 2016; Graziano et al., 2017; Graziano et al., 2018a, b; Kara et al., 2019).

The abovementioned papers all use quantitative methodologies, including statistical models (regression model, count data model, variance decomposition analysis, and Bayesian network model) or big data mining technologies to apply to case data sets and find out the determinant factors of PSC inspection results. The conclusions are concordant: ships of elder age, of some certain types, sizes, recognized societies and flags perform worse in the PSC inspection all have significant impact on the results of PSC inspection, while the inspection authorities and background of PSC inspectors will also impact the results.

2.2 SHIP SELECTION SCHEME IN PSC INSPECTION

A considerable amount of literature has been focused on ship selection scheme to make the selection process more efficient, that is, to select the high-risk ships which are with more deficiencies and with higher probability of detention. Early models usually adopted scoring system to identify ship risk level. For example, Li examined 20 years data and proposed a new ship assessment system to automatically give each coming ship a risk score (Li, 1999). Similarly, Degré (2007) demonstrated a high risk vessels selection scheme based on “Risk Concept”.

Several more recent studies used machine learning models for ship selection in PSC inspections. Xu et al. (2007a) demonstrated a Support Vector Machine (SVM) ship risk assessment system based on target factors. They then combined website scrapper technology to extract more target factors and included them in the SVM model to improve its efficiency (Xu et al. 2007b). Based on these studies, Gao et al. (2008) further improved the classification accuracy of the proposed SVM model by combing K-Nearest Neighbor (KNN). In addition, Zhou and Sun (2010) introduced a new model to select ships by using Generalized Additive Modeling (GAM) corrected by the parameter of Excess Factor. After identifying the determinant factors of ship detention, Yang et al. (2018a) then used the Bayesian network model to predict the probability of vessel detention to help the decision of ship selection. Based on the predicted ship detention rates, Yang et al. (2018b) proposed a strategic game model to identify the optimal detention rate for the port state authorities. Heij and Knapp (2019) developed a new ship risk analysis system by combining past incident and detention information for targeting high-risk vessels, which are two strong indicators of ship risk dimension.

Overall, these studies all take factors related to ship itself, such as ship age, ship flag, ship type, ship company, and ship size into account when analyzing the results of PSC inspection. Some of the studies also consider ship insurers. Conversely, factors related to historical inspection information, such as last inspection time, previous number of detentions and last inspection authority are seldom included in the above studies. Similarly, dynamic factors of the ships, such as change of flag, change of ship company or classification society and change of captain and sailors are not considered in the above papers. As a result, whether these factors are related to the results of PSC inspection remains to be validated. Regarding the methodology proposed in these studies, they all use mathematical models to quantitatively illustrate the influence of the factors on PSC inspection results. Compared with ship selection methods adopted by most of the PSC MoUs which are based on weighted-sum methods with fixed and expert knowledge-based weighting points attached to the factors, these models can identify sub-standard ships more efficiently and accurately.

2.3 EFFECTS OF PSC INSPECTION

PSC inspection is seen as the second line of defence in eliminating substandard vessels (Li and Zheng, 2008). It aims at "verifying that a number of requirements derived from various international agreements were met and that conditions on board ships were not hazardous to safety or health" (Cariou et al., 2007). After the first PSC program was introduced in 1982, a large volume of studies has discussed the effects of it.

2.3.1 PSC inspection effects on maritime safety

The main research stream focuses on the effectiveness of PSC inspection on improving maritime safety. Knapp and Franses (2007a) figured out that the more times a ship had been inspected, the less likely it would involve in very serious accidents. Li and Zheng (2008) pointed out that PSC programs were powerful in improving maritime safety level by reducing total accident loss number and loss rate. More specific, Knapp et al. (2011) figured out that the estimated range of monetary benefit of PSC inspection was from about 70,000 to 190,000 dollars, with median values ranging from 20,000 to 45,000 dollars. Regarding the specific relationship between ship inspection factors and accident involvement, Hänninen and Kujala (2014) identified that ship type, PSC inspection type and the number of structural conditions related deficiencies were the most influential factors of accident involvement by constructing a Bayesian network model. Recently, Heij and Knapp (2018) figured out that a worse PSC inspection outcome in the previous year, the higher probability of shipping accident in the next year. The above papers all aim to validate the effectiveness of PSC inspection. On the contrary, Bateman (2012) pointed out that the PSC inspection appeared to be inefficient in reducing the substandard ships in the Indian Ocean Region (IOR) where a large number of piracies, robberies, and other illegal activities still existed.

Overall, although PSC inspection may be inefficient in some developing world due to the complicated conditions and limited inspection resources, it has been shown that introducing PSC can help improve the safety of global maritime environment, especially by reducing the occurrence of maritime accident and the maritime risk loss rate.

2.3.2 PSC inspection effect on inspected ships

Another research stream is the effect of PSC inspections on the inspected ships. Cariou et al. (2008) suggested that the deficiencies detected in the next PSC inspection were reduced by 63% compared with the previous inspection. As the ship selection schemes adopted by PSC MoUs took ship flag and classification society into account, Cariou and Wolff (2011) noted that two types of ships were more likely to get involved in flag- and class- hopping: vessels with relatively bad conditions and the ones that had changed flag and class before. Fan et al. (2014) also argued that PSC inspection may influence ship flag choice.

Together, these studies outline that PSC inspection is impactful in reducing maritime risks and improving the condition of ships. However, there may be some drawbacks brought by the PSC inspections. As ship selection scheme for PSC inspection takes the performance of ship flag and classification society into account, this may give rise to opportunistic behaviors including ships' flag-hopping and class-hopping to reduce inspection frequency.

2.4 SUGGESTIONS FOR PSC INSPECTION

Harmonization of PSC MoUs' databases and combining with other inspection reports and casualty databases have been suggested in many papers. Knapp and Franses (2007b) claimed differences towards detention probabilities in different PSC MoUs and advocated harmonization of PSC inspection. After analyzing the differences in PSC regimes, Knapp and van de Veldon (2009) suggested accelerating the regimes harmonization process. Knapp and Franses (2008) also recommended developing the Global Integrated Ship Information System (GISIS) of the International Maritime Organization. Heij et al. (2011) pointed out that incorporating casualty reports and PSC inspection database could help select ships for inspections and gain safety improvements.

In view of all that has been mentioned so far, there is no doubt that PSC inspection is effective in rectifying substandard ships and improving maritime safety. Nevertheless, there is still room to develop its inspection strategies by adjustment of PSC inspection authority, combining databases of different MoUs, and with accident and casualty reports, or adopting some mathematical models to better trade-off the inspection costs and rates.

Chapter 3: Ship Selection in PSC Inspection[2]

This chapter deals with one of the most significant practical problem faced by port states: how to select the high-risk ships among all the foreign visiting ships for inspection. A data-driven Bayesian network classifier named Tree Augmented Naive Bayes (TAN) classifier is developed to identify high-risk foreign vessels coming to the PSC inspection authorities. By using data on 250 PSC inspection records from Hong Kong port in 2017, we construct the structure and quantitative parts of the TAN classifier. Then the proposed classifier is validated by another 50 PSC inspection records from the same port. The results show that, compared with the Ship Risk Profile selection scheme that is currently implemented in practice, the TAN classifier can discover 130% more deficiencies on average. The proposed classifier can help the PSC authorities to better identify substandard ships as well as to allocate inspection resources. The outline of this chapter is as follows: Section 3.1 introduces the background of the problem and the contribution of this chapter. Section 3.2 reviews the studies on application of Bayesian network in maritime risk analysis. Section 3.3 discusses the methodology used in this chapter. Section 3.4 introduces the data used in this chapter and constructs the classification model. Section 3.5 validates the model and presents the results of the numerical experiments. Section 3.6 presents the variable analysis in this model. Section 3.7 discusses future research of this topic and concludes this chapter.

3.1 PROBLEM DESCRIPTION

3.1.1 Background

PSC inspection is conducted by regional port state control authorities. One of the key issues faced by PSC authorities is how to select ships on which to conduct PSC inspections (IMO, 2018). On the one hand, the cost of PSC inspection to the port authorities is high. It is estimated by Knapp (2007) that the costs for a PSC inspection with and without deficiencies are 759 USD and 509 USD, respectively. Further, non-

[2] Wang, S., Yan, R., Qu, X., 2019. Development of a non-parametric classifier: Effective identification, algorithm, and applications in port state control for maritime transportation. Transportation Research Part B: Methodological 128, 129-157.

essential inspections may also delay the fast turnover of the maritime logistics system. On the other hand, not all ships are substandard. Tokyo MoU, which is the MoU on PSC in the Asia-Pacific Region and was signed in December 1993, reported that the total number of inspections conducted by its 20 member authorities in 2017 was 41,616, while only 18,113 inspections found deficiencies (Tokyo MoU, 2018a). Due to the high costs and limited time and resources, it is impossible and unnecessary to inspect all coming ships. In order to identify as many substandard ships and ship deficiencies as possible after inspecting a certain number of ships, different PSC MoUs adopt different ship selection schemes. Taking Tokyo MoU as an example, it introduced a New Inspection Regime (NIR) from 2014 (Tokyo MoU, 2014) to calculate the ship risk profile (SRP) using criteria on an information sheet. The information sheet is shown in Figure 3.1.

1. SHIP RISK PROFILE

Parameters		Profile			
		High Risk Ship (HRS) (When sum of weighting points >=4)		Standard Risk Ship (SRS)	Low Risk Ship (LRS)
		Criteria	Weighting points	Criteria	Criteria
Type of Ship		Chemical tanker, Gas Carrier, Oil tanker, Bulk carrier, Passenger ship, Container ship	2	Neither LRS nor HRS	-
Age of Ship		All types > 12y	1		-
Flag	BGW-list[1)]	Black	1		White
	IMO Audit[2)]	-	-		Yes
Recognized Organization	RO of Tokyo MOU[3)]	-	-		Yes
	Performance[4)]	Low Very Low	1		High
Company performance[5)]		Low Very Low No inspection within previous 36 months	2		High
Deficiencies	Number of deficiencies recorded in each inspection within previous 36 months	How many inspections were there which recorded over 5 deficiencies?	No. of inspections which recorded over 5 deficiencies		All inspections have 5 or less deficiencies (at least one inspection within previous 36 months)
Detentions	Number of Detention within previous 36 months	3 or more detentions	1		No detention

Figure 3-1: Information sheet of SRP (Tokyo MoU, 2014)

As indicated by Figure 3-1, the information sheet takes into consideration several parameters including ship type, age, ship company performance, previous detentions, etc. Each parameter is given a fixed weighting point and the SRP is determined by the total weighting points (Tokyo MoU, 2014). Based on the total points, all ships are divided into three types: low risk ship (LRS), standard risk ship (SRS) and high risk ship (HRS). The higher risk a ship has, the more frequently it will be inspected. As the SRP adopts a simple weighted sum model to classify the incoming ships, the weight of each parameter is determined simply by expert judgement. In addition, it does not take the dependencies between different parameters into account. Another issue is that even if each incoming ship is given a risk profile, there is no further information about the risk level of the ships in the same risk profiles. As a result, when ships of the same SRP come to the port state, the selection of ships to be inspected is dependent on the PSCOs' subjective judgements.

3.1.2 Contribution

To address the abovementioned problems, this study aims to propose a data-driven Bayesian network classifier called a Tree Augmented Naive Bayes (TAN) classifier as a new scheme to select ships for PSC inspection. The TAN classifier is constructed and validated from a case data set which is built based on the online database of Tokyo MoU. It takes into account factors related to a ship itself and its inspection history and calculates their mutual dependencies and contributions to the total number of ship deficiencies. The TAN classifier provides PSC officers with an informed estimate of the number of deficiencies an incoming ship will have, which helps them to identify higher risk ships and better allocate resources to PSC inspections. The contribution of the chapter is as follows. (i) The proposed TAN classifier is one of the first few models to take into consideration historical factors (including the number of previous detentions, last inspection time, number of deficiencies in the last inspection and number of flag changes) and the performance of the shipping company (which is responsible for verifying that the ship complies with the International Safety Management (ISM) code) when analyzing PSC inspection from a quantitative perspective. After inputting the above-mentioned information of a coming ship, the TAN classifier can generate the probabilities for the ship to have 0 to 2, 3 to 6, and more than 7 deficiencies immediately based on the trained CPTs, and the timely risk index of this ship can also be given for the PSCOs' reference. Thus, the proposed classifier can act as a real-time predictor of the number of deficiencies before conducting the PSC inspection. (ii) The newly proposed ship selection scheme for PSC inspection adopts a data-driven non-parametric model. This is the very first model that makes predictions on the possible number of deficiencies of incoming ships for PSC inspection. Compared with the currently used SRP ship selection scheme, it can identify an average of 130% more deficiencies in ships. (iii) Theoretically, our study proposes a dynamic programming approach to optimally discretize input data into discrete states so that they can be analyzed by the TAN classifier. Moreover, by induction, it is rigorously proved that in the TAN classifier, random selection of root attribute variables will not influence the classification process.

3.2 LITERATURE REVIEW

Studies on application of Bayesian network in maritime risk analysis is presented in this section. In recent years, we have witnessed a fast-growing number of maritime risk studies based on the Bayesian networks (BNs). Hänninen (2014) searched for and presented papers related to BNs applied to maritime safety. The author concluded that BNs are rather well-suited tools for maritime safety management and development. There is a growing interest in and promising development of using BNs to conduct maritime risk analysis. In order to integrate different stakeholders' views and foundational perspectives on a risk ranking which could be used in complex systems such as the maritime transportation system, Goerlandt and Reniers (2017) proposed a BN model to combine the ranking methods based on the expected values, uncertainty, and moral perspective. Trucco et al. (2008) proposed a Bayesian belief network with conditional probabilities estimated using expert knowledge to model the Maritime Transportation System (MTS). Li et al. (2014) integrated logistic regression and BN to analyze maritime risks. The logistic regression model was able to provide parameters for the BN model to alleviate the bias brought by the expert estimation. Zhang et al. (2016) synthesized the statistics of historical accident data from 2008 to 2013 and expert judgement in the Bayesian belief network to express the dependencies between the indicator variables. Zhang et al. (2013) applied a formal safety assessment to evaluate the navigation risk of the Yangtze River and then constructed a data-based BN model to identify accident consequences. To reduce ship risk in ice-covered waters, Li et al. (2017) developed a BN model to link the ice conditions with the ship speed. The model could be used to generate the probability of a certain speed when the ice conditions were given and could be applied in risk assessment of route finding problems. Wróbel et al. (2016) analyzed the risk associated with unmanned ships by using a three-level BN model whose structure was determined based on the causes and effects of unfortunate events affecting ships' safety. Lu et al. (2019) proposed a BN model for assessing the effectiveness of oil spill recovery in icy conditions. A systematic approach was applied to establish the content and structure of the model, while various datasets were combined to estimate the probabilities of the model variables.

A serious drawback of the abovementioned BNs is that, due to the lack of historic data, most of the proposed BN models rely on expert knowledge in structure construction or model parameterization. The involvement of subjective judgements may bring about uncertainty and biases. Zhang and Thai (2016) thus pointed out that data-driven BNs are considered to be more objective since they are based on empirical data.

3.3 METHODOLOGY

3.3.1 Bayesian network (BN)

A Bayesian network (BN) is a directed acyclic graph containing a set of nodes and a set of directed arcs (Friedman et al., 1997). The nodes in the network represent the variables. The node at the tail of an arc is the parent node, which acts as the condition, while the node at the head is the child node of that parent node and is the consequence of that condition (Wang and Vassileva, 2003). The arcs from one node to its child nodes represent their dependencies. The BN is acyclic, which means that from any node, there must not be a way back to the same node. All the nodes in the network have a finite number of mutually exclusive states that represent the values of the corresponding variables. The values of a node can be either continuous or discrete, and our study only focuses on discrete values. A BN contains a network structure as the qualitative part and several probability parameters as the quantitative part. Compared to other prediction models, BNs have a solid mathematical background and present a graphical relationship that is easy to understand. In addition, the Bayesian approach performs well in coping with unknown probability parameters (Yu et al., 2012). It is therefore a commonly used method to analyze and predict maritime risks (Li et al., 2014; Zhang et al., 2016; Hänninen and Kujala, 2014).

3.3.2 The structure of the Tree Augmented Naive Bayes (TAN) classifier

Statistical classification identifies to which of a set of categories a new observation belongs based on the data training observations (Warfield et al., 2000). In the classification, the classifier is built from a set of training data and can be used to perform prediction on the testing data. One of the most widely used classifiers is the Naive Bayesian classifier, which is a simple probabilistic classifier based on Bayes' Theorem with strong (naive) independence assumptions between the features (Domingos and Pazzani, 1997; Hänninen, 2014; Zhang and Thai, 2016; Hazelton, 2010). An example of a Naive Bayesian classier is illustrated in Figure 3-2. The Naive Bayesian classifier contains a class variable C , which is the classification target, e.g., the total number of deficiencies in a PSC inspection, and several attribute variables A_1 to A_4. Usually, the attribute variables are the properties and characteristics used to describe the cases, e.g., ship age, ship type, ship flag, and ship recognized organization. They are easy to access and thus act as the evidence for classifying. The classifier will be trained using a set of cases with known states of attribute variables and class variable (e.g., 250 past records of PSC inspection). Then, a new case with a set of attribute variables can be classified by the classifier to one state of the class variable (e.g., a ship visits a port and the PSC authority knows its age, type, flag and recognized organization, so the PSC authority can have an estimate of the number of deficiencies the ship has). In the Naive Bayesian classifier, it is assumed that, given the class variable, every attribute variable is conditionally independent of the other attribute variables (Cheng and Greiner, 1999). However, there are actually more or fewer connections between the attribute variables (e.g., the flag states can authorize some certain recognized organizations to act on their behalf to carry out statutory survey and certification work of their ships). Hence, this assumption will influence the classification accuracy of the Naive Bayesian classifier (Dong et al., 2007).

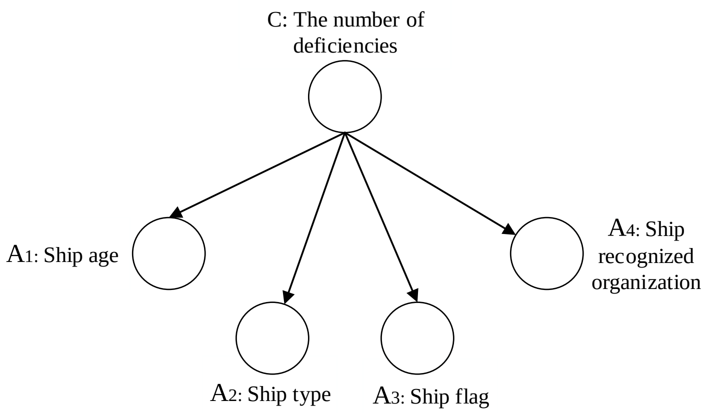


Figure 3-2: Example of a Naive Bayesian model

To deal with the over-simplified assumption, the Tree Augmented Naive Bayes (TAN) classifier is proposed to identify the interactions between the attribute variables by using a tree structure (Friedman, 1997). An example of the TAN model is presented in Figure 3-3. As illustrated in the figure, a typical TAN classifier contains a class variable and several attribute variables. The class variable has no parent and is the parent of every attribute variable. Each attribute variable can have at most two parent variables including the class variable (Pernkopf, 2005). In this example, for instance, a flag state has expertise for registering certain types of ships, and it can authorize certain recognized organizations to act on its behalf to carry out statutory survey and certification work of their ships, so the node "Ship flag" depends on the node "Ship type", and "Ship recognized organization" depends on "Ship flag".

We now describe the TAN classifier mathematically. The class variable C has a total of N_C states; the set of these states is denoted by $S_C = \{c_1, ..., c_{N_C}\}$. The number of attribute variables is denoted by I and all the attribute variables are presented by a vector $A = (A_1, ..., A_I)$. The i th attribute, A_i, $i = 1, ..., I$, can take a total of N_i states, denoted by a state set $S_i = \{a_{i,1}, a_{i,2}, ..., a_{i,N_i}\}$.

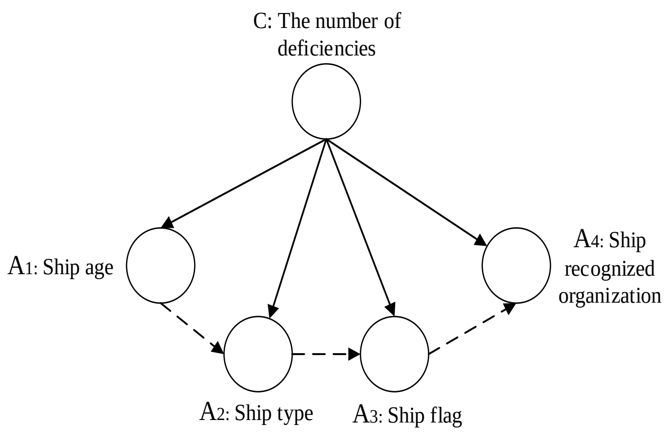


Figure 3-3: Example of TAN model

The TAN classifier will be trained by a full case data set, which is a case whose values of both the class variable and attribute variables are known. The full case data set is denoted by $\mathbb{K} = \{1, ..., K\}$, and one certain case is denoted by $k \in \mathbb{K}$. The state of the class variable of case k is denoted by $c^k \in S_C$; in other words, case k is classified to c^k. The state of attribute variable A_i of case k is denoted by $a_i^k \in S_i$, and thus its state vector of the attribute variables is denoted by $ATT^k = (a_1^k, ..., a_I^k)$.

Based on the full data set $\mathbb{K}$, we can evaluate the dependency between two attribute variables. The dependency between two attribute variables A_i and A_j given the class variable C, $i, j = 1, ..., I$, $i \neq j$, is described by the conditional mutual information $I(A_i; A_j \mid C)$, which is the expected value of the mutual information of two random variables given the value of the third (Wyner, 1978). For a data set $\mathbb{K}$, the conditional mutual information for two attribute variables A_i and A_j is defined as (Cover and Thomas, 2012)

$$I(A_i; A_j \mid C) = \sum_{s'=1}^{N_i} \sum_{s''=1}^{N_j} \sum_{s=1}^{N_C} P(a_{i,s'}, a_{j,s''}, c_s) \log \frac{P(a_{i,s'}, a_{j,s''} \mid c_s)}{P(a_{i,s'} \mid c_s) P(a_{j,s''} \mid c_s)} \tag{3.1}$$

where the "log" means the logarithmic operation with base 2 in this study[3] and $P(a_{i,s'}, a_{j,s''}, c_s)$, $P(a_{i,s'}, a_{j,s''} \mid c_s)$, and $P(a_{i,s'} \mid c_s)$ are abbreviated forms of $P(A_i = a_{i,s'}, A_j = a_{j,s''}, C = c_s)$, $P(A_i = a_{i,s'}, A_j = a_{j,s''} \mid C = c_s)$, and $P(A_i = a_{i,s'} \mid C = c_s)$, respectively. This also applies to the remainder of the chapter. $P(a_{i,s'}, a_{j,s''}, c_s)$ is the joint probability and $P(a_{i,s'}, a_{j,s''} \mid c_s)$ and $P(a_{i,s'} \mid c_s)$ are conditional probabilities. Since we use the data set $\mathbb{K}$ to calibrate the TAN network, $P(a_{i,s'}, a_{j,s''}, c_s)$ should be understood as the *proportion* of cases in $\mathbb{K}$ whose states of attribute variable A_i, attribute variable A_j, and class variable C are $a_{i,s'}$, $a_{j,s''}$, and c_s, respectively. Similarly, $P(a_{i,s'}, a_{j,s''} \mid c_s)$ should be understood as: among cases in $\mathbb{K}$ whose class variable state is c_s, the *proportion* of cases whose states of attribute variable A_i and attribute variable A_j are $a_{i,s'}$ and $a_{j,s''}$, respectively.

A complete TAN classifier contains the structure part and the quantitative part (Hruschka Jr and Ebecken, 2007). To learn the structure of the TAN classifier containing $A_1, ..., A_i$ as the attribute variables and C as the class variable, let function $\pi : \{1, ..., I\} \mapsto \{0, ..., I\}$ identify the parent attribute variable index for each attribute variable, and

[3] The base of the logarithmic operation can be any value greater than 1, as long as all pairs of attribute variables use the same base. This is because it is not the absolute values but the ratios of the conditional mutual information for each pair of attribute variables that will affect the result of the TAN classifier.

$$\pi(i)=\begin{cases} i', \text{ if } A_i \text{ has a parent attribute variable } A_{i'},\ i=1,...,I, i'=1,...,I \text{ and } i'\neq i \\ 0, \text{ if } A_i \text{ has no parent attribute variable, } i=1,...,I. \end{cases} \tag{3.2}$$

The construction of the TAN classifier consists of an optimization problem to find a tree defining a function π over $A_1,...,A_I$ such that the tree sum of mutual information is maximized (Chow and Liu, 1968). In this study, a procedure called Construct-TAN (Friedman, 1997) is adopted to identify the tree, which is the qualitative part of the TAN classifier. The conditional probability tables constitute the quantitative part of the TAN classifier, and the conditional probabilities are estimated based on the full case data set and the learned TAN structure. The detailed procedure of constructing the TAN classifier will be explained in Section 3.4.

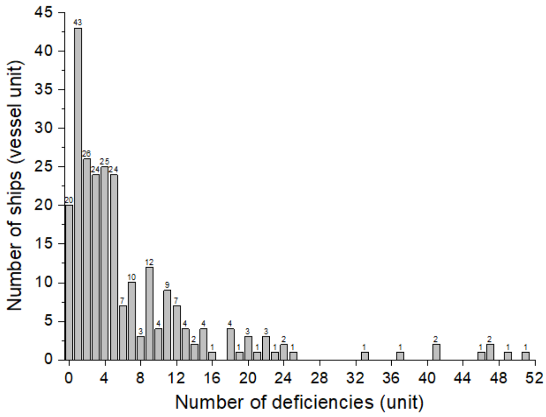
3.4 MODEL CONSTRUCTION

3.4.1 Data

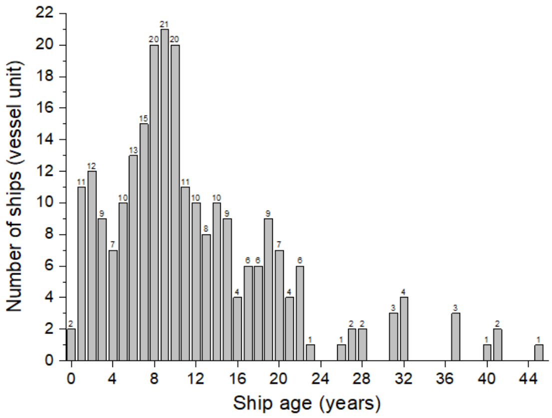
A case data set containing 250 PSC inspection records (full case data) from Hong Kong is denoted by $\mathbb{K}$ and established from the database of Tokyo MoU (http://www.tokyo-mou.org/inspections_detentions/psc_database.php). Inspected vessels with incomplete information are omitted. The inspection time range of these cases is from January 2017 to July 2017. Among the 250 records, 14 ships were inspected by PSC for the first time.

3.4.2 Identified variables

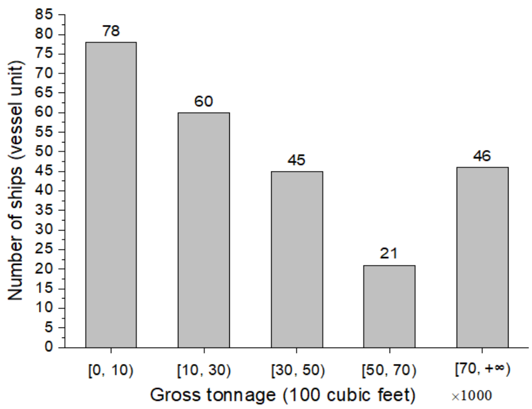
When a ship comes to the PSC inspection authority, it can be decided whether or not to inspect the ship if predictive information about the total number of deficiencies is available. To achieve this goal, we first choose the number of deficiencies as the class variable. According to the literature related to the factors influencing the inspection results (Yang et al., 2018a, b; Zhou and Sun, 2010; Xu et al., 2007; Gao et al., 2008), we select 10 attribute variables whose states are available once the ships come to the PSC authority and that may have an impact on the class variable (i.e. the number of deficiencies) to construct a TAN classifier. The 10 attribute variables are ship age, ship gross tonnage, number of previous detentions, last inspection time (months ago), number of deficiencies in last inspection, number of times of changing flag, ship type, ship flag, ship company, and ship recognized organization. The distribution of the 11 variables over the 250 cases is shown in Figure 3-4.



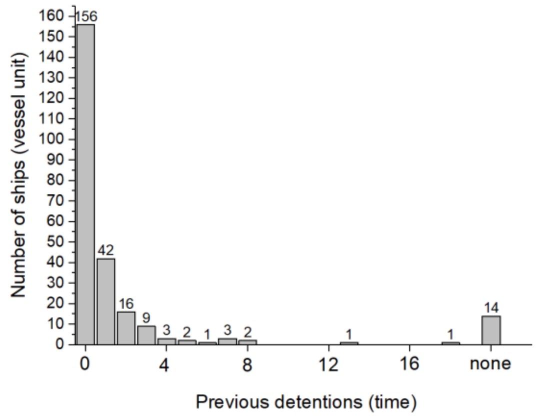
(a) Distribution of number of deficiencies



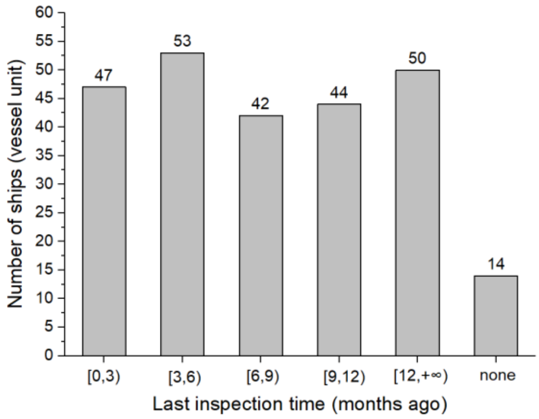
(b) Distribution of ship age



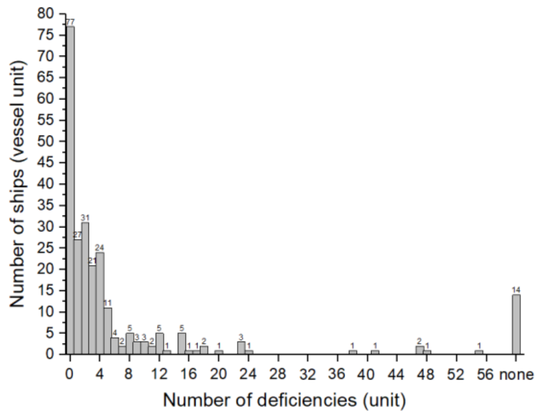
(c) Distribution of gross tonnage



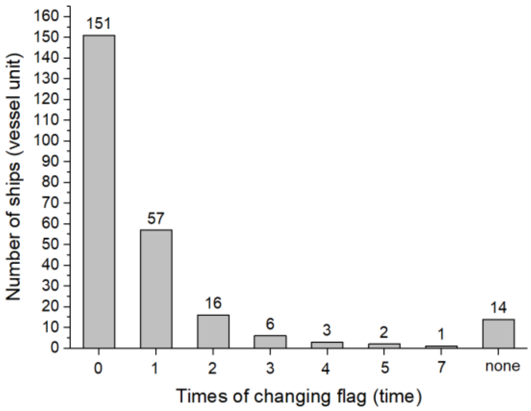
(d) Distribution of number of previous detentions



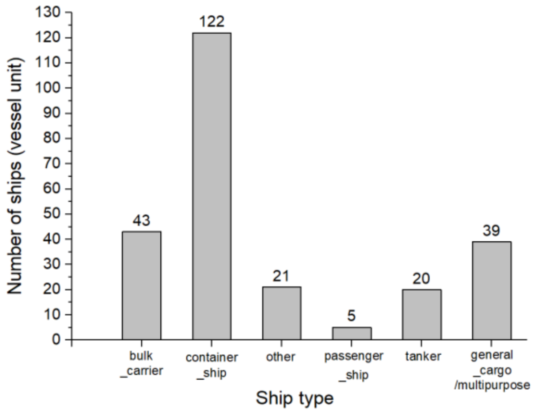
(e) Distribution of last inspection time



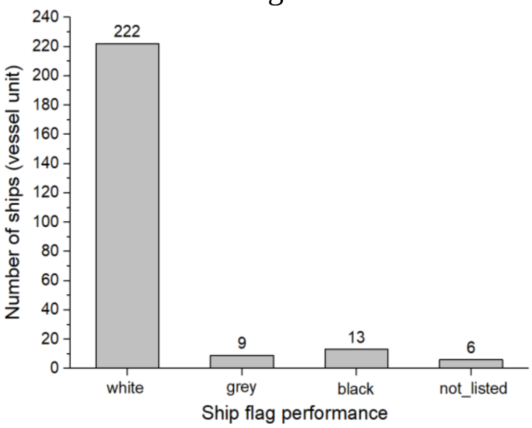
(f) Distribution of number of deficiencies in last inspection



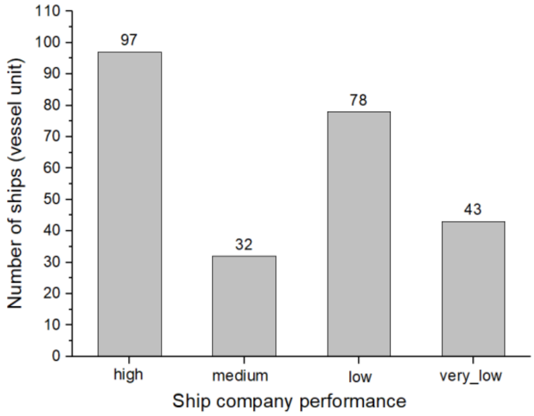
(g) Distribution of times of changing flag



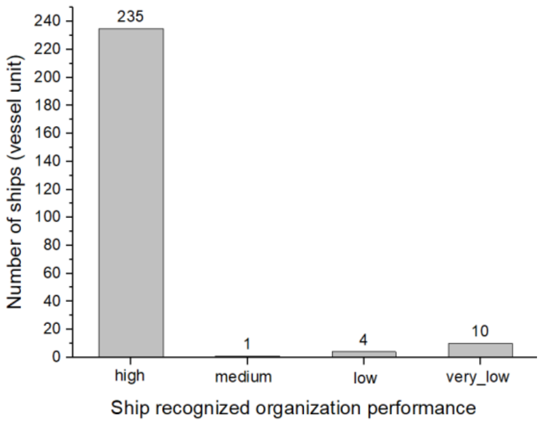
(h) Distribution of ship type



(i) Distribution of ship flag performance



(j) Distribution of ship company performance



(k) Distribution of ship RO performance

Figure 3-4: Distribution of the variables of all cases in the data set

(1) Number of deficiencies (class variable)

The number of deficiencies is the total number of deficiencies identified after the PSC inspection is conducted. It is the only variable that cannot be obtained when a ship comes to the PSC inspection authority. In the 250 inspection records, the number of deficiencies is between 0 and 51.

(2) Ship age

The age of a ship is the time difference (in years) between the keel laid date and the PSC inspection date. In the 250 inspection records, ship age is between 0 and 45.

(3) Gross tonnage

The gross tonnage (GT) is a nonlinear measure of a ship's overall internal volume, with 100 cubic feet as the unit. In the 250 inspection records, ship GT is between 299 and 194,308.

(4) Number of previous detentions

The number of previous detentions of a ship is the sum of the detentions from the first time the ship went through a PSC inspection. We use "none" as the state for this attribute variable for the 14 ships that were inspected for the first time. In the other 236 inspection records, the number of previous detentions is between 0 and 18.

(5) Last inspection time

The last inspection time of a ship is the time interval (in month) from the last PSC inspection to the time of the current PSC inspection. For the 14 ships that were inspected for the first time, we use "none" to represent the state of this attribute variable. In the other 236 inspection records, the last inspection time is between 0 and 180.7 months.

(6) Number of deficiencies in last inspection

The number of deficiencies in the last inspection is the number of deficiencies identified in the last PSC inspection. Similarly, we use "none" to denote the state for this attribute variable for the 14 ships that were inspected for the first time. In the other 236 inspection records, the deficiency number in the last PSC inspection is between 0 and 55.

(7) Number of times of changing flag

The number of times of changing flag is the sum of the times the ship's flag has been changed since the first PSC inspection. Cariou and Wolff (2011) pointed out that vessels in relatively bad condition (resulting in detention or a large number of deficiencies) were more likely to be involved in flag changing activities to reduce the PSC inspection rate. In addition, Fan et al. (2014) concluded that a high PSC inspection rate would motivate ship flagging-out, i.e., changing the flag of the ship by registering the ship in a country other than the one in which it operates. Thus, we include this attribute variable in the TAN classifier. For the 14 ships that were inspected for the first time, we use "none" to represent the state of this attribute variable. In the other 236 inspection records, the flags of the ships were changed between 0 and 7 times.

(8) Ship type

According to the annual report on PSC from Tokyo MoU (Tokyo MoU, 2017a), the main types of ships that have been inspected in the Asia-Pacific region in 2017 are bulk carrier, container ship, general cargo/multipurpose, passenger ship, and tanker. Thus, the states of this variable are bulk carrier, container ship, general cargo/multipurpose, passenger ship, tanker and others.

(9) Ship flag

The performances of ship flags are reported in the annual report from Tokyo MoU (Tokyo MoU, 2017b). Assessment of the performance of each flag state takes into account the inspection and detention history over the preceding three calendar years and the flags are classified to be on the black list, grey list or white list. Only flags that have been involved in more than 30 PSC inspections during the previous three years are listed in the black-grey-white lists; otherwise the performance of the flag will not be listed (Tokyo MoU, 2017b). Thus, the states of this variable are white, grey, black and not listed.

(10) Ship company

The ship company refers to the ISM company for the ship (Tokyo MoU, 2017c), i.e., the ship operating company which is responsible for implementing the International Safety Management (ISM) code on ships. The performance of each company is judged by Tokyo MoU based on the company's deficiency and detention performance and can be obtained by searching for the company IMO number in the Tokyo MoU database (Tokyo MoU, 2014). The states of ship company performance are high, medium, low and very low (Yang et al., 2018b).

(11) Ship recognized organization

Ship recognized organization (RO) is the classification society that carries out surveys and issues or endorses statutory certificates on behalf of a flag state. The performance of ROs is established annually and determined by the inspection and detention history over the last three calendar years (Paris MoU, 2013). The states of performance of the ship recognized organization are high, medium, low and not listed.

3.4.3 Discretizing the values of the variables into discrete states

As mentioned above, the TAN classifier works on discrete states of variables. The state of a variable can be represented by nominal data (nominal data has no order of rank), ordinal data (the order of rank is meaningful, e.g., strongly agree, agree, neutral, disagree, strongly disagree), and quantitative data. Quantitative data can be classified as discrete data and continuous data. The class variable and attribute variables in this study belong to the following categories: (i) "Ship type" is nominal data, and "ship flag", "ship company" and "ship recognized organization" are all ordinal data if we exclude the value "not listed". For nominal and ordinal states of variables, we consider each category of the values of a variable as a state of the variable. (ii) Gross tonnage and last inspection time are continuous quantitative data. Since the TAN classifier only deals with discrete states, we need to discretize the values of each continuous variable into a few states. Intuitively, we should discretize the possible values of a continuous variable into states of equal proportion. (iii) Ship age[4], number of previous detentions, number of times of changing flag, and number of deficiencies in last inspection are discrete quantitative data. Although they are discrete variables, their sets of possible values are too large and we need to propose a method to group the possible values into a smaller number of states.

For continuous variables (i.e., gross tonnage and last inspection time), the procedure of discretization into states of equal proportion is straightforward, because the values of the variable for all cases in $\mathbb{K}$ are different[5]. For example, suppose we want to discretize the possible values of a variable into states N of equal proportion, and the values of the variable in the K cases in $\mathbb{K}$ are listed in ascending order $v_1, \ldots, v_K$, $K \geq N$. Then, defining $\lceil x \rceil$ as the smallest integer greater than or equal to x, values in the interval $[v_1, v_{\lceil K/N \rceil}]$ should be in the first state, values in the interval $[v_{\lceil K/N \rceil + 1}, v_{\lceil 2K/N \rceil}]$ should be in the second state, and values in $[v_{\lceil (N-1)K/N \rceil + 1}, v_K]$ should be in the N th state. To ensure that the states cover all possible values of the variable,

[4] Ship age should normally be continuous data. But in our study the ship age is recorded as an integer number of years and hence it is considered to be discrete data.
[5] Due to the limited precision of measurement and recording, it is possible that two values are equal. The chance that two values are equal is small and has little effect on our model.

including values that are not included in the full data set but may appear in future cases, we can define the first state as $(-\infty, \quad (v_{\lceil K/N \rceil} + v_{\lceil K/N \rceil+1})/2]$, the second state as $((v_{\lceil K/N \rceil} + v_{\lceil K/N \rceil+1})/2, \quad (v_{\lceil 2K/N \rceil} + v_{\lceil 2K/N \rceil+1})/2]$, and the N th state as $((v_{\lceil (N-1)K/N \rceil} + v_{\lceil (N-1)K/N \rceil+1})/2, \quad +\infty)$.

For discrete variables (i.e., ship age, number of previous detentions, number of times of changing flag, and number of deficiencies in last inspection), a natural way is to consider each possible value (e.g., 1, 2, … for ship age) as a state. However, this will lead to a large number of combinations of states considering that the TAN classifier accounts for the dependencies between variables. A large number of combinations of states require an extremely large full data set (e.g., billions of records), otherwise the number of cases in some states will be extremely small. Since we have only 250 records, we combine several possible values of a variable into one state; for example, ages between 0 and 5 can be considered as one state, ages between 6 and 10 can be considered as another state. Aggregating values of a variable into states should not be conducted in an arbitrary way. Instead, the possible values of a variable should be discretized into states of equal or approximately equal proportion. The process of discretizing the values of a discrete variable into a few states of equal proportion is not as straightforward as that of discretizing the values of a continuous variable. For a discrete variable, it is highly probable that some cases have exactly the same value and these cases should be in the same state. It should be noted that although the idea of the equal-frequency discretization method has been used in the BN-related literature (Dougherty and Sahami, 1995; Flores et al., 2011), no rigorous discretization method is proposed and there are ambiguities in implementation. We formally state the problem of discretizing the values of a discrete variable into states of as equal proportion as possible:

Data discretization problem: A data set of K cases has a discrete variable. There are V categories of values in ascending order for the discrete variable in the K cases and the number of cases in category $v = 1, ..., V$ is θ_v. $K = \sum_{v=1}^{V} \theta_v$. The data discretization problem aims to discretize the V categories into N states of consecutive categories, $N \le V$, such that each state has at least one category and the proportion of cases that fall into each state is as close to $1/N$ as possible. Letting Z^+ be the set of non-negative integers, the problem is to find integer values $s_0, s_1, s_2, ..., s_N$ that solve the following optimization problem:

$$\min \sum_{n=1}^{N} \left(\frac{\sum_{v=s_{n-1}+1}^{s_n} \theta_v}{K} - \frac{1}{N} \right)^2 \tag{3.3}$$

subject to

$$s_n \geq s_{n-1} + 1, n = 1, ..., N \tag{3.4}$$

$$s_n \in Z^+, n = 1, ..., N \tag{3.5}$$

$$s_0 = 0 \tag{3.6}$$

$$s_N = N. \tag{3.7}$$

The objective function (3.3) minimizes the sum of squared deviations of the proportion of each state from the average proportion $1/N$. The first state will be $(-\infty,\ \ (v_{s_1} + v_{s_1+1})/2]$, the second state will be $((v_{s_1} + v_{s_1+1})/2,\ \ (v_{s_2} + v_{s_2+1})/2]$, and the N th state will be $((v_{s_{N-1}} + v_{s_{N-1}+1})/2,\ \ +\infty)$ [6].

Theorem 1: The data discretization problem can be solved in time bounded by $O(NV^2)$.■

The proof of Theorem 1 is given in Appendix B.

3.4.4 States of the variables

The total data set contains $K = 250$ inspected ships, where there are 14 ships without previous PSC inspections. For the variables "the number of deficiencies", "ship age" and "ship gross tonnage", which are irrelevant to the previous inspections, we discretize their states into $N = 3$ states. For the variables that are related to previous PSC inspections, including "the number of previous detentions", "last inspection time", "the number of deficiencies in last inspection" and "the number of times of changing flag", we discretize them into $N' = 4$ states, with the state "none" for the 14 ships without former inspection, while the remaining three states contain $K' = 250 - 14 = 236$ ships. The states of the variables are in Table 3-1.

[6] If the values of the variable can only be integers, then the intervals for the states can be truncated so that the end points of each interval are both integers.

Table 3-1: Variables in TAN classifier

Variable	Unit	Type	Node name	States
Number of deficiencies		discrete	deficiency_no	S1:0to2, S2:3to6, S3:7+
Ship age	year	discrete	age	S1:0to7, S2:8to12, S3:13+
Gross tonnage	100 cubic feet	continuous	GT	S1:0to11228, S2:11229to40053, S3:40054+
Number of previous detentions		discrete	pre_detention	S1:zero, S2:one, S3:2+, S4:none
Last inspection time	month	continuous	last_inspection	S1:0to5.5, S2:5.6to9.6, S3:9.7+, S4:none
Number of deficiencies in last inspection		discrete	last_deficiency_no	S1:zero, S2:1to3, S3:4+, S4:none
Times of changing flag		discrete	change_flag	S1:zero, S2:one, S3:2+, S4:none
Ship type		nominal data	type	S1:bulk_carrier, S2: container_ship, S3:general_cargo/multipurpose, S4:passenger_ship, S5:tanker, S6:other
Ship flag		ordinal data	flag	S1:white, S2:grey, S3:black, S4:not_listed
Ship company		ordinal data	company	S1:high, S2:medium, S3:low, S4:very_low
Ship recognized organization		ordinal data	RO	S1:high, S2:medium, S3:low, S4:not_listed

3.4.5 Construct the qualitative part of the TAN classifier

There are six steps to construct the qualitative part of a TAN classifier in PSC inspection according to the Construct-TAN procedure (Friedman et al., 1997).

Table 3-2: Conditional mutual information of attribute variables

	age	GT	type	flag	company	RO	pre_ detention	last_ inspection	last_ deficiency _no	change_ flag
age		0.051	0.081	0.030	0.031	0.032	0.073	0.063	0.069	**0.108**
GT			**0.198**	0.063	0.075	0.013	0.069	0.092	0.043	0.069
type				**0.099**	**0.141**	0.054	0.110	0.083	0.103	0.074
flag					0.080	**0.067**	0.068	0.067	0.065	0.089
company						0.033	0.108	**0.122**	0.060	0.118
RO							0.044	0.045	0.036	0.045
pre_detention								**0.276**	**0.250**	**0.268**
last_inspection									0.246	0.247
last_deficiency_no										0.243
change_flag										

Procedure 1. Construct-TAN procedure.	
Step 1:	Select deficiency_no as the class variable, and age, GT, type, flag, company, RO, pre_detention, last_inspection, last_deficiency_no and change_flag as attribute variables.
Step 2:	Compute the conditional mutual information between all pairs of attribute variables given the class variable $I(A_i; A_j \mid C)$ to identify their dependency, $A_i \neq A_j$, $i = 1,...,10,\ j = 1,...,10, i \neq j$.
Step 3:	Build a complete undirected graph with attribute variables as the nodes and the conditional mutual information $I(A_i; A_j \mid C)$ as the weight of the edge of A_i and A_j. The results are shown in Table 3-2.
Step 4:	Build the maximum weighted spanning tree by sorting the weights of the edges from large to small, and then choose the edges from the largest weight to the smallest weight without forming a circle. For each chosen edge, if adding this edge forms a circle, it will not be chosen anymore; instead, edges with weights smaller than this edge will be chosen from larger weight to smaller weight. Keep the chosen edges and delete the others. The selected edge weights are in bold in Table 3-2.
Step 5:	Transform the undirected spanning tree into a directed tree by choosing age as the root variable and setting the directions of all arcs to other attribute variables to be outward from it.
Step 6:	Add the class variable C (i.e. deficiency_no) to the tree and arcs from the class variable to every attribute variable. The structure of the TAN classifier is presented in Figure 3-5.

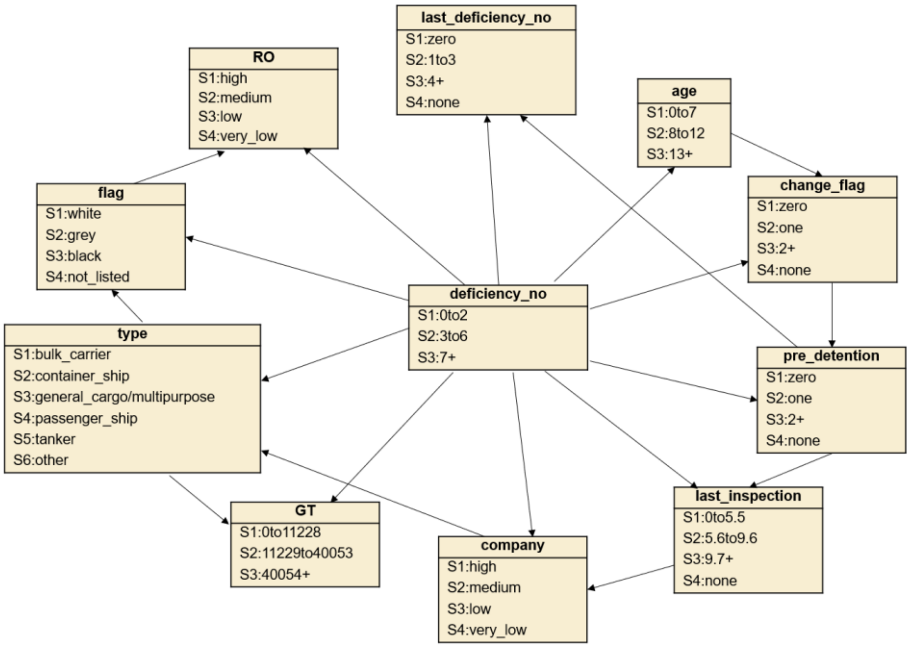


Figure 3-5: Structure of the TAN classifier for PSC inspection

3.4.6 Constructing the quantitative part of the TAN classifier

There are two components in the quantitative part of the TAN classifier: the marginal probability distribution of each variable and the conditional probability table (CPT) for each variable. Marginal probability, denoted by $P(X = x)$, is an unconditional probability of the occurrence of state x of event X . The probabilities of states corresponding to each variable are the marginal probabilities in percentage form, as shown in Figure 3-6.

Conditional probability $P(A \mid B)$ is the probability of A under condition B . In the BN models, the conditional probabilities of each attribute variable are presented in conditional probability tables (CPTs). The method used to calculate the CPTs is presented in Appendix D. The root variable (i.e., the class variable deficiency_no) has no parent and therefore its conditional probabilities are reduced to prior probabilities. Now, the construction process of the quantitative part of the TAN classifier is done, which involves generating the marginal probability distribution of each variable as presented in Figure 3-6 and the CPT for each variable as presented in Appendix D.

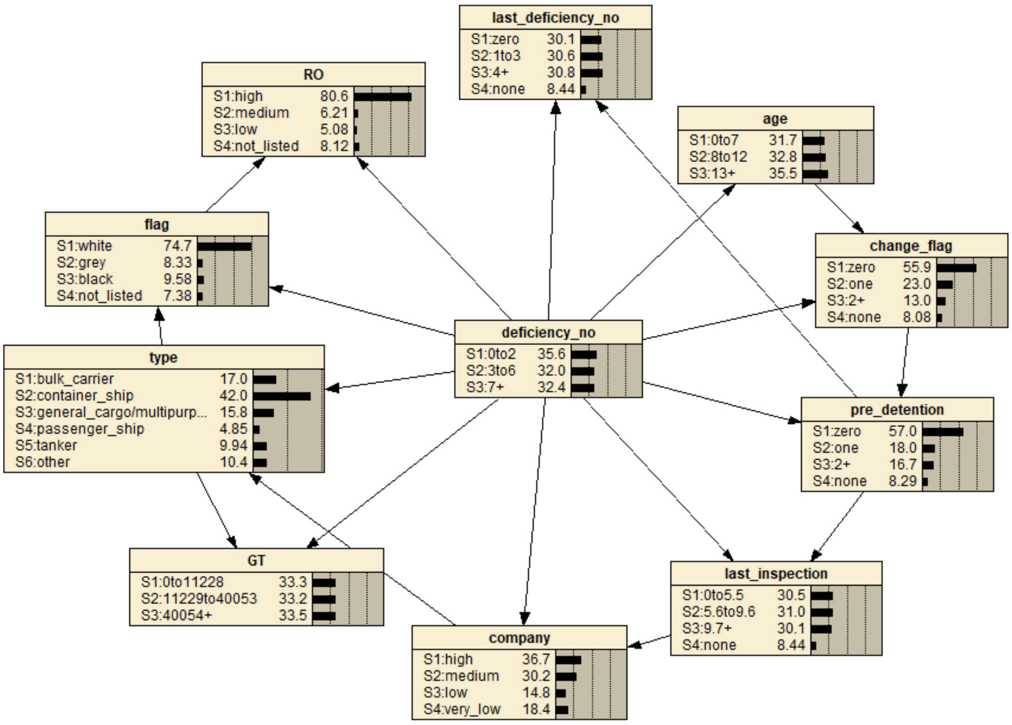


Figure 3-6: TAN model with marginal probabilities for PSC inspection

3.4.7 Classification process for coming vessels

The TAN classifier obtained in the previous subsections has $I = 10$ attribute variables, and its class variable has $N_C = 3$ states: "0to2" is the first state, "3to6" is the second state, and "7+" is the third state. We define A_{i_0} as the root attribute variable (A_{i_0} is "age" for this classifier). Recall that $A_{\pi(i)}$ is the parent attribute variable of attribute variable $A_i, i = 1,...,I, i \neq i_0$. For a specific incoming vessel k with attribute variable set $ATT^k = (a_1^k,...,a_I^k)$, the TAN classifier can calculate the probability for it to belong to each state $c_s \in S_C$ of the class variable. For ease of exposition, we define

$$\begin{aligned}
&\tilde{P}^I(a_{1,k^{(1)}},...,a_{I,k^{(I)}},c_{\bar{s}}) \\
&= P^I(c_{\bar{s}}) \times P^I(a_{i_0,k^{(i_0)}} \mid c_{\bar{s}}) \times \prod_{i=1,i\neq i_0}^{I} P^I(a_{i,k^{(i)}} \mid a_{\pi(i),k^{(\pi(i))}}, c_{\bar{s}}) \\
&= P^I(c_{\bar{s}}) \times P^I(a_{i_0,k^{(i_0)}} \mid c_{\bar{s}}) \times \prod_{i=1,i\neq i_0}^{I} \frac{P^I(a_{i,k^{(i)}}, a_{\pi(i),k^{(\pi(i))}} \mid c_{\bar{s}})}{P^I(a_{\pi(i),k^{(\pi(i))}} \mid c_{\bar{s}})}, \bar{s} = 1,...,N_C
\end{aligned} \tag{3.8}$$

where the superscript "I" means the TAN has I attribute variables and $\bar{s} = 1,...,N_C$ refers to the three states of the class variable. Then, the probability that vessel k belongs to $c_s \in S_C$ is calculated by the following posterior probabilities formula:

$$P^I(c_s \mid a_{1,k^{(1)}},\ldots,a_{I,k^{(I)}}) = \frac{\tilde{P}^I(a_{1,k^{(1)}},\ldots,a_{I,k^{(I)}},c_s)}{\sum_{\bar{s}=1}^{N_C}\tilde{P}^I(a_{1,k^{(1)}},\ldots,a_{I,k^{(I)}},c_{\bar{s}})}, s=1,\ldots,N_C. \tag{3.9}$$

Two ships chosen from the testing data set are used to show the deficiency number classification process. The detailed information of the attribute variables of the two incoming ships is shown in Table 3-3. The results of the classification process are shown in Table 3-4.

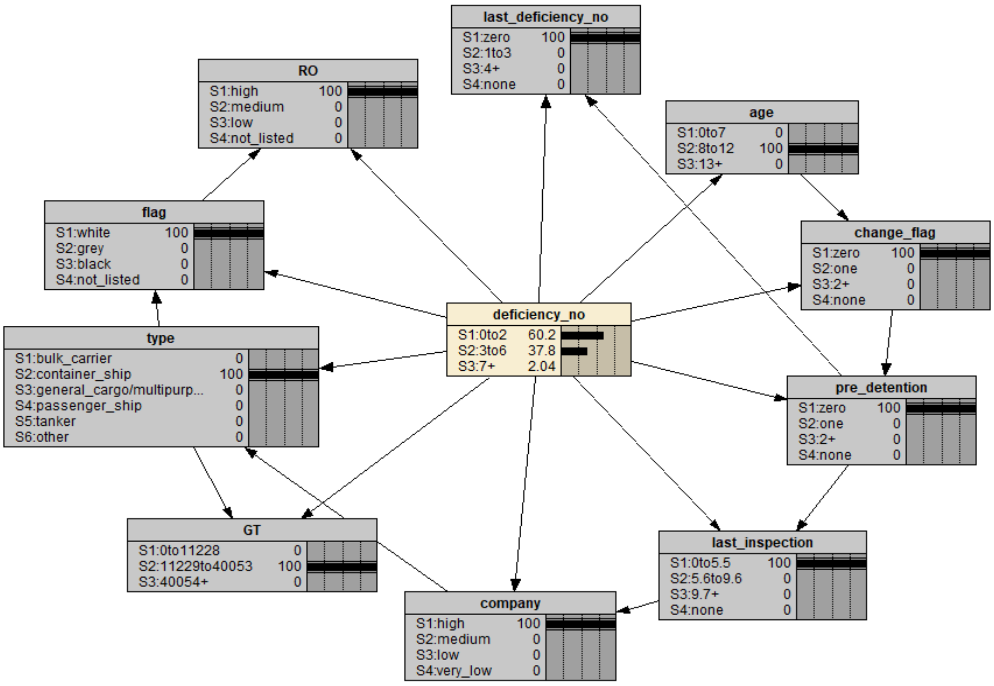
Table 3-3: Information on the incoming vessels

Ship 1: Attribute variables	State	**Ship 2**: Attribute variables	State
age	S2:8to12	age	S3:13+
type	S2:container_ship	type	S3:general_cargo /multipurpose
GT	S2:11229 to40053	GT	S3:0to11228
RO	S1:high	RO	S2:medium
flag	S1:white	flag	S4:not_listed
company	S1:high	company	S4:very_low
change_flag	S1:zero	change_flag	S1:zero
pre_detention	S1:zero	pre_detention	S2:one
last_inspection	S1:0to5.5	last_inspection	S1:0to5.5
last_deficiency_no	S1:zero	last_deficiency_no	S3:4+

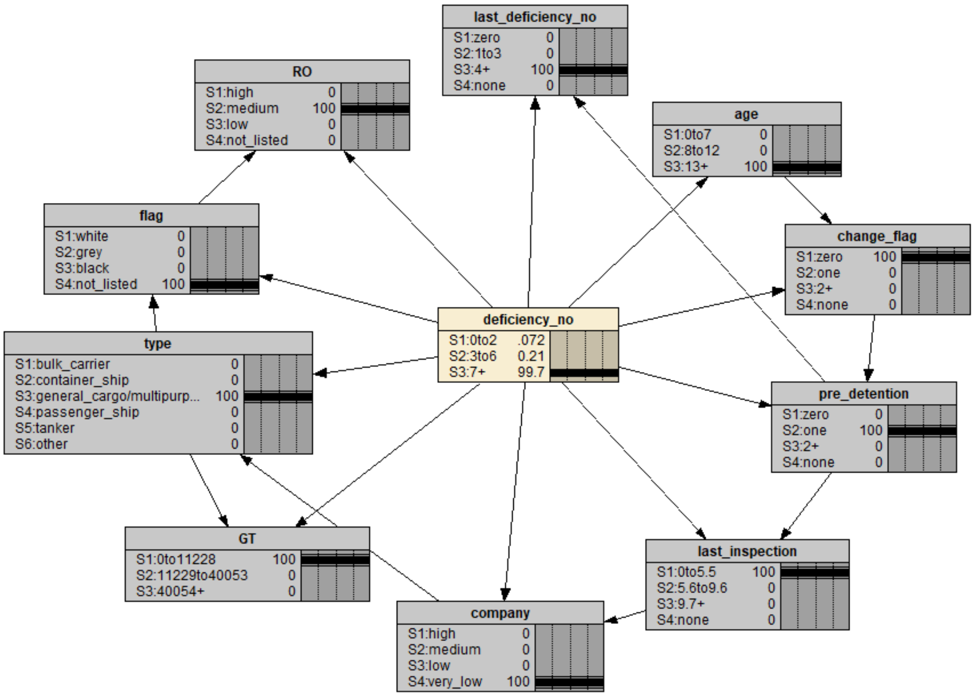
Table 3-4: Classification results of the incoming vessels

Ship 1		**Ship 2**	
$\tilde{P}(S1:0to2)$ in Eq. (8)	3.46×10^{-4}	$\tilde{P}(S1:0to2)$ in Eq. (8)	3.44×10^{-8}
$\tilde{P}(S2:3to6)$ in Eq. (8)	2.17×10^{-4}	$\tilde{P}(S2:3to6)$ in Eq. (8)	1.00×10^{-7}
$\tilde{P}(S3:7+)$ in Eq. (8)	1.17×10^{-5}	$\tilde{P}(S3:7+)$ in Eq. (8)	4.77×10^{-5}
$P(S1:0to2)$ in Eq. (9)	60.17%	$P(S1:0to2)$ in Eq. (9)	0.07%
$P(S2:3to6)$ in Eq. (9)	37.79%	$P(S2:3to6)$ in Eq. (9)	0.21%
$P(S3:7+)$ in Eq. (9)	2.04%	$P(S3:7+)$ in Eq. (9)	99.70%

This classification process can also be shown visually by selecting the corresponding states of each variable in Figure 3-7. The posterior probability distribution of the deficiency_no is shown in the corresponding node.



(a) Classification process of ship 1



(b) Classification process of ship 2

Figure 3-7. Illustration of the classification process of the new incoming ships

Now we are ready to present the results: the probabilities for ship 1 to have 0 to 2 deficiencies, 3 to 6 deficiencies and more than 7 deficiencies are 60.17%, 37.79%, and 2.04% respectively. As the state with the highest probability is the predicted range of the number of deficiencies, we can conclude that the incoming vessel is most likely to have 0 to 2 deficiencies. Meanwhile, the probabilities for ship 2 to have 0 to 2 deficiencies, 3 to 6 deficiencies and more than 7 deficiencies are 0.72%, 0.21%, and 99.70% respectively, and thus the estimated deficiency number of this vessel is more than 7.

3.4.8 Effect of the choice of root attribute variable

Based on the construction of the TAN classifier and the posterior probabilities formulae (7) and (8) for classifying a case k, we have the following theorem:

Theorem 2: To construct a TAN classifier with I attribute variables, $I \geq 2$, different choices of root attribute variable node in Step 5 of the Construct-TAN procedure all have the same posterior probability of classifying a case k into a state to $c_s \in S_C$ in Eq. (8).■

We use mathematical induction to prove Theorem 2. The detailed proof is in Appendix C.

3.5 MODEL VALIDATION AND RESULTS

As a classifier, a typical way to validate the model is to evaluate how well it performs on unseen data, i.e., to check the classification accuracy using a testing data set (Hänninen, 2014; Hänninen and Kujala, 2014). We construct the TAN model by inputting the ships' attribute variable states (i.e., states of age, flag, GT, etc.) and the class variable state (i.e., state of deficiency_no) in the training case set to learn the structure and parameters of the TAN classifier. To validate the model, in addition to the 250 cases in set Ψ, we collected a set of another 50 cases, denoted by Ψ', which is mainly used as the testing data set.

3.5.1 Classification accuracy

To analyze the classification accuracy of the TAN model, we first construct a test case set containing the first $m \in \{50,100,150,200,250\}$ inspections in Ψ. Then, we input the attribute variable states of each ship in Ψ' and use the TAN classifier to calculate the state of deficiency_no. If the ship is indeed in the deficiency_no state, then the classification is accurate; otherwise it is inaccurate. The classification accuracy results for $m \in \{50,100,150,200,250\}$ training cases are listed in Table 3-5.

It can be seen from the table that as the scale of the training set increases, the classification accuracy shows an upward trend. When the training set contains more than 200 cases, the prediction accuracy is beyond 60%. This is almost twice as accurate as a random guess.

Table 3-5: TAN classifier accuracy

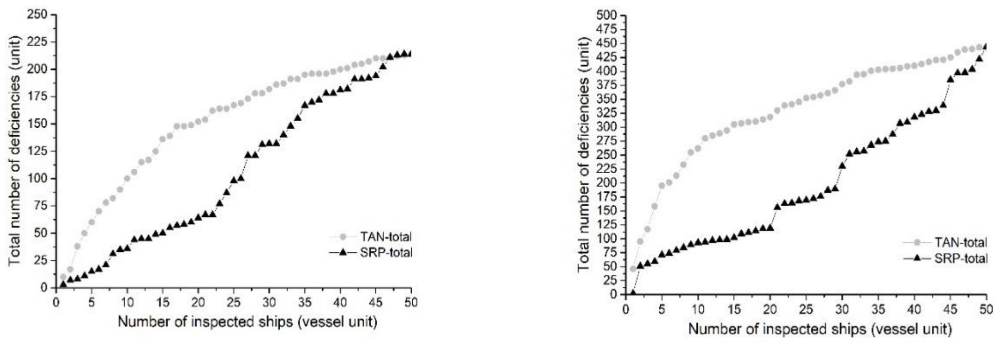
Number of training cases	Number of testing cases	Error rate	Accuracy rate
50	50	50%	50%
100	50	48%	52%
150	50	42%	58%
200	50	40%	60%
250	50	38%	62%

3.5.2 Comparison between TAN classifier and Ship Risk Profile (SRP)

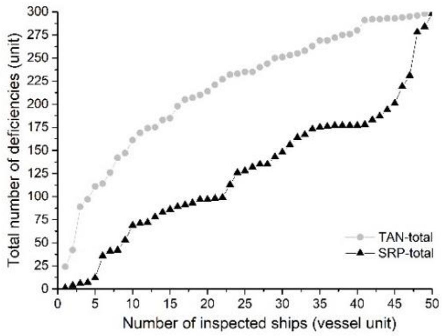
The Ship Risk Profile (SRP) is the method currently used by Tokyo MoU for selecting ships to conduct PSC inspections, which is calculated daily in the corresponding PSC MoU's database (Tokyo MoU, 2014). Different weighting points are given to different states of ship type, ship age, ship flag performance, ship RO performance, ship company performance, previous number of deficiencies and detentions. Based on the total weighting points, the ships are classified into three risk profiles: high risk ship (HRS), standard risk ship (SRS) and low risk ship (LRS). At the same time, time windows of 2 to 4 months, 5 to 8 months, and 9 to 18 months, which refer to the time since last PSC inspection and within which a ship does not need to be inspected, are attached to HRS, SRS, and LSR, respectively. The current inspection selection scheme is based on the ship inspection priority: ships without prior inspection are Priority I; incoming ships whose time window has been closed (i.e., HRS, SRS and LRS with last inspection time of more than 4 months, 8 months, and 18 months respectively) are Priority II. Ships within the time window (i.e., HRS, SRS and LRS with the last inspection time between 2 to 4 months, 5 to 8 months and 9 to 18 months respectively) are Priority III. Ships that do not enter the time window are of Priority IV.

We compare the "effectiveness" of the currently used SRP inspection scheme and the newly constructed TAN classifier. The port authority wishes to identify as many deficiencies as possible after inspecting a certain number of ships for the following two reasons: first, the inspection results only contain ship deficiencies and ship detention, but the ship detention rate is low. A more direct approach to improve the inspection efficiency is to inspect ships with a larger expected number of deficiencies. Second, larger numbers of deficiencies are also supposed to have strong relationship with ship detention (Yang et al., 2018a; Cariou and Wolff, 2015). Thus, the “effectiveness” here refers to the “quickness” of identifying the ships with expected larger numbers of deficiencies. This can be reflected by the inspection sequence of the incoming ships generated by using the two selection methods. Actually, PSC inspection is a time-consuming task and the total number of ships that can be inspected for a day is limited at a port. Therefore, the port states and the MoUs are trying to find higher risk ships with expected larger number of deficiencies and higher probability of detention. The TAN classifier used for comparison is the one proposed in Section 3.4, which is trained by data set Ψ (training set 1). Both SRP and the TAN classifier use the same testing data set Ψ' (testing set 1). Suppose that the ships in Ψ' arrive at the PSC authority at the same time, and the PSC authority has the resources to inspect $n = 1, 2, ..., 50$ ships. If the SRP selection scheme is used, a list of n ships will be chosen for inspection based on Procedure 2 in Appendix E; if the TAN classifier is used, another list of n ships will be chosen for inspection based on Procedure 3 in Appendix F. We can then calculate the total numbers of deficiencies they can detect after inspecting the same number of ships n to compare their efficiency.

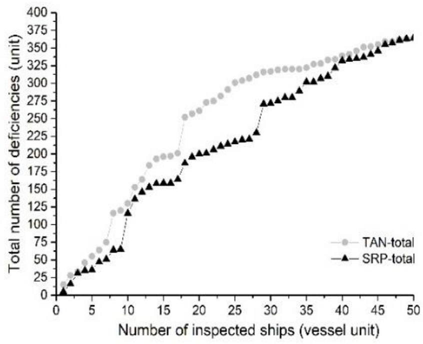
We enumerate the possible values of $n = 1, 2, ..., 50$ and draw the two total detected deficiency number curves in Figure 3-8.



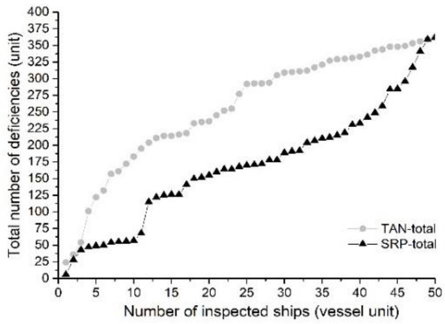
(a) Comparison results of Testing set 1 (b) Comparison results of Testing set 2



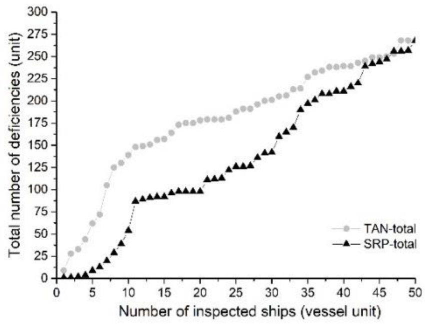
(c) Comparison results of Testing set 3



(d) Comparison results of Testing set 4



(e) Comparison results of Testing set 5



(f) Comparison results of Testing set 6

Figure 3-8: Comparisons of ship selection efficiency between SRP and TAN classifier

Figure 3-8(a) illustrates that the selection performance of the TAN classifier significantly outperforms the currently used SRP selection scheme. We define the improvement of the TAN classifier over the SRP selection scheme at the m th inspection (denoted by $I(m)$) and the average improvement (denoted by AI) after the total M inspections as follows:

$$I(m) = \frac{total\_de(TAN(m)) - total\_de(SRP(m))}{total\_de(SRP(m))} \times 100\% \tag{3.10}$$

$$AI = \frac{\sum_{m=1}^{M} I(m)}{M} \tag{3.11}$$

where $total\_de(TAN(m))$ and $total\_de(SRP(m))$ are the total numbers of deficiencies detected after the m th inspection by the TAN classifier and SRP selection scheme respectively, and $M = 50$. In Figure 3-8(a), the average improvement over the 50 ships in testing set 1 is 101.00%. We further assume that the port authority has the ability to inspect 10%, 20%, …, 60% of all the 50 incoming ships, and the improvements of the TAN classifier over the SRP ship selection scheme after inspecting 5, 10, 15, 20, 25, and 30 ships are 300%, 177.78%, 172%, 137.5%, 70.41%, and 37.88% respectively. These statistics tell us that when the PSC authority only has limited resources to inspect the incoming ships, the TAN classifier can help to identify ships with higher risk level better.

It is worth mentioning that, in Figure 3-8(a), the ship with the largest number of deficiencies among the total 50 ships (i.e. 21 deficiencies) is ranked 3rd in the inspection list generated by the TAN classifier, while it is 27th on the inspection list in the SRP selection scheme. Although this ship is in the HRS category, it was inspected in Shandong, China, 2.3 months ago and is thus within the inspection time window. As the SRP only takes the inspection time window into consideration among all the high-risk ships, ships that have been inspected a short time ago would have lower risk indices than many other ships and are thus at the end of the SRP inspection list. In addition, the weighting points given to the risk parameters in SRP are rough; for example, all types of ships with age more than 12 will be given 1 weighting point, those with low or very low RO performance will be given 1 weighting point and those with low or very low company performance will be given 2 weighting points. Moreover, if the total weighting point is larger than or equal to 4, it is classified as an HRS, with no more information attached except for an inspection time window. On the contrary, the TAN classifier is more sensitive to the states of the attribute variables, as it treats them in a detailed manner (e.g., all the states of the attribute variables are taken into account instead of some extreme states) while also taking the dependencies between the variables into consideration. What is more, the TAN classifier can generate an expected number of deficiencies (i.e. $E(deficiency\_no)$) for each individual ship, which can better distinguish the ships instead of roughly classifying them into three risk profiles. For this ship, the age of 8 to 12, flag on the grey list, company of very low performance, RO of medium performance, more than two times of changing flag and previous detentions all give it a higher probability of having a larger number of deficiencies in the TAN classifier. As a consequence, the TAN classifier assigns a higher priority to this ship than the SRP selection scheme does.

To further test the robustness of the performance of the TAN classifier, we randomly divide the 250 training data cases in Ψ into five mutually exclusive data sets, denoted by Ψ_1, Ψ_2, Ψ_3, Ψ_4, and Ψ_5, each containing 50 cases. Then, we obtain five new training sets and the corresponding testing sets:

$\Psi' \cup \Psi_2 \cup \Psi_3 \cup \Psi_4 \cup \Psi_5$ (training set 2) and Ψ_1 (testing set 2), $\Psi_1 \cup \Psi' \cup \Psi_3 \cup \Psi_4 \cup \Psi_5$ (training set 3) and Ψ_2 (testing set 3), $\Psi_1 \cup \Psi_2 \cup \Psi' \cup \Psi_4 \cup \Psi_5$ (training set 4) and Ψ_3 (testing set 4), $\Psi_1 \cup \Psi_2 \cup \Psi_3 \cup \Psi' \cup \Psi_5$ (training set 5) and Ψ_4 (testing set 5), and $\Psi_1 \cup \Psi_2 \cup \Psi_3 \cup \Psi_4 \cup \Psi'$ (training set 6) and Ψ_5 (testing set 6). After comparing the TAN and SRP selection scheme by using the five training sets and the corresponding testing sets, we find that the TAN classifier can detect 141.29%, 215.54%, 25.83%, 75.31% and 193.76% more deficiencies on average each time, with 130.35% more deficiencies than the SRP selection scheme on average in total. After further assuming that the port state has the resources to inspect 10%, 20%, 30%, 40%, 50%, and 60% of the 50 total incoming ships, we can calculate that the average improvement of the TAN classifier is 348.38%, 147.23%, 108.32%, 98.29%, 70.33%, and 48.83% after inspecting 5, 10, 15, 20, 25, and 30 ships, respectively. The comparisons are illustrated in Figure 3-8. The reasons for the superior performance of the TAN classifier are as follows. First, the SRP selection scheme attaches a fixed time window for the ships and this will unconditionally give a high priority for ships out of the time window to be inspected first, even if some of them have fewer deficiencies. Meanwhile, in the TAN classifier, the last inspection time is just viewed as one attribute variable. Second, the weighting point given to each parameter is based on expert knowledge and is fixed in the SRP selection scheme. In contrast, the TAN classifier is based on a mathematical model, as the probabilities are all based on the statistical data and the classification process is based on Bayes' Theorem. Third, the ships are divided into three categories (excluding the small number of ships that have not been inspected before) in the SRP selection scheme, which means that there are 1/3 ships in each category on average and these ships will have the same inspection time window (i.e., the same inspection priority). On the contrary, the TAN classifier can generate a different risk index for each incoming ship to better distinguish them in order to identify the ships of higher risk.

3.5.3 Comparison between TAN classifier and ordered logistic regression

Among the most widely adopted methods in the research on PSC inspection are logistic regression models (Knapp and Franses, 2007a; Knapp et al., 2011; Knapp and Hänninen, 2014; Li et al., 2014). Thus, we compare the performance of the TAN classifier and the logistic regression model in identifying ships with larger numbers of deficiencies. It should be noted that the logistic regression models proposed in the abovementioned studies in the brackets are all binary logistic regression models, in which the regression target has only two states. In our study, there are three states of "deficiency_no", and its states are ordinal (i.e., the conditions of ships with 0 to 2 deficiencies are better than ships with 3 to 6 deficiencies and are much better than ships with more than 7 deficiencies). We thus extend the binary logistic regression model to a multilevel ordered logistic regression model, which is a regression model used for ordinal dependent variables with multiple states (McCullagh, 1980). For more detail on the multilevel ordered logistic regression models, please refer to Menard (2002). We use the input data set that is used to construct the TAN classifier in Section 3.4, and the assumptions of the multilevel ordered logistic regression on the input data are guaranteed: (a) the input data are categorical; (b) there is no multicollinearity in the input data; (c) the input data are proportional odds, i.e., each independent input variable has an identical effect at each cumulative split of the ordinal dependent variable (Menard, 2002). It should be noted that the "independence" of the input data does not mean that the input variables are statistically independent with each other; instead, only the non-multicollinearity of the input data needs to be guaranteed. The verification of input data and the construction of the multilevel ordered logistic regression model are conducted in SPSS software (SPSS Inc., 1990).

After estimating the parameters in the multilevel ordered logistic regression model, we use testing set 1, which is used to test the TAN classifier, to test the performance of the logistic regression model. The testing method is almost the same as Procedure 3 proposed in Appendix F, which is used to test the performance of the TAN classifier, i.e., calculating the estimated deficiency number based on the probabilities and average deficiency numbers of different states of "deficiency_no". The comparison results are shown in Figure 3-9.

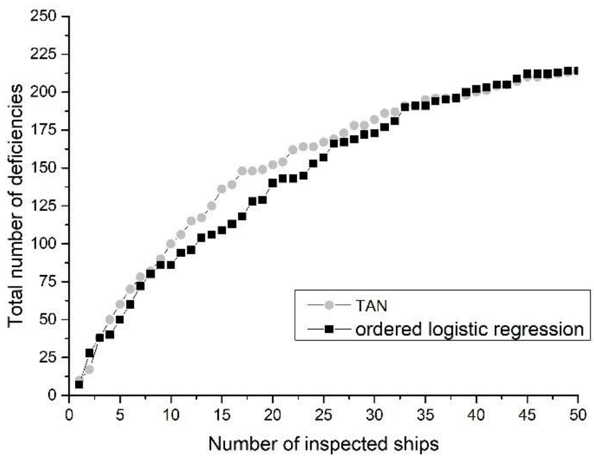


Figure 3-9: Comparison between TAN classifier and ordered logistic regression model

We can see from Figure 3-9 that the TAN classifier outperforms the multilevel ordered logistic regression model. It can detect 6.70% more deficiencies on average than the ordered logistic regression model. We further assume that the port state has the resources to inspect 10%, 20%, 30%, 40%, 50%, and 60% of all the incoming ships, and that the TAN classifier can detect 20%, 16.28%, 24.77%, 8.57%, 6.37%, and 5.20% more deficiencies than the ordered logistic regression model. Apart from the larger number of deficiencies identified by the TAN classifier compared to the ordered logistic regression model, the TAN classifier is more intuitive and easier to understand as TAN is a probabilistic graphical model represented via a directed acyclic graph.

3.6 VARIABLE ANALYSIS

3.6.1 Dependency of class variable on attribute variables

Mutual information on two random variables is a measure of the mutual dependence between two variables (Fraser and Swinney, 1986). In the proposed TAN classifier trained by 250 cases, we use the mutual information $I(A_i;C)$ between each attribute variable and the class variable to present the extent to which the attribute variables have an influence on the number of deficiencies. $I(A_i;C)$ can be calculated by the following formula:

$$I(A_i;C) = \sum_{s'=1}^{N_i}\sum_{s=1}^{N_c} P(a_{i,s'}, c_s)\log\frac{P(a_{i,s'}, c_s)}{P(a_{i,s'})P(c_s)} \tag{3.12}$$

where "log" means the logarithmic operation with base 2 in this study. $P(a_{i,s'}, c_s)$ is the non-negative joint probability distribution of A_i and C. If A_i has a state $a_{i,\bar{s}'}$ with $P(a_{i,\bar{s}'}, c_s) = 0$, then $P(a_{i,s'}, c_s) \log \frac{P(a_{i,s'}, c_s)}{P(a_{i,s'})P(c_s)} = 0$. $P(a_{i,s'})$ and $P(c_s)$ are marginal probability distributions of A_i and C. $I(A_i;C)$ is non-negative if and only if A_i and C are independent, then $I(A_i;C) = 0$. Larger $I(A_i;C)$ means that A_i and C are more dependent on each other. Table 3-6 presents the mutual information between each attribute variable and the class variable.

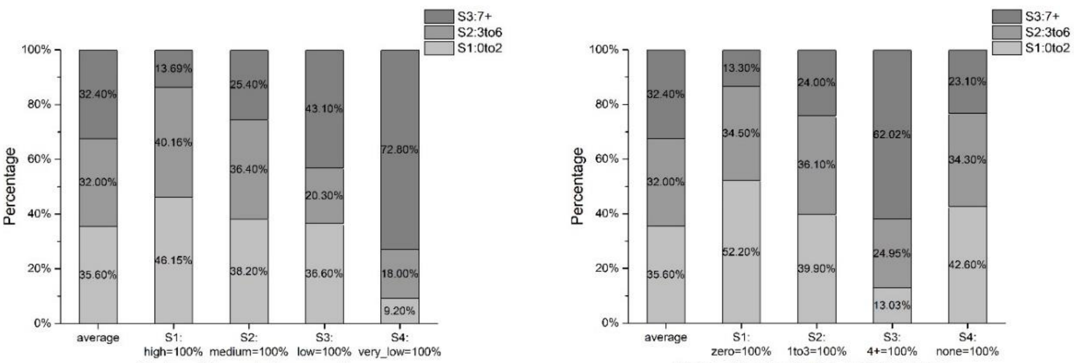
Table 3-6: Mutual information between attribute variables and class variable

Mutual information	Value
$I(\text{company};\text{deficiency\_no})$	0.15904
$I(\text{last\_deficiency\_no};\text{deficiency\_no})$	0.14938
$I(\text{age};\text{deficiency\_no})$	0.11398
$I(\text{pre\_detention};\text{deficiency\_no})$	0.10494
$I(GT;\text{deficiency\_no})$	0.09490
$I(\text{type};\text{deficiency\_no})$	0.08780
$I(\text{flag};\text{deficiency\_no})$	0.04956
$I(\text{change\_flag};\text{deficiency\_no})$	0.04946
$I(\text{last\_inspection};\text{deficiency\_no})$	0.04075
$I(RO;\text{deficiency\_no})$	0.00625

It can be seen from Table 3-6 that the ship company has the most significant influence on the number of deficiencies detected in the PSC inspection. This may be because, after the NIR was introduced in 2014, the performance of the companies was divided into four grades according to the inspection results of their ships in the PSC inspection. In addition, company performance is also a determinant of the ship risk profile. As a result, low performance will give the company a bad reputation, and may thus decrease its revenue. Also, the number of deficiencies in the last PSC inspection is one of the dominant predictors of the number of deficiencies in the next inspection. Ship age and previous detention times can also have a big impact on the ship deficiency number. Meanwhile, last inspection time and the performance of ship RO have the least influence on the number of deficiencies of a ship.

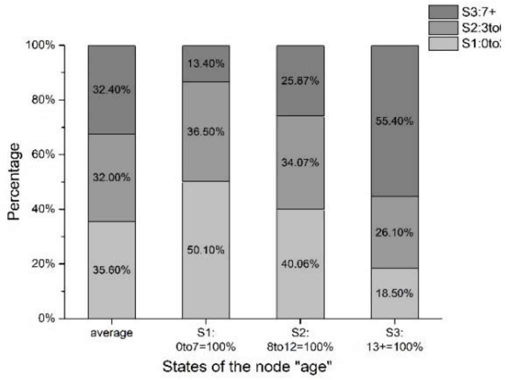
3.6.2 Effects of attribute variables on class variable

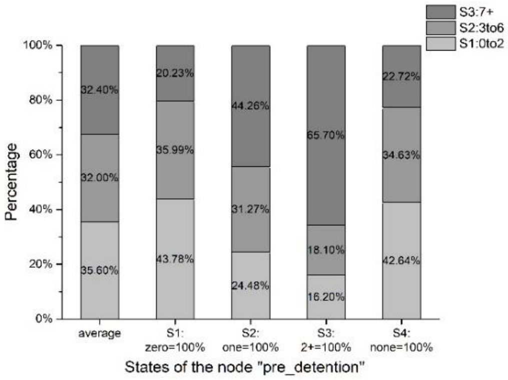
Recall the states of the variables in the TAN classifier as presented in Figure 3-4, in which the probability distribution of the class variable presents the proportions of the ships in the training data set belonging to the corresponding states of that variable. To identify how each state of each attribute variable will have an influence on the class variable, i.e., to identify in what states ships are more likely to have larger or smaller number of deficiencies, we assume that all the incoming ships are in one particular state of an attribute variable. To be more specific, to identify the influence of the states of "company" on the deficiency number, we can set the proportion of "S1: high", "S2: medium", "S3: low", and "S4: very_low" equal to 100% respectively, i.e., we assume that the company performance of all the incoming ships is high, medium, low and very low, respectively, and then record the proportions of the states of "deficiency_no" each time. The results are shown in the second to fifth columns in Figure 3-10(a). The first column in Figure 3-10(a) is the distribution of the variable among all the training cases, and we denote it as "average" in the horizontal ordinate. Comparing the first column with each column after the first column, if a column has the proportion of "S1: 0to2" of the class variable higher than that of the "average" column, and the proportion of "S3: 7+" of the class variable of this column is less than that of the "average" column, then it can be concluded that ships in this state of the attribute variable may have fewer deficiencies and are in better conditions than average. Conversely, if a column has the proportion of "S3: 7+" of the class variable higher than that of the "average" column and the proportion of "S1: 0to2" of the class variable of this column is lower than that of the "average" column, then the ships with this state of the attribute variable may have more deficiencies and are in worse conditions than average. The effects of different states of the states of the class variable are presented in Figure 3-10.



(a) Effect of different states of "company" on "deficiency_no"

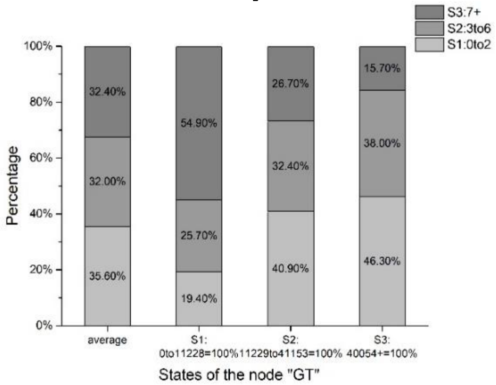
(b) Effect of different states of "last_deficiency_no" on "deficiency_no"

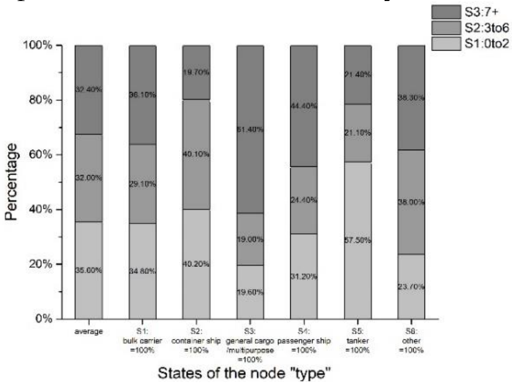




(c) Effect of different states of "age" on "deficiency_no"

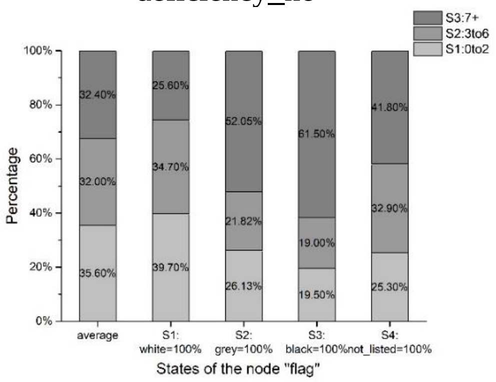
(d) Effect of different states of "pre_detention" on "deficiency_no"

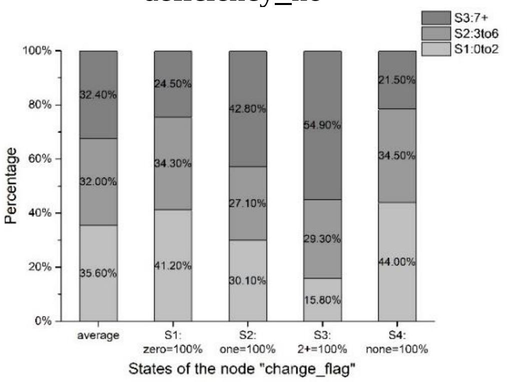




(e) Effect of different states of "GT" on "deficiency_no"

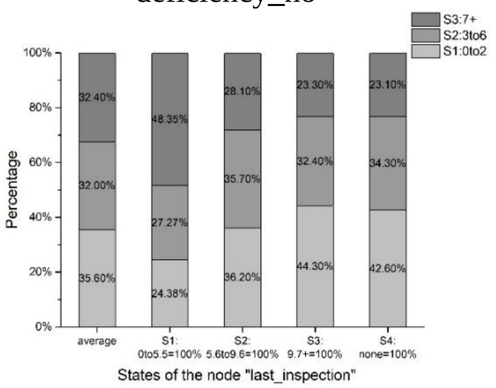
(f) Effect of different states of "type" on "deficiency_no"

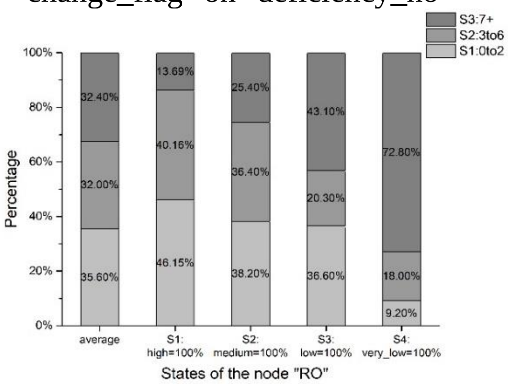




(g) Effect of different states of "flag" on "deficiency_no"

(h) Effect of different states of "change_flag" on "deficiency_no"





(i) Effect of different states of "last_inspection" on "deficiency_no"

(j) Effect of different states of "RO" on "deficiency_no"

Figure 3-10: Effect of different states of the attribute variables on class variable

Figure 3-10(a) shows that for the ship companies, the higher the company' performance is, the fewer deficiencies in PSC inspections its ships may have. Figure 3-10(b) indicates that, except for those ships that have no PSC inspection records, the more deficiencies there were in the last PSC inspection, the more likely that the ship will have more deficiencies in the next inspection. Figure 3-10(c) indicates that old ships may have more deficiencies than younger ships. Figure 3-10(d) shows that the greater the number of times a ship has been detained before, the worse performance in the latter PSC inspections it has. It is also the same for the number of times the ship changed its flag, as shown in Figure 3-10(h). As for the gross tonnage of ships, Figure 3-10(e) illustrates that ships with GT less than 11,228 are more likely to have more deficiencies. One of the reasons for this is that the ship's GT will be used to determine the ship's manning regulations, safety rules, registration fees, and port dues (IMO, 1969) and can thus influence the ship's conditions. Another reason is that compared to larger ships, the detention cost of smaller ships is lower, and they are more likely to have a higher number of deficiencies due to the lack of professional management of the ship companies. Figure 3-10(f) shows that general cargo and multipurpose ships are more likely to have a large number of deficiencies, while tankers have fewer deficiencies. Regarding the impact of ship flag performance on the number of deficiencies shown in Figure 3-10(g), if a ship's flag is on the white list, then it is more likely to have fewer deficiencies than ships whose flags are on the grey or black list. Nevertheless, this may not be true for ships whose flags are not listed, as there are insufficient observations. It may be surprising that the longer the time since the last inspection, the more likely the ship is to have a smaller number of deficiencies, as indicated in Figure 3-10(i). That may be because ships with a lower risk profile are less frequently inspected, while ships with a worse condition are inspected more often. It is also surprising that the ships belonging to low performance ROs have fewer deficiencies in the PSC inspection than those belonging to medium performance ROs, as shown in Figure 3-10(j). The reason for this may be that there are only 6.21% and 5.08% ships belonging to the medium and low performance ROs respectively in the total 250 cases in the TAN classifier. The small number of cases is not typical enough to reflect the true situation.

3.7 CONCLUSION AND FUTURE RESEARCH

PSC inspection is viewed as an effective way to eliminate substandard shipping. One of the key issues faced by the PSC authorities is how to identify high-risk incoming ships to inspect in order to find more deficiencies after inspecting a certain number of ships. To select the high-risk ships more efficiently, a data-driven Bayesian network classifier called the Tree Augmented Naive Bayes (TAN) classifier is proposed in this study. By using historical inspection data downloaded from the database of Tokyo MoU, which include both ship information and inspection information, the structure part and quantitative part of the TAN classifier are constructed.

The proposed model is validated by a numerical experiment based on the historical data from Hong Kong port, which shows that when the number of training cases is more than 200, the classification accuracy of the TAN model is beyond 60%. Compared with the currently used Ship Risk Profile (SRP) ship selection scheme, the TAN classifier can identify about 130.35% more deficiencies on average after inspecting the 50 ships in the testing data set. The results of the numerical experiment also show that after inspecting 10%, 20%, 30%, 40%, 50%, and 60% of the 50 total incoming ships in each testing data set, the average improvement of the TAN classifier is 348.38%, 147.23%, 108.32%, 98.29%, 70.33%, and 48.83% after inspecting 5, 10, 15, 20, 25, and 30 ships, respectively. The variable analysis shows that among all the attribute variables in the TAN classifier, the performance of the ship company and the number of deficiencies in the last PSC inspection are the dominant factors that influence the deficiency number. The results also show how the state of a specific attribute variable can have an impact on the class variable (i.e., the deficiency number). Theoretically, we propose a data equal-frequency discretization problem and present it in a mathematical and rigorous way. Then, by using dynamic programming we prove that this discretization method is bounded by $O(NV^2)$ when it is used in our model. Also, by induction, we prove that random selection of the root attribute variable of the TAN classifier will not influence the classification process of the cases in the testing data set. Practically, the proposed TAN classifier can help address the significant PSC inspection problem compared with the currently used ship selection method and the logistic regression model which is widely used in other literature on PSC inspection.

The proposed model is one of the first few data-driven models to act as a real-time predictor of the number of deficiencies of incoming ships for PSC inspection. It can predict the possible number of deficiencies of incoming foreign ships and help the PSC officers to better identify high-risk ships, as well as to make rational resource allocations.

One limitation of this research is the limited input data (i.e., the inspection records). On the one hand, some special cases may not be covered by the limited input cases. On the other hand, the CPTs may not be that accurate to reflect the real situation. In future research, more data cases, as well as more attribute variables, can be incorporated to construct the TAN model in order to further improve its prediction accuracy.

Chapter 4: Inspection Schemes in PSC Inspection[7]

This chapter deals with another important practical problem in PSC inspection: after selecting the ships coming to a port for inspection, what deficiency items and in what sequence they should be inspected. To address this problem, two innovative and high-efficient PSC inspection schemes describing specific PSC inspection sequences are proposed for the inspectors' reference when time and resources are limited, especially when there are difficulties in estimating the possible deficiencies in advance. Both schemes take the occurrence probability, inspection cost, and ignoring loss of each deficiency item into account. More specifically, the first inspection scheme is based on the occurrence probabilities of the deficiency items in the whole data set, while the second scheme further considers the correlations among the deficiency items extracted by association rules. The results of numerical experiments show that the efficiency of the two proposed inspection schemes is about 1.5 times higher than that of the currently used inspection scheme. In addition, the second inspection scheme performs better than the first inspection scheme, especially when inspecting ships with no less than 5 deficiency items and limited inspection resources. The outline of this chapter is as follows: Section 4.1 introduces the background of the problem and the contribution of this study. Section 4.2 reviews the studies on application of association rule learning methods in transportation area. Section 4.3 develops Inspection Scheme I for PSC inspection. Section 4.4 develops Inspection Scheme II for PSC inspection. Section 4.5 presents the results of numerical experiments which compare the performance of the currently implemented inspection scheme, and the two novel inspection schemes. Section 4.6 discusses some issues related to this study. Section 4.7 concludes this chapter.

[7] Yan R., Zhuge D., Wang S., 2020. Development of two highly-efficient and innovative inspection schemes for PSC inspection. Accepted by Asia-Pacific Journal of Operational Research.

4.1 INTRODUCTION

4.1.1 Background

According to the documents of Tokyo MoU, there are 17 types of deficiency items related to the international maritime conventions, including but not limited to SOLAS, MARPOL, the International Convention on Tonnage Measurement of Ships, and the International Convention on Civil Liability for Oil Pollution Damage (CLC), as listed in Table 4-1(IMO, 2019; Tokyo MoU, 2018b).

Table 4-1: List of deficiency codes and items (Tokyo MoU, 2018b)

Code	Deficiency item	Code	Deficiency item	Code	Deficiency item
D1	Certificates and documentation	D7	Fire safety	D13	Propulsion and auxiliary machinery
D2	Structural condition	D8	Alarms	D14	Pollution prevention
D3	Water/Weathertight condition	D9	Working and living conditions	D15	ISM
D4	Emergency system	D10	Safety of navigation	D18	Labour conditions
D5	Radio communication	D11	Life saving appliances	D99	Other
D6	Cargo operations including equipment	D12	Dangerous goods		

To guarantee inspection efficiency, it is clearly stated that the main purpose of PSC is to prevent a ship proceeding to the sea if it is unsafe to the marine environment and to avoid unnecessary ship detention or delay (IMO, 2017). Thus, not every deficiency item of all the coming ships will be inspected. Instead, only some deficiency items of the high-risk ships will be inspected due to limited time and human resources. However, in practice, since there are rare instructions on the inspection sequence for the PSCOs, the inspected areas of a ship and to what extent they will be inspected are highly dependent on PSCOs' expert judgments. Nevertheless, personal judgments might be biased and inaccurate. First, even if possible deficiencies can be estimated in advance by the PSCOs, since some of them may lack experience, it is likely that the limited resources are allocated to inspect those less important or less frequently occurring deficiencies so that the relative serious deficiencies are ignored. As a result, inequality and inefficiency may be caused and the detected deficiencies of a single ship can be quite different when inspected by different PSCOs. Second, some ship deficiency items might be too veiled to be easily judged in advance even if the PSCOs are professional enough and familiar with ship conditions. Therefore, if the inspection decisions are purely dependent on expert estimation, fatal deficiencies may be missed.

4.1.2 Contribution

One possible way to improve the effectiveness of the inspection sequence is to develop inspection schemes that could identify as many deficiency items as possible after inspecting a certain number of deficiencies. In this study, we develop two instructive inspection schemes based on historical PSC inspection data and association rule learning method to draw a balance between the limited inspection resources and ship safety. First, we develop a new inspection scheme which takes the value of each deficiency item into account. The value of a deficiency item comprises the possibility of occurrence of a deficiency item, the cost of inspecting the deficiency item, and the loss of ignoring the deficiency item. To better illustrate the relationship between the deficiency items, we then develop another inspection scheme by considering the correlations among the deficiency items, which means that the probability of the occurrence of a deficiency when its related deficiencies are detected is higher than that when no related deficiencies are detected. The relevance between the deficiencies is identified by the association rules that are derived from the frequent itemset using Apriori algorithm (Agrawal and Srikant, 1994). Thus, the inspection decisions are dynamic since the possibility of detecting a certain deficiency item depends on the previously detected deficiencies. By selecting the deficiency item with the highest value in the remaining deficiencies, the PSCOs can make the subsequent inspection decisions more accurately and efficiently. The results of the numerical experiments show that both of the newly proposed inspection schemes can identify the deficiency items about 1.5 times more efficiently than the currently used inspection scheme. Moreover, the second inspection scheme, which takes the relevance among the deficiency items into consideration, is better than the first inspection scheme when inspecting ships containing no less than 5 deficiency items while the inspection time and resources only allow 5 or 6 deficiency items to be inspected.

4.2 LITERATURE REVIEW

This section reviews the literature on applying association rule learning methods to transport research. Association rule learning algorithm is a rule-based learning method to discover the inherent and interesting rules between variables in large database. The concept of association rule was proposed by Agrawal et al. (1993). Popular algorithms used to mine association rules include but are not limited to Apriori algorithm, Eclat algorithm, and FP-growth algorithm (Zhang and Zhang, 2002). In the past decade, there has been an increasing number of studies that apply association rule learning method to road transport research. Among them, various studies applied association rule mining methods to analyze road transport casualties, such as Weng et al. (2016), Ait-Mlouk et al. (2017), Besharati and Tavakoli Kashani (2018), Yu et al. (2019), Kumar and Toshniwal (2016), and Zhang et al. (2018). Association rule mining methods are also employed to extract the transition patters in public transport, such research includes Zhao et al. (2018) and Zhao et al. (2019). The concept of association rule is also used in the field of rail transport, and the representative studies are Mirabadi and Sharifian (2010), Tang and Qin (2015), and Ghomi et al. (2016).

With regard to the field of air transport and maritime transport, there are much fewer studies. In air transport field, Sternberg et al. (2016) applied data indexing techniques together with association rules to identify the hidden patterns of flight delays in Brazil. In maritime transport field, contributory factors to both nonserious and serious shipping accidents were listed respectively by using association rules (Weng and Li, 2019). Correlations among the detention deficiencies and external factors were examined by applying association rule mining algorithms to the ship detention records in Tokyo MoU database (Tsou, 2018).

From the above-mentioned literature in this section and the literature review part in Chapter 2, it can be seen that on the one hand, despite a large number of studies on PSC inspection, to the best of our knowledge, the inspection sequence of the deficiency items has seldom been studied in the existing literature. On the other hand, although association rule learning method performs well in the field of road transport, there is rare attempt in applying this method to maritime transport research. Thus, in this study, two new PSC deficiency item inspection schemes are developed based on historical inspection records and association rule mining method. The hidden correlations among the deficiency items are extracted by the association rules and the new schemes can give instructions on ship inspection to the PSCOs.

4.3 DEVELOPMENT OF INSPECTION SCHEME I FOR PSC INSPECTION

4.3.1 Data set, indexes and definitions

In this study, we use the initial inspection records at the Port of Hong Kong from January 1, 2018 to June 30, 2018 with at least one deficiency item detected as the whole data set. Totally, there are $M = 297$ records and $N = 17$ types of deficiencies. The types and detected times of the deficiency items are shown in Table 4-2.

Table 4-2: Types and detected times of ship deficiency items

Deficiency item in I	Deficiency code	Deficiency type	Total detected times
it_1	D1	Certificates and documentation	87
it_2	D2	Structural condition	17
it_3	D3	Water/Weathertight condition	97
it_4	D4	Emergency system	42
it_5	D5	Radio communication	46
it_6	D6	Cargo operations including equipment	8
it_7	D7	Fire safety	164
it_8	D8	Alarms	33
it_9	D9	Working and living conditions	115
it_{10}	D10	Safety of navigation	133
it_{11}	D11	Life saving appliances	120
it_{12}	D12	Dangerous goods	2
it_{13}	D13	Propulsion and auxiliary machinery	30
it_{14}	D14	Pollution prevention	89
it_{15}	D15	ISM	23
it_{16}	D18	Labour conditions	0
it_{17}	D99	Other	12

The set of inspection records is denoted by $R = \{R_{1,...,} R_M\}$. A certain inspection, which can also be called an experiment, is denoted by $R_m \in R$. The set of deficiency items is denoted by $I = \{it_1, ..., it_N\}$, which contains the total 17 types of deficiency items as required by Tokyo MoU. Regarding each record, we denote the deficiency set of record R_m with N_m detected deficiency items as $D_{R_m} = \{D_{R_m,1}, ..., D_{R_m,N_m}\}$. Note that $D_{R_m} \subseteq I$ and $D_{R_m} \neq \varnothing$, as we only take the inspections with deficiencies detected into consideration.

To develop Inspection Scheme I, we first introduce the concept of an itemset. An itemset is a specific collection of deficiencies. An itemset containing $i \in [1, N]$ deficiency items is called an i-itemset and is denoted by I_i. We then define the event of observing a particular itemset I_i as $E(I_i)$, which means after inspecting a ship, it is found that the ship has all the deficiency items in the itemset I_i. We define $P(E(I_i))$ as the proportion of the M records that have all the deficiencies in the itemset I_i, i.e., the probability of the occurrence of $E(I_i)$. Note that a record that has all the deficiency items in the itemset I_i may also include deficiency items not in I_i.

We then define the probability of observing the event $E(I_i)$ as the Support of the itemset I_i, i.e., $Sup(I_i) = P(E(I_i))$, and thus $Sup(I_i) \in [0,1]$. It is obvious that the larger the Support value is, the more frequently this itemset occurs in the inspection records. In order to find out the itemsets that frequently appear in the M records, we define the minimum threshold of Support as $\min Sup$. The itemsets with their Support values no less than $\min Sup$ are called large itemsets, i.e., if and only if $I_i^* \subseteq I$ is a large itemset, $Sup(I_i^*) \geq \min Sup$ (Tan et al., 2015).

4.3.2 Generation of large itemsets

Given the value of $\min Sup$, an algorithm called Apriori is adopted to generate the large itemsets (Agrawal and Srikant, 1994). This algorithm is used to discover useful and hidden relationships between data. We assume that the items in each deficiency set D_{R_m} and by all itemsets are ordered in the alphabet. The Apriori algorithm is based on the following two properties of large itemsets (Agrawal and Srikant, 1994).

Property I. Any non-empty and strict subset of a large itemset is large.

Property II. Any superset of a non-large itemset cannot be large.

Now we describe the Apriori algorithm for generating the large itemsets (Agrawal and Srikant, 1994; Tan et al., 2005). We denote a large itemset containing k items as a large $k-$itemset. Denote L_k as the set of all large $k-$itemsets. Denote C_k as the set of candidate large $k-$itemsets. Denote $Num(I_i)$ as the occurrence times of itemset I_i in the record set R.

Algorithm 1. Generate large itemsets L_k, $K = 1, 2, ..., N$.

Step 1: $k = 1$; //generate all large 1-itemsets

$L_k = \varnothing$;

for all $it_n \in I$

$Sup(it_n) = 0$;

$Num(it_n) = 0$;

for all $R_m \in R$

if it_n is contained in R_m

$Num(it_n) = Num(it_n) + 1$;

end if;

end for;

$Sup(it_n) = \frac{Num(it_n)}{M}$;

If $Sup(it_n) \geq \min Sup$

$L_1 = L_1 \cup \{it_n\}$;

end if;

end for.

Step 2: for ($k = 2$; $L_{k-1} \neq \varnothing$ and $k \leq N$; $k++$) //generate all large $k-$itemsets,

$C_k =$ generate_candidate (L_{k-1}) //generate candidate large $k-$itemsets from the existing large $(k-1)-$itemsets by using Algorithm 2.

$L_k = \varnothing$;

for each $c \subset C_k$

$Num(c) = 0$;

$Sup(c) = 0$;

for all $R_m \in R$

if c is contained in R_m

$Num(c) = Num(c) + 1$;

end if;

end for;

$Sup(c) = \frac{Num(c)}{M}$;

if $Sup(c) \geq \min Sup$

$L_k = L_k \cup \{c\}$

end if;

end for;

end for.

Denote a pair of large itemsets in L_{k-1} by $I_{k-1}^{*'} = \{it_1', it_2', ..., it_{k-2}', it_{k-1}'\}$ and $I_{k-1}^{*''} = \{it_1'', it_2'', ..., it_{k-2}'', it_{k-1}''\}$. We use "<" to denote that the left-hand side item precedes the right-hand side item in the alphabet.

Algorithm 2. generate_candidate (L_{k-1}).	

Step 1: Joining Step	$C_k = \varnothing$; //Based on Property I
	for all pairs of itemsets in L_{k-1} , $k \geq 2$
	  if ($k = 2$ or $it'_1 = it''_1$, $it'_2 = it''_2$,…, $it'_{k-2} = it''_{k-2}$)
	    if $it'_{k-1} < it''_{k-1}$
	      $C_k = C_k \cup \{it'_1, it'_2, ..., it'_{k-2}, it'_{k-1}, it''_{k-1}\}$;
	    else
	      $C_k = C_k \cup \{it'_1, it'_2, ..., it'_{k-2}, it''_{k-1}, it'_{k-1}\}$;
	    end if;
	  end if;
	end for.

Step 2: Pruning Step	for all itemsets $c \subset C_k$ //Based on Property II
	  for all subsets s containing $(k-1)$ items of c
	    if $s \not\subset L_{k-1}$
	      delete c from C_k ;
	    end if;
	  end for;
	end for;
	return C_k .

In Algorithm 1, the first step is to find all large 1-itemsets by scanning the whole record set R . By iteration, the set of all large $k-$ itemsets ($k \geq 2$) L_k is found based on the candidate large $k-$ itemsets C_k generated by the set of large $(k-1)-$ itemsets $L_{k\text{-}1}$. The algorithm terminates until all the large itemsets are found. Algorithm 2 describes a way to find the set of candidate large $k-$ itemsets C_k based on L_{k-1} . A candidate large $k-$ itemset is a combination of a pair of large itemsets which have the same first $(k-2)$ items and a different $(k-1)\text{th}$ item. After the combinations are formulated in Step 1, the subsets containing $(k-1)$ items of each combination are checked in Step 2. If any subset of a candidate itemset is not a large itemset, then this candidate itemset is deleted from the set of candidate large itemsets. After the Joining Step and Pruning Step, all the candidate large $k-$ itemsets $\bar{I}_k$ can be found.

4.3.3 Description of Inspection Scheme I

Inspection Scheme I (short for Scheme I) is based on the large 1-itemsets. We set $\min Sup = 0.1$. After applying the Apriori algorithm in the input data set, large 1-itemsets can be generated as shown in Table 4-3.

Table 4-3: Large 1-intemsets

Large 1-intemset	Support
{D7 - Fire safety}	0.55
{D10 - Safety of navigation}	0.45
{D11 - Life saving appliances}	0.40
{D9 - Working and living conditions}	0.39
{D3 - Water/Weathertight condition}	0.33
{D14 - Pollution prevention}	0.30
{D1 - Certificates and documentation}	0.29
{D5 - Radio communication}	0.15
{D4 - Emergency system}	0.14
{D8 – Alarms}	0.11
{D13 - Propulsion and auxiliary machinery}	0.10

To develop the inspection scheme, we take the probability of a deficiency item occurs, the cost of inspecting the deficiency item and the loss of ignoring the deficiency item into consideration. The possibility of the occurrence of it_i is denoted by P_{it_i}. Denote the inspection cost of deficiency item it_i by C_{it_i}, $C_{it_i} > 0$. If an existing deficiency item is not identified, the loss is huge and denoted by L_{it_i}, $L_{it_i} > C_{it_i}$. Note that ideally, the cost and loss values of a deficiency item are not only at financial level, but also reflect the effects on marine safety and environment, time delay, allocated inspection resources, etc. Denote the value of inspecting deficiency item it_i as V_{it_i}, and we have $V_{it_i} = P_{it_i} \times L_{it_i} - C_{it_i}$. The larger the value of a deficiency item, the more worthy of being inspected.

Due to the lack of data and the sake of simplicity, we assume that the value of L_{it_i} and the value of C_{it_i} are identical to each deficiency item, respectively. It should be noted that it is reasonable to assume the ignoring loss and inspection cost are the same for each deficiency item respectively for two reasons. First, as suggested by a senior PSCO in a port within the Tokyo MoU, all the deficiency items are related to important international maritime regulations and conventions, and thus they can be viewed of the same level of importance and their loss values can be viewed as identical. Second, as suggested by the PSCOs we interviewed, they usually walk around the ship to observe its conditions as well as to inspect the deficiency items, and thus the cost of inspecting a deficiency item can also be roughly treated as the same. As positive V_{it_i} indicates that the deficiency item is worthy of being inspected, we need to compare

$P_{it_i} \times L_{it_i} - C_{it_i}$ and 0, i.e., we need to know the value of C_{it_i} / L_{it_i}. To determine the inspection sequence of the deficiency items, we also need to compare the values of P_{it_i} of all the deficiency items with positive V_{it_i}. As estimating the value of C_{it_i} / L_{it_i} is quite complicated and there are few references, for the sake of simplicity, we set C_{it_i} / L_{it_i} equal to the PSC inspection rate at the Port of Hong Kong during the time period from 2015 to 2017. According to the annual reports of Tokyo MoU in 2015, 2016, and 2017, there were a total of 10,239 ships visiting the Port of Hong Kong and 1,324 of them were inspected during this period (Tokyo MoU, 2016; Tokyo MoU, 2017a; Tokyo MoU, 2018a). Therefore, we set $C_{it_i} / L_{it_i} = 0.1293$. By converting $V_{it_i} = P_{it_i} \times L_{it_i} - C_{it_i}$ to $\frac{V_{it_i}}{L_{it_i}} = P_{it_i} - \frac{C_{it_i}}{L_{it_i}}$, we can view L_{it_i} as the unit of V_{it_i}, and the value of a deficiency item equals the difference between P_{it_i} and $\frac{C_{it_i}}{L_{it_i}}$. The value of each deficiency item is listed in Table 4-4.

Table 4-4: Values of all deficiency items in large1-itemsets

Large 1-intemset	Value (unit: $/L_{it_i}$)
{D7 - Fire safety}	0.4207
{D10 - Safety of navigation}	0.3207
{D11 - Life saving appliances}	0.2707
{D9 - Working and living conditions}	0.2607
{D3 - Water/Weathertight condition}	0.2007
{D14 - Pollution prevention}	0.1707
{D1 - Certificates and documentation}	0.1607
{D5 - Radio communication}	0.0207
{D4 - Emergency system}	0.0107
{D8 – Alarms}	−0.0193
{D13 - Propulsion and auxiliary machinery}	−0.0293

Based on V_{it_i} of each deficiency item, we first propose Inspection Scheme I for the PSCO's reference when conducting PSC inspection. The inspection scheme lies on two basic assumptions:

(a) The cost of inspecting a deficiency is identical no matter if this deficiency item exists.

(b) If an existing deficiency item exists and it is inspected, it can be detected.

Inspection Scheme I

The values of the deficiency items in Inspection Scheme I are based on the Support values of the items in large 1-itemsets, and the value of each deficiency item $V_{it_i} = P_{it_i} \times L_{it_i} - C_{it_i}$ is fixed. The general inspection sequence is as follows: staring from inspecting D1- certificates and documentation as suggested by Tokyo MoU (2018b), all the remaining deficiency items with positive V_{it_i} will be inspected from larger V_{it_i} to smaller V_{it_i}. Totally, 9 deficiencies, namely D1, D7, D10, D11, D9, D3, D14, D5, and D4, are worthy of being inspected. The inspection sequence is shown in Figure 4-1.

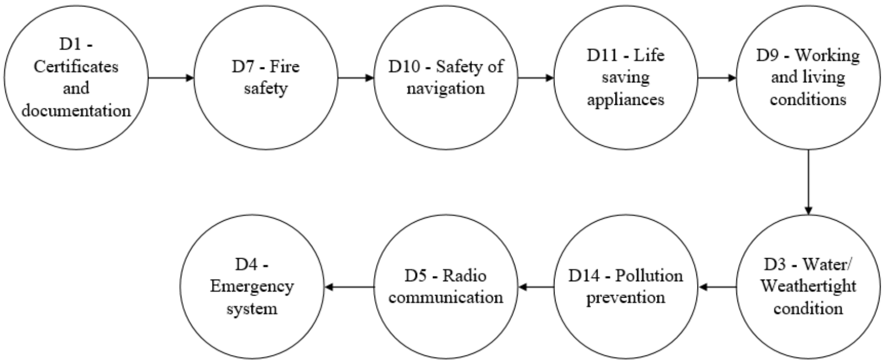


Figure 4-1: Inspection sequence of Inspection Scheme I

4.4 DEVELOPMENT OF INSPECTION SCHEME II FOR PSC INSPECTION

4.4.1 Indexes and definitions

The data set used to develop Inspection Scheme II (short for scheme II) is the same as that is used for developing scheme I. In scheme II, we further consider the relevance among the deficiency items to better illustrate their relationships, i.e., the deficiency items are dependent and the probability of the occurrence of each deficiency item is influenced by other deficiency items. The dependency is presented by the association rules generated from the large 2-itemsets and large 3-itemsets, which are shown in Table 4-5 and Table 4-6. Note that no Support of the itemsets containing 4 items is greater than or equal to $\min Sup$, and hence the biggest large itemsets only contain 3 items. One main reason for generating the association rules from the large itemsets is that only the rules with occurrence beyond the minimum support threshold are statistically significant and worth being considered (Agrawal, 1993).

Table 4-5: Large 2-intemsets

Large 2-intemset	Support	Large 2-intemset	Support	Large 2-intemset	Support
{D7, D10}	0.28	{D1, D7}	0.17	{D3, D9}	0.15
{D7, D11}	0.24	{D3, D10}	0.17	{D3, D14}	0.13
{D7, D9}	0.23	{D9, D11}	0.17	{D1, D14}	0.11
{D10, D11}	0.21	{D1, D10}	0.17	{D4, D11}	0.10
{D7, D14}	0.19	{D1, D11}	0.17	{D9, D14}	0.10
{D9, D10}	0.19	{D3, D11}	0.16	{D1, D9}	0.10
{D3, D7}	0.18	{D11, D14}	0.16	{D1, D3}	0.10
{D10, D14}	0.18				

Table 4-6: Large 3-intemsets

Large 3-intemset	Support	Large 3-intemset	Support	Large 3-intemset	Support
{D7, D10, D11}	0.14	{D10, D11, D14}	0.12	{D1, D7, D11}	0.10
{D7, D9, D10}	0.13	{D3, D10, D11}	0.11	{D1, D10, D14}	0.10
{D7, D10, D14}	0.13	{D7, D9, D11}	0.11	{D3, D7, D11}	0.10
{D1, D7, D10}	0.12	{D1, D10, D11}	0.11	{D3, D7, D10}	0.10
{D7, D11, D14}	0.12				

A rule is generated by dividing a large i- itemset I_i^* ($i \geq 2$) into two mutually exclusive and non-empty deficiency itemsets, I_j and I_k, with $I_j \cup I_k = I_i^*$. Note that both I_j and I_k are large itemsets. To determine whether the rule from I_j to I_k (denoted by $I_j \rightarrow I_k$) is an association rule, we further introduce two indexes: Confidence and Lift (McNicholas et al., 2008). The Confidence of $I_j \rightarrow I_k$ (denoted by $Conf(I_j \rightarrow I_k)$) can be interpreted as the conditional probability of the event of $E(I_k)$ under the condition that the event of $E(I_j)$ has occurred, i.e., $Conf(I_j \rightarrow I_k) = \dfrac{P(E(I_k) \cap E(I_j))}{P(E(I_j))} = P(E(I_k) \mid E(I_j))$. $Conf(I_j \rightarrow I_k) \in [0,1]$. The larger value the Confidence is, the more likely the deficiency items in I_k will be detected after the deficiency items in I_j are detected. Lift of $I_j \rightarrow I_k$ (denoted by $Lift(I_j \rightarrow I_k)$) is the measure of the influence of the occurrence of event $E(I_j)$ on the occurrence of event $E(I_k)$. $Lift(I_j \rightarrow I_k) = \dfrac{P(E(I_k) \cap E(I_j))}{P(E(I_j)) \times P(E(I_k))} = \dfrac{P(E(I_k) \mid E(I_j))}{P(E(I_k))}$ and $Lift(I_j \rightarrow I_k) \in [0,+\infty)$. It represents the ratio of the probability of the occurrence of event $E(I_k)$ under the condition that event $E(I_j)$ occurs and the probability that event $E(I_k)$ occurs unconditionally in the record set. If $Lift(I_j \rightarrow I_k) = 1$, i.e.,

$P(E(I_j), E(I_k)) = P(E(I_j)) \times P(E(I_k))$, $E(I_j)$ and $E(I_k)$ are independent. If $Lift(I_j \to I_k) \in [0,1)$, the occurrence of $E(I_j)$ reduces the probability that $E(I_k)$ occurs. If $Lift(I_j \to I_k) \in (1, +\infty)$, the occurrence of $E(I_j)$ increases the probability of the occurrence of $E(I_k)$. After introducing the indexes, we can now define an association rule:

Definition 1: Suppose that there is a large i - itemset I_i^* ($i \geq 2$) and its two mutually exclusive and non-empty deficiency itemsets I_j and I_k such that $I_j \cup I_k = I_i^*$. Given the minimum threshold of Confidence, $\min Conf$, and the minimum threshold of Lift, $\min Lift$, the rule $I_j \to I_k$ is an association rule if and only if $Conf(I_j \to I_k) \geq \min Conf$ and $Lift(I_j \to I_k) \geq \min Lift$.

The implication of this association rule is that during the PSC inspection if the deficiency items in I_j are detected, there is a high probability that this ship also has deficiency items in I_k. The left-hand side of an association rule is called antecedent and the right-hand side is called consequent (Agrawal et al., 1993).

4.4.2 Generation of association rules

After all the large $k-$ itemsets are obtained and the values of $\min Conf$ and $\min Lift$ are given, we can then generate the corresponding association rules. Similar to Property I and II, we can have the following Property III (Agrawal et al., 1993):

Property III. Partition a large $i-$itemset I_i^* ($i \geq 2$) into two itemsets I_j and I_k. The rule from I_j to I_k is denoted by $I_j \to I_k$. $Conf(I_j \to I_k) < \min Conf$. For any non-empty and strict subset of I_j, denoted by $\underline{I}_j$, and the superset of I_k, denoted by $\overline{I}_k = I_i - \underline{I}_j$, the rule from $\underline{I}_j$ to $\overline{I}_k$ is called a sub-rule of $I_j \to I_k$, and $Conf(\underline{I}_j \to \overline{I}_k) < \min Conf$ (Agrawal and Srikant, 1994).

Proof:

We first denote the events of observing I_j and I_k as $E(I_j)$ and $E(I_k)$, respectively, and the events of observing $\underline{I}_j$ and $\overline{I}_k$ as $E(\underline{I}_j)$ and $E(\overline{I}_k)$, respectively. The Confidence of $I_j \to I_k$ can be presented as $Conf(I_j \to I_k) = \dfrac{P(E(I_j) \cap E(I_k))}{P(E(I_j))} = \dfrac{P(E(I_i))}{P(E(I_j))}$, and the Confidence of $\underline{I}_j \to \overline{I}_k$ can be presented as $Conf(\underline{I}_j \to \bar{I}_k) = \dfrac{P(E(\underline{I}_j) \cap E(\bar{I}_k))}{P(E(\underline{I}_j))} = \dfrac{P(E(I_i))}{P(E(\underline{I}_j))}$. As $\underline{I}_j \subset I_j$, we have $P(E(\underline{I}_j)) \geq P(E(I_j))$ and $Conf(\underline{I}_j \to \bar{I}_k) \leq Conf(I_j \to I_k) < \min Conf$. Therefore, we can conclude that $Conf(\underline{I}_j \to \bar{I}_k) < \min Conf$.■

It can be seen from the above property that the sub-rules of a rule with its Confidence less than $\min Conf$ cannot be association rules. We can use this property to simplify the process by ignoring the sub-rules of the rules with Confidence less than $\min Conf$.

We now describe the process of generating association rules of all large $k-$ itemsets in L_k (Agrawal and Srikant, 1994). A consequent containing m ($1 \leq m < k$) items is denoted by h_m and the set of all h_m is denoted by H_m . we use a recursive algorithm called Association rules generation involving Ap-AssRule, which can first generate the rules with their Confidence larger than or equal to $\min Conf$ and then generate the set of association rules by deleting rules with Lift less than $\min Lift$.

Algorithm 3. *Association rules generation.*

Step 1:
Generating_Rules
	$Rules = \varnothing$;
	for each large $k-$ itemset I_k^*, $k \geq 2$
	  Ap-AssRule (I_k^*); //recursively call the function
	end for;

Step 2:
Pruning_Rules
($Rules$)
	for each $rule$ in $Rules$
	  Calculate $Lift(rule)$;
	  if $Lift(rule) < \min Lift$
	      Delete $rule$ from $Rules$; //Filter rules by Lift
	  end if;
	end for;
	Return $Rules$.

Algorithm 4. *Ap-AssRule* (I_k^*).

$m=1$;
$H_m=\{h_m \mid h_m \subset I_k^*\}$; //generate all consequents containing one item
while ($k \geq m+1$)
  for each $h_m \subset H_m$
    //Divide I_k^* into two parts with h_m as the consequent
    $rule = I_k^* - h_m \rightarrow h_m$;
      Calculate $Conf(rule)$;
      if ($Conf(rule) \geq \min Conf$)
        $Rules \cup rule$; //Filter rules by Confidence
      else
        Delete h_m from H_m; //Based on Property III
      end if;
  end for;
$m=m+1$;
H_m = *generate_candidate* (H_{m-1}); //generate H_m from H_{m-1} by calling Algorithm 2.
end while; //loop until $k < m+1$

4.4.3 Description of Inspection Scheme II

Inspection Scheme II is based on the association rules of the deficiency items. We set $\min Conf = 0.6$ and $\min Lift = 1.2$ as the thresholds and the generated association rules are presented in Table 4-7. Except for Rule NO. 4, which is generated by a large 2-itemset, all the other association rules are generated by the large 3-itemsets. As the Confidence value is used to determine the strongness of an association rule, and the Lift value is used to verify if it is meaningful, the association rules with higher Confidence values are of higher priority to be adopted.

Table 4-7: Association rules of the deficiency items

Rule NO.	Left-hand side	Right-hand side	Confidence	Lift	Rule NO.	Left-hand side	Right-hand side	Confidence	Lift
1	D1, D14	D10	0.91	2.03	12	D7, D14	D10	0.66	1.49
2	D11, D14	D10	0.77	1.72	13	D7, D14	D11	0.65	1.61
3	D11, D14	D7	0.77	1.40	14	D1, D10	D11	0.64	1.58
4	D4	D11	0.74	1.83	15	D1, D11	D10	0.64	1.43
5	D1, D10	D7	0.74	1.34	16	D3, D10	D11	0.63	1.55
6	D1, D7	D10	0.73	1.62	17	D10, D11	D14	0.61	2.02
7	D10, D11	D7	0.72	1.30	18	D1, D7	D11	0.61	1.50
8	D10, D14	D7	0.72	1.28	19	D7, D11	D10	0.61	1.35
9	D10, D14	D11	0.70	1.73	20	D1, D10	D14	0.60	2.00
10	D9, D10	D7	0.70	1.26	21	D3, D7	D10	0.60	1.35
11	D3, D11	D10	0.68	1.52					

Inspection scheme II

In Inspection Scheme II, we also consider the value of each deficiency item V_{it_i}, which contains its occurrence probability, the cost of inspecting it and the loss of ignoring it the same as that of Inspection Scheme I. Regarding V_{it_i} of all the deficiency items, 9 deficiency items, namely D1, D7, D10, D11, D9, D3, D14, D5, and D4, are worthy of being inspected in total. The differences between Inspection Schemes I and II are that in Inspection Scheme II, the values for some deficiency items are dynamic after some certain deficiencies are detected according to the association rules as indicated in Table 4-5, while the values for all deficiency items in Inspection Scheme I are static. There are four types of deficiency items on the right-hand side among all the correlation rules: D7, D10, D11, and D14, which means that only P_{D_7}, P_{D10}, $P_{D_{11}}$, and $P_{D_{14}}$ are dynamic and related to the detected deficiencies, while the probabilities of other deficiency items are static. Starting from inspecting D1 as the first inspection item, the probabilities of the uninspected deficiency items are updated based on the association rules. Then, the deficiency item with the highest probability to occur is selected to be inspected as the next item. Note that as the minimum Confidence value of the association rules is 0.6, if items on the left-hand side of an association rule are detected, the value of the deficiency item on the right-hand side is the largest (larger than 0.4207) among all the uninspected items and should be inspected as the next item. The first 6 items of inspection are presented in Figure 4-2. In this figure, “Y” means the deficiency is detected while “N” means the deficiency does not exist. The red nodes represent that the probabilities of these deficiency items are updated according to the association rules. The brackets contain the left-hand side of the used association rules. It should be noted that the first 5 items inspection have already updated all the updatable deficiency probabilities among the uninspected deficiencies (recall that only P_{D_7} , $P_{D_{10}}$, $P_{D_{11}}$, and $P_{D_{14}}$ can be updated). From the 6th item of inspection, the probability of each deficiency item is equal to its Support value.

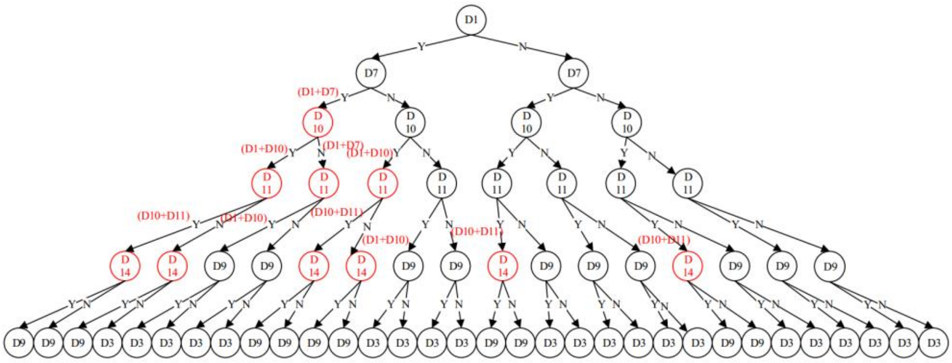


Figure 4-2: Inspection sequence of Inspection Scheme II

4.5 NUMERICAL EXPERIMENTS

4.5.1 Comparison of the current and new inspection schemes

To the best of our knowledge, the inspection sequence of the deficiency items is not clearly stated in any documents, and thus we assume that the current inspection scheme requires all the deficiency items to be inspected in theory. The ratio of the total detected deficiency items and the number of inspection items can be regarded as the inspection efficiency, as it indicates the probability of detecting a deficiency item after inspecting each one of them. By using the testing data set Ψ_1 which contains the detected deficiency items in initial PSC inspection with at least one deficiency item detected from 1 July 2018 to 31 August 2018 at the Port of Hong Kong, we compare the inspection efficiency of the current inspection scheme and the two new inspection schemes. Totally, there are 138 inspection records and 519 detected deficiency items in the testing data set Ψ_1 . The inspection efficiency of the three schemes is shown in Table 4-8. The current inspection scheme requires all the deficiency items listed in Table 4-1 to be inspected, and hence there are totally $17 \times 138 = 2346$ inspection items.

Schemes I and II both require 9 out of the total 17 deficiency items to be inspected, so there are $9 \times 138 = 1242$ items of inspection.

Table 4-8: Inspection efficiency of the current and new inspection schemes

Inspection scheme	Inspection items	Total detected deficiency items	Inspection efficiency
Current	2,346	519	22.12%
Scheme I	1,242	435	35.02%
Scheme II	1,242	435	35.02%

It can be seen from Table 4-8 that each of the two new inspection schemes can identify 83.82% of the real detected deficiency items by inspecting only 53% of all the possible deficiency items. It also shows that the inspection efficiency of the two new inspection schemes is the same and is about 1.5 times higher than that of the currently used inspection scheme. Therefore, we can conclude that the new schemes have higher efficiency and perform better than the currently used one, which means that if one of the new inspection schemes is adopted, more deficiency items can be detected after inspecting a certain number of inspection items.

4.5.2 Comparison of the two new inspection schemes

As both of the new inspection schemes contain 9 items for inspection, we also compare their performance. Data set Ψ_1 is used in the first comparison. The total number of identified deficiency items after inspecting each deficiency item of the two schemes is shown the Table 4-9.

Table 4-9: Identified deficiencies of the two new inspection schemes in the 1st comparison

Inspection Scheme	1st item	2nd item	3rd item	4th item	5th item	6th item	7th item	8th item	9th item
I	42	124	186	242	298	333	378	401	435
II	42	124	186	242	299	337	378	401	435

Table 4-9 indicates that the first 4 items of inspection are the same in both schemes, and after inspecting the 5th and 6th deficiency items, the performance of Inspection Scheme II is a little better than that of Inspection Scheme I, with 1 and 4 more deficiencies detected. The differences between the two schemes depend on the inspected item in the 5th inspection item: if the first 4 detected deficiency items contain D1 and D10, or D10 and D11, D14 will be inspected in Scheme II, while D9 will be inspected in Scheme I no matter what deficiencies are detected; Otherwise the inspection sequences are the same in the two schemes.

To further compare their performance, we do the second comparison by selecting the deficiency items in the inspection records with larger than or equal to 5 deficiency items detected from 1 September 2018 to 31 December 2018 at the Port of Hong Kong as testing data set Ψ_2. There are 52 records in total, with 380 deficiency items detected. Then, we use the two proposed inspection schemes to conduct PSC inspection and the total number of identified deficiency items after inspecting each inspection item is shown in Table 4-10.

Table 4-10: Identified deficiencies of the two new inspection schemes in the 2nd comparison

Inspection Scheme	1st item	2nd item	3rd item	4th item	5th item	6th item	7th item	8th item	9th item
I	39	89	132	163	**192**	**205**	246	258	278
II	39	89	132	163	**204**	**228**	246	258	278
Difference	0	0	0	0	**12**	**23**	0	0	0
Percentage*	0	0	0	0	**6.25%**	**11.22%**	0	0	0

Note*: calculated by $\frac{\text{Difference of identified deficiency number between scheme I and scheme II}}{\text{Deficiency number identified by scheme I}} \times 100\%$

The above table shows that when inspecting ships with deficiency items no less than 5, these two inspection schemes can identify 73.16% deficiencies after inspecting about 50% of all the possible deficiency items. Besides, it is indicated that Scheme II outperforms Scheme I, with 12 (6.25%) and 23 (11.22%) more deficiency items detected after finishing the 5th and 6th inspection items. Thus, we can conclude that although Inspection Scheme I is intuitive and easy to understand, Inspection Scheme II works better than Inspection Scheme I, especially when inspecting ships with no less than 5 deficiency items.

4.6 DISCUSSION

In this study, we used 297 PSC inspection records with no less than 1 deficiency item detected at the Port of Hong Kong as the training set to calibrate the inspection scheme models. Although some interesting insights are generated, such as the large itemsets and valid association rules, it is worth mentioning that if more inspection data can be incorporated, for example, inspection records of 12 to 24 months, we can find more comprehensive and accurate correlations among the deficiency items. Meanwhile, these two innovative inspection schemes may also cause some possible consequences. First, the ship operators may take some measures before the inspection to prevent their ships from being identified the related deficiencies and even detained if they are aware of the inspection schemes. Second, only some of the deficiency items are included in these two inspection schemes while other deficiency items are omitted. Regarding the first consequence, it is believed that the goal of PSC inspection is to guarantee the ships to comply with the various international conventions by conducting inspection as well as its deterrence. Thus, if the ship operators are willing to spare their efforts to keep the ships in satisfactory condition and conforming to the regulations, we can say that the goal of PSC inspection has been achieved. Regarding the second consequence, both the relevant documents on PSC and the PSCOs we interviewed suggest that in practice, after checking the documentation, the PSCOs will walk around the ship to observe its overall condition. If deficiencies are detected, they will pay more attention to the corresponding deficiency categories and conduct a more comprehensive inspection. If there are no clear findings, they may let the ship go without further inspection. Under this situation, both of the inspection schemes are designed to give some instructions and reference to the PSCOs when time and inspection resources are limited and the deficiencies are not that obvious instead of interfering with their own expert judgment.

4.7 CONCLUSION

PSC inspection is viewed as an effective way to contribute to the enhancement of maritime safety and security, and the prevention of marine pollution. Due to the limited time and human resources, not every deficiency item listed by the MoUs can be inspected. Thus, it is worthy of developing inspection schemes that can give instructions to the PSCOs in order to improve inspection efficiency. The goal of the inspection schemes is to identify as many deficiency items as possible after inspecting certain deficiency items. In this study, two inspection schemes based on the inspection value of each deficiency item are proposed. The inspection value of a deficiency item comprises its probability of occurrence, the cost of inspecting it and the loss of ignoring it. To be more specific, the probabilities in Inspection Scheme I are the occurrence probabilities of the deficiency items in the whole data set and are static, while the probabilities in Inspection Scheme II also depend on the interdependencies among the deficiency items and are dynamic. As the data and references are limited, we approximate the values of the cost and loss by setting the ratio of cost and loss equal to the PSC inspection rate at the Port of the Hong Kong from 2015 to 2017.

Both of the inspection schemes suggest that 9 deficiency items with positive values, i.e. D1, D7, D10, D11, D9, D3, D14, D5, and D4, should be inspected. The inspection sequence of Scheme I is fixed, while in Scheme II, 4 types of deficiency items occur on the right-hand side of the generated association rules: D7, D10, D11, and D14, which means that their probabilities (i.e., values) and inspection sequence are dynamic. Thus, the inspection sequence of Scheme II is dynamic and is related to the detected deficiencies. The detailed inspection sequences of the schemes are also provided.

To the best of our knowledge, this is the first research on developing inspection schemes containing detailed inspection sequence for PSC inspection. Numerical experiments show that both the newly proposed inspection schemes are about 1.5 times more efficient when used to identify the deficiency items compared with the currently used inspection scheme. Further, the performance of Inspection Scheme II is better than Inspection Scheme I, with 6.25% and 11.22% more deficiency items detected after finishing inspecting 5th and 6th deficiency items when inspecting ships with no less than 5 deficiency items. In the future research, the value of the inspection cost and ignoring loss of each deficiency item can be estimated more accurately to further improve the performance of the two schemes.

Chapter 5: Conclusions and Future Research

5.1 CONCLUSION

This thesis comprises two studies: one regarding developing an effective and efficient ship selection method for PSC authorities and the other regarding developing innovative and highly-efficient onboard inspection sequence in PSC inspection. The first study proposes a data-driven Bayesian network classifier called the Tree Augmented Naive Bayes (TAN) classifier by using historical inspection data downloaded from the database of Tokyo MoU, which include both ship information and inspection information, the structure part and quantitative part of the TAN classifier are constructed. The proposed model is validated by a numerical experiment based on the historic data from Hong Kong port, which shows that when the number of training cases is more than 200, the classification accuracy of the TAN model is beyond 60%. Compared with the currently used Ship Risk Profile (SRP) ship selection scheme, the TAN classifier can identify about 130.35% more deficiencies on average after inspecting the 50 ships in the testing data set. The results of the numerical experiment also show that after inspecting 10%, 20%, 30%, 40%, 50%, and 60% of the 50 total incoming ships in each testing data set, the average improvement of the TAN classifier is 348.38%, 147.23%, 108.32%, 98.29%, 70.33%, and 48.83% after inspecting 5, 10, 15, 20, 25, and 30 ships, respectively. The variable analysis shows that among all the attribute variables in the TAN classifier, the performance of the ship company and the number of deficiencies in the last PSC inspection are the dominant factors that influence the deficiency number. The results also show how the states of a specific attribute variable can have an impact on the class variable (i.e., the deficiency number). Theoretically, we propose a data equal-frequency discretization problem and present it in a mathematical and rigorous way. Then, by using dynamic programming we prove that this discretization method is bounded by $O(NV^2)$ when it is used in our model. Also, by induction, we prove that random selection of the root attribute variable of the TAN classifier will not influence the classification process of the cases in the testing data set.

In the second study, two inspection schemes based on the inspection value of each deficiency item are proposed. To be specific, Inspection Scheme I considers the occurrence probabilities of the deficiency items in the whole data set and the probabilities are static. Inspection Scheme II takes the dependencies of the deficiency items into account and is dynamic, which are presented by the association rules in terms of the deficiency items. Numerical experiments show that both the newly proposed inspection schemes are about 1.5 times more efficient when used to identify the deficiency items compared with the currently used inspection scheme. Further, the performance of Inspection Scheme II is better than Inspection Scheme I, with 6.25% and 11.22% more deficiency items detected after finishing inspecting 5th and 6th deficiency item when inspecting ships with no less than 5 deficiency items.

5.2 FUTURE RESEARCH

Several future research directions related to the above studies are introduced as follows.

For the first study, to develop more efficient ship selection schemes, one possible way is to combine different databases, including databases of different PSC MoUs and databases containing ship information, maritime accidents and incidents and databases of other inspections in order to get more comprehensive case data sets. Also, more historical data can be taken into account when developing ship selection schemes despite the access difficulties, as ship inspection history is a strong indicator for future inspection results. In addition, more advanced methods can be hired, especially those machine learning methods that are good at classification and prediction.

For the second study, the value of inspection cost and ignoring loss of each deficiency item can be estimated more accurately to further improve the performance of the two schemes. For example, databases of ship incidents and casualties can be taken into account together with data sets of PSC inspection records. Deficiencies on ship detention list can also be incorporated in calculating the inspection cost and ignoring loss of each deficiency items.

In recent years, marine environment protection and human factors of ship operations are receiving more attention than before. As a result, PSC authorities are focusing more on maritime pollution caused by substandard ships as well as onboard living and working conditions (Heij et al., 2011). However, there are few papers that are related to the effect of PSC inspections on protecting the marine environment and improving onboard conditions. Thus, future research should further evaluate the effects of PSC inspections on these two areas.

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Appendices

Appendix A

Investigations on PSC inspection at the HK port and the Mainland China

To have a deeper discussion about the research results with professional staff and have a better understanding of the real needs of the Port State Control Section of the Marine Department (MD) of Hong Kong, we visited the MD on 16 July 2019 and discussed with the PSCO at the Hong Kong Port. In addition, we also discussed with a researcher at the Ministry of Transport (MOT) of the People's Republic of China. We summarize the key points as follows.

a. Actual ship selection process in PSC inspection under SRP

At the Port of Hong Kong, an Excel sheet with all the visiting ships of that day and their SRP will be generated every morning. About 10% or more ships will be selected for inspection by about 3 PSCOs, and each PSCO can inspect up to 3 ships for one day.

Normally, ships that do not enter the inspection time window will not be inspected, and ships within or out of the inspection time window can be inspected. Ships without PSC inspections before will be first inspected. For the ships with previous PSC inspections, high risk ships will always be inspected first, no matter whether they are within or out of their time window. For high risk ships, ships out of time window will be first inspected, followed by those within the time window. An illustration of the ship selection process is shown in Figure A-1.

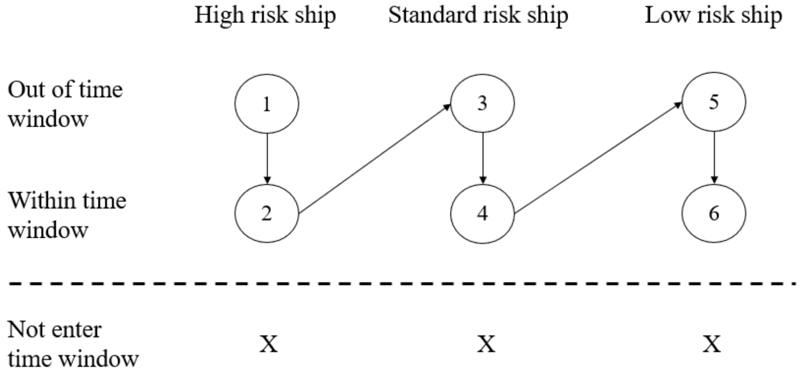


Figure A-1: Actual ship inspection sequence at the Hong Kong Port

Note 1: not all the ships selected for inspection can be finally inspected. For example, when the weather condition is quite bad, when the resource of PSCOs is quite limited, and when the ships call the port at night or weekends.

Note 2: the process of ship selection can be changed when encountering extreme situations. For example, when a very old standard risk ship (e.g. more than 40), or a ship with many times of previous detention, or a ship with the flag state of very bad performance (e.g. Mongolia) comes to the port state, this ship may be preferentially inspected than the high risk ships.

b. Actual onboard inspection sequence in PSC inspection

At the Hong Kong Port, the PSC inspection is conducted by only 1 PSCO. Among all the 17 deficiency items required by Tokyo MoU, onboard inspection will start from D1 - Certificates and documentation generally. Only the important sub-categories of deficiency items will be inspected, and the PSCO will also ask the captain and crew some questions to see whether they are familiar with onboard conditions. If the overall condition is satisfactory, the PSCO can decide to terminate the inspection and record the identified deficiencies. The PSCO can also proceed to inspect other conditions of the ship. The PSCO will first walk around the ship to observe its overall condition. If deficiencies under some certain deficiency items are detected, other sub-category deficiencies under that deficiency item will be further inspected. Normally, a PSC inspection lasts for about 1.5 hours, and about 50 sub-category deficiencies will be inspected among all the 200 sub-category deficiencies in 17 deficiency items.

Note 1: the onboard inspection sequence is not fixed, and thus the habit, preference, and judgment of the PSCOs can have a big influence. For example, if a PSCO was a captain who is good at inspecting the ships' bridges, he would prefer inspecting these areas; if a PSCO worked in the engine room, he would concentrate on inspecting the ships' engine rooms.

Note 2: even for the same PSCO, the onboard inspection sequence is not fixed and is dependent on the actual ship's conditions. For example, if few deficiencies are detected after walking around the ship, the subsequent inspection will not be very strict. Otherwise, if many deficiencies are identified, the subsequent inspection will be strict and the PSCO will pay more attention to the deficiency categories with deficiencies detected.

Note 3: the actual ship inspection sequence is influenced by the real condition of the ships, such as the compliance degree of the crews onboard, loading and unloading of cargos, and the routine of the crews.

c. Inspection results of PSC inspection

The results of a PSC inspection contain two parts: ship deficiencies and ship detention. For the deficiencies that are already detected, there will be "action taken" specified. The commonly used codes for "action taken" are shown below (** represents the detected deficiencies):

**17: deficiency to be rectified before departure

**10: the ship has already rectified the deficiency

**30: detainable deficiency

Note 1: If a ship comes to the port state with outstanding deficiencies but the deficiencies are not rectified, the ship can be detained (but not a must).

Note 2: the decision to detain a ship is highly determined by the PSCO himself. The documentation of IMO and the Tokyo MoU can only give some general guidelines.

d. Current situation of PSC inspection in Mainland China

The researcher of MOT thinks the research on ship selection using the TAN classifier is useful to the Chinese Mainland. Each year, about ten million ships call the ports of Chinses Mainland, and it is required that 0.2% of the ships be inspected. If the ship selection method is effective, only the ships in bad conditions need to be inspected and the inspection working load can be alleviated.

In the PSC inspection conducted at the port state in Mainland China, more than 1 (usually 2) PSCO will get on board for the inspection. The reasons are twofold: different PSCOs have different backgrounds, and more people can improve the efficiency of inspecting documentation and certificates. During the inspection process, the crew members should do the hands-on operations following the instructions of the PSCOs. The PSC inspection results in Mainland China are not reported to Tokyo MoU real-timely: they are first reported to the local Marine Department, then reported to China Maritime Safety Administration (MSA), and finally reported to Tokyo MoU.

One problem faced by PSC inspections in the ports of Mainland China is that sulphur content of ship fuel will not be inspected in PSC inspection. As a result, a group of PSCOs will get onboard to conduct PSC inspection, and then another group of officers will get onboard to inspect ship fuel. It would be better to combine different inspections instead of having multiple inspections.

e. Example of inspection records at the Hong Kong Port

Figure A-2 shows an example of the inspection record list at the Hong Kong Port from 17 December 2019 to 31 December 2019 which is captured from the database provided by Tokyo MoU (http://www.tokyo-mou.org/inspections_detentions/psc_database.php). The inspection list gives general inspection data and ship data, such as the inspection date, place, and type (initial, follow-up, or remote follow-up) in the first three columns, ship risk profile in the last column, PSC inspection result, i.e. the number of deficiencies and ship detention in the last two and three columns, and ship information including ship IMO number, ship name, callsign, MMSI, and ship flag in the middle columns.

MEMORANDUM OF UNDERSTANDING ON PORT STATE CONTROL IN THE ASIA-PACIFIC REGION

INSPECTIONS SEARCH RESULTS

Found 49 elements in 1 page(s). Pages from 1 to 25

Legend: □ - initial inspection ■ - follow-up inspection ◪ - Remote follow-up inspection

Type	Date	Place	IMO number	Ship Name	Callsign	MMSI	Flag	Deficiencies (□: recorded/ ■: for checking)	Detention	Ship Risk Profile at the time of inspection
□	31.12.2019	Hong Kong (Hong Kong, China)	9044138	GRAND MIDAS	9LU2309	667001506	Sierra Leone	8	no	High Risk Ship
□	31.12.2019	Hong Kong (Hong Kong, China)	9284506	CHRIS GR	9HA2939	256829000	Malta	0	no	High Risk Ship
■	30.12.2019	Hong Kong (Hong Kong, China)	9604108	EVER LEARNED	2GNG3	235098885	United Kingdom	2	no	
□	30.12.2019	Hong Kong (Hong Kong, China)	9604108	EVER LEARNED	2GNG3	235098885	United Kingdom	0	no	Standard Risk Ship
□	24.12.2019	Hong Kong (Hong Kong, China)	9790050	EVER BOARD	BKLQ	416038000	Taiwan, Province of China	1	no	Standard Risk Ship
□	20.12.2019	Hong Kong (Hong Kong, China)	9516739	HANSA ALTENBURG	A8YI9	636018769	Liberia	1	no	Standard Risk Ship
□	19.12.2019	Hong Kong (Hong Kong, China)	9158848	WAN HAI 163	S6EN6	565096000	Singapore	1	no	Low Risk Ship
□	18.12.2019	Hong Kong (Hong Kong, China)	9303742	TIM-S	D5TK9	636019205	Liberia	0	no	High Risk Ship
□	18.12.2019	Hong Kong (Hong Kong, China)	9321134	KS IRIS	3EZF2	351991000	Panama	4	no	High Risk Ship
□	17.12.2019	Hong Kong (Hong Kong, China)	9292204	ADYGEYA	A8GT9	636012647	Liberia	0	no	Standard Risk Ship
□	17.12.2019	Hong Kong (Hong Kong, China)	9111450	PL YUI LAAM	V3CJ	312828000	Belize	13	yes	High Risk Ship

Figure A-2: Example of inspection record list at Hong Kong port (http://www.tokyo-mou.org/inspections_detentions/psc_database.php)

More detailed inspection information can be found by clicking on a record, including inspection data, ship data, ship company details, certificates, and detailed ship deficiencies. An example is shown in Figure A-3.

MEMORANDUM OF UNDERSTANDING ON PORT STATE CONTROL IN THE ASIA-PACIFIC REGION

Inspection data

Date	Authority	Port	Type	Detention
31.12.2019	Hong Kong, China	Hong Kong	initial	no

Ship data

Ship Name	IMO number	MMSI	Callsign	Classification Society	Flag	Type	Date keel laid	Deadweight	Tonnage
GRAND MIDAS	9044138	667001506	9LU2309	Overseas Marine Certification Services	Sierra Leone	Container ship	1992-04-23		3986

Company details

Name	IMO number	Residence	Registered	Phone	Fax	Email
VAST OCEAN GLOBAL LTD	6033544	Seychelles	Seychelles			

Certificates

Code	Nature	Issuing Authority/RO	Date of issue	Date of expire	Surveying Authority/RO	Date of survey	Surveyed Port
501	Cargo Ship Safety Construction	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
502	Cargo Ship Safety Equipment	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
503	Cargo Ship Safety Radio	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
505	International Oil Pollution Prevention (IOPP)	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
506	International Air Pollution Prevention	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
507	International Sewage Pollution Prevention	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
508	Load Line	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
509	Document of Compliance	New United International Marine Services Ltd. (250)	20.05.2019	19.05.2020			
510	Safety Management Certificate	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
512	Minimum Safe Manning Document	Sierra Leone (SL)	18.10.2019				
528	International Ballast Water Management	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
529	International Anti-Fouling System	Overseas Marine Certification Services (216)	27.10.2019				
532	International Energy Efficiency (IEE)	Overseas Marine Certification Services (216)	27.10.2019				
533	Maritime Labour Certificate	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			

Ship deficiencies

#	Code	Nature	Ground for detention
1	10109	SAFETY OF NAVIGATION (Lights, shapes, sound-signals)	No
2	07110	FIRE SAFETY (Fire fighting equipment and appliances)	No
3	03105	WATER/WEATHERTIGHT CONDITIONS (Covers (hatchway-, portable-, tarpaulins, etc.))	No
4	10136	SAFETY OF NAVIGATION (Estabilishment of working language onboard)	No
5	10127	SAFETY OF NAVIGATION (Voyage or passage plan)	No
6	05118	RADIO COMMUNICATIONS (Operation of GMDSS equipment)	No
7	09204	LIVING AND WORKING CONDITIONS - WORKING CONDITIONS (Safe means of access)	No
8	01315	CERTIFICATE AND DOCUMENTATION - DOCUMENTS (Oil record book)	No

Figure A-3: Example of detailed information of an inspection record (http://www.tokyo-mou.org/inspections_detentions/psc_database.php)

Appendix B

Proof of Theorem 1 in Chapter 3

The problem can be solved by dynamic programming. The dynamic programming approach has N stages. The state ω of a stage $s = 2,...,N$ means that the categories $\omega+1,...,V$ belong to stages $s,...,N$ and that the categories $1,...,\omega$ belong to stages $1,...,s-1$ and stage $s=1$ has only one state $\omega = 0$. The set of possible states of a stage s is denoted by $\Omega_s = \{s-1,...,V-(N-s+1)\}$. At state ω of stage s, the immediate decision is the number of categories that are incorporated in state s. That is, if the immediate decision is d, then categories $\omega+1,...,\omega+d$ belong to stage s and the resulting state of stage s is $\omega+d$. The set of possible immediate decisions is $D(s,\omega) = \{1,...,V-\omega-(N-s)\}$. Let $u(s,\omega)$ be the minimum sum of squared errors over stages $s,...,N$ when the system is at state ω of stage s. The recursive relation is:

$$u(s,\omega) = \min_{d \in D(s,\omega)} \left(\frac{\sum_{v=\omega+1}^{\omega+d} \theta_v}{K} - \frac{1}{N} \right)^2 + u(s+1,\omega+d), s = 1,...,N-1, \omega \in \Omega_s \qquad \text{(B1)}$$

and the boundary conditions are

$$u(N,\omega) = \left(\frac{\sum_{v=\omega+1}^{V} \theta_v}{K} - \frac{1}{N} \right)^2, \omega \in \Omega_N . \qquad \text{(B2)}$$

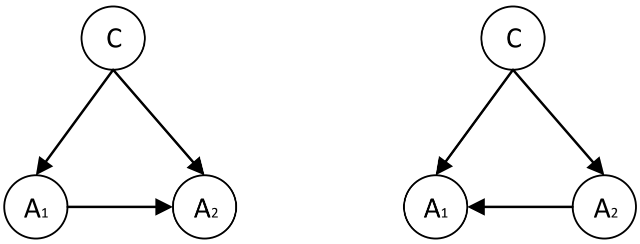
The optimal solution can be obtained by solving $u(1,0)$. Since the dynamic programming approach has N stages, each stage has at most V states, at each state of each stage, there are at most V decisions, and the time required to evaluate a decision is bounded by $O(1)$, the problem can be solved in time bounded by $O(NV^2)$.□

Appendix C

Proof of Theorem 2 in Chapter 3

To prove the theorem, we will prove that, for a TAN classifier with I attribute variables, $I \geq 2$, different choices of root attribute variable node all have the same value $\tilde{P}^I(a_{1,s^{(1)}},...,a_{I,s^{(I)}},c_{\bar{s}})$ in Eq. (3.8) for a particular combination of $\bar{s}=1,...,N_C$, $j=1,...,I, s^{(j)}=1,...,N_j$. We will prove this conclusion by induction. That is, we first prove that this conclusion is true for a TAN classifier with two attribute variables; we then prove that if this conclusion is true for a TAN classifier with I attribute variables, $I \geq 2$, it will also be true for a TAN classifier with $I+1$ attribute variables.

First, consider a TAN classifier with two attribute variables $A=(A_1,A_2)$ and one class variable C. Two structures of the TAN classifier are shown in Figure C-1.



(a) A_1 is the parent variable of A_2 (b) A_2 is the parent variable of A_1

Figure C-1: TAN classifier with two attribute variables

For any case k with states of the attribute variables $ATT_k=(a_{1,s'},a_{2,s''})$, $s'=1,...,N_1$, $s''=1,...,N_2$, we can use either the TAN classifier in Figure C-1(a) (referred to hereafter as the left classifier, or "L" for short) or the TAN classifier in Figure C-1(b) (the right classifier, or "R" for short) to calculate the values in Eq. (3.8). If we use the left TAN classifier, we have

$$\begin{aligned}
&\tilde{P}^L(a_{1,s'},a_{2,s''},c_{\bar{s}}) \\
&= P^L(c_{\bar{s}})\times P^L(a_{1,s'}\mid c_{\bar{s}})\times P^L(a_{2,s''}\mid a_{1,s'},c_{\bar{s}}) \\
&= P^L(c_{\bar{s}})\times P^L(a_{1,s'}\mid c_{\bar{s}})\times \frac{P^L(a_{2,s''},a_{1,s'}\mid c_{\bar{s}})}{P^L(a_{1,s'}\mid c_{\bar{s}})}, \bar{s}=1,...,N_C
\end{aligned} \tag{C1}$$

If we use the right TAN classifier, we have

$$\begin{aligned}
&\tilde{P}^R(a_{1,s'}, a_{2,s''}, c_{\bar{s}}) \\
&= P^R(c_{\bar{s}}) \times P^R(a_{2,s''} \mid c_{\bar{s}}) \times P^R(a_{1,s'} \mid a_{2,s''}, c_{\bar{s}}) \\
&= P^R(c_{\bar{s}}) \times P^R(a_{2,s''} \mid c_{\bar{s}}) \times \frac{P^R(a_{2,s''}, a_{1,s'} \mid c_{\bar{s}})}{P^R(a_{2,s''} \mid c_{\bar{s}})}, \bar{s} = 1, \dots, N_C.
\end{aligned} \tag{C2}$$

Note that in Eqs. (C1) and (C2), both $P^L(c_{\bar{s}})$ and $P^R(c_{\bar{s}})$ refer to the proportion of cases in the data set whose class state is $c_{\bar{s}}$, and both $P^L(a_{2,s''}, a_{1,s'} \mid c_{\bar{s}})$ and $P^R(a_{2,s''}, a_{1,s'} \mid c_{\bar{s}})$ refer to the proportion of cases with $a_{1,s'}$ as the state of attribute variable A_1 and $a_{2,s''}$ as the state of attribute variable A_2 among cases in the data set with class state $c_{\bar{s}}$. Therefore,

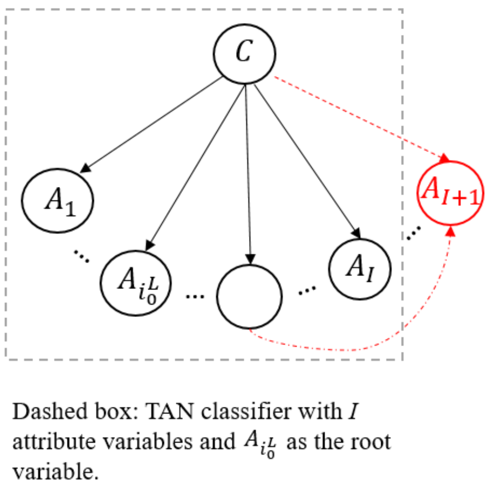
$$\tilde{P}^L(c_{\bar{s}} \mid a_{1,s'}, a_{2,s''}) = \tilde{P}^R(c_{\bar{s}} \mid a_{1,s'}, a_{2,s''}), \quad \bar{s} = 1, \dots, N_C. \tag{C3}$$

For a TAN classifier with I attribute variables, we have (the superscript "I" means the TAN classifier has I attribute variables)

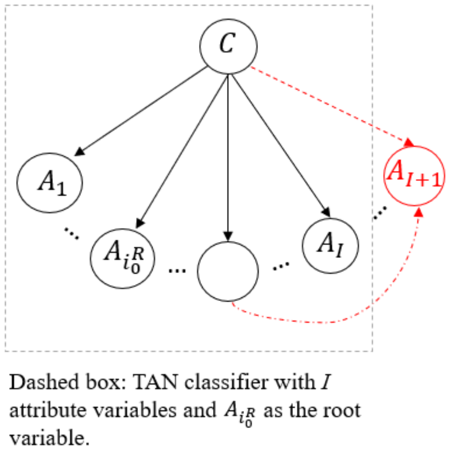
$$\begin{aligned}
&\tilde{P}^I(a_{1,s^{(1)}}, \dots, a_{I,s^{(I)}}, c_{\bar{s}}) \\
&= P^I(c_{\bar{s}}) \times P^I(a_{i_0,s^{(i_0)}} \mid c_{\bar{s}}) \times \prod_{i=1, i \neq i_0}^{I} \frac{P^I(a_{i,s^{(i)}}, a_{\pi(i),s^{(\pi(i))}} \mid c_{\bar{s}})}{P^I(a_{\pi(i),s^{(\pi(i))}} \mid c_{\bar{s}})}, \bar{s} = 1, \dots, N_C, j = 1, \dots, I, s^{(j)} = 1, \dots, N_j
\end{aligned} \tag{C4}$$

Suppose that for a TAN classifier with I attribute variables, $I \geq 2$, different choices of root attribute variable node all have the same value of $\tilde{P}^I(a_{1,s^{(1)}}, \dots, a_{I,s^{(I)}}, c_{\bar{s}})$ in Eq. (C4). Next, we prove that for a TAN classifier with $I+1$ attribute variables and with a given maximum spanning tree, different choices of root attribute variable node all have the same value of $\tilde{P}^{I+1}(a_{1,s^{(1)}}, \dots, a_{I,s^{(I)}}, a_{I+1,s^{(I+1)}}, c_{\bar{s}})$.

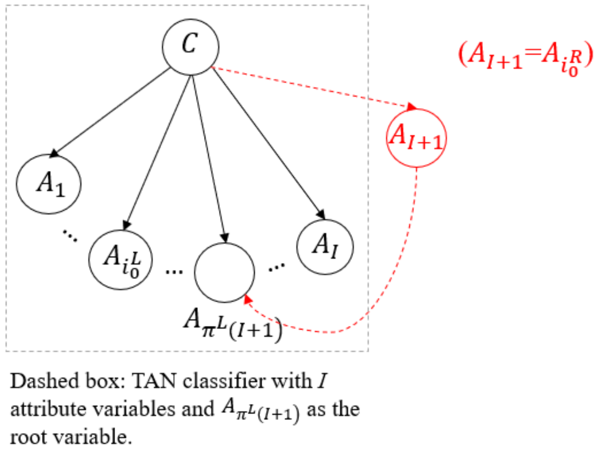
Consider two TAN classifiers with the same maximum spanning tree of $I+1$ attribute variables, and one classifier (left classifier, or "L") has root attribute variable $A_{i_0^L}$ and the other (right classifier, or "R") has root attribute variable $A_{i_0^R}$, $i_0^R \neq i_0^L$, as shown in Figure C-2. $A_{\pi^L(i)}$ is the unique parent attribute variable of attribute variable A_i, $i = 1, \dots, I, i \neq i_0^L$, in the left classifier and $A_{\pi^R(i)}$ is the unique parent attribute variable of attribute variable A_i in the right classifier.



(a) The left classifier with *I+1* as the root variable



(b) The right classifier with *I+1* as the root variable (case i)



(c) The right classifier with *I+1* as the root variable (case ii)

Figure C-2: The structures of left classifier and right classifier

In a maximum spanning tree with at least two nodes, there exist at least two nodes, each of which is connected to exactly one other node in the tree. Therefore, in the left classifier, we can find a node that is not the root attribute variable and that is connected to exactly one other node in the tree. Without loss of generality, we assume that this node is the attribute variable A_{I+1} (otherwise we just swap its sequence with the sequence of A_{I+1} in vector A).

Then, in the left classifier,

$$
\begin{aligned}
&\tilde{P}^{I+1,L}(a_{1,s^{(1)}},\ldots,a_{I,s^{(I)}},a_{I+1,s^{(I+1)}},c_{\bar{s}}) \\
&= P^{I+1,L}(c_{\bar{s}})\times P^{I+1}(a_{i_0^L,s^{(i_0^L)}}\,|\,c_{\bar{s}})\times \prod_{i=1,i\neq i_0^L}^{I} P^{I+1,L}(a_{i,s^{(i)}}\,|\,a_{\pi^L(i),s^{(\pi^L(i))}},c_{\bar{s}})\times P^{I+1,L}(a_{I+1,s^{(I+1)}}\,|\,a_{\pi^L(I+1),s^{(\pi^L(I+1))}},c_{\bar{s}}) \\
&= \underbrace{P^{I+1,L}(c_{\bar{s}})\times P^{I+1,L}(a_{i_0^L,s^{(i_0^L)}}\,|\,c_{\bar{s}})\times \prod_{i=1,i\neq i_0}^{I} \frac{P^{I+1,L}(a_{i,s^{(i)}},a_{\pi^L(i),s^{(\pi^L(i))}}\,|\,c_{\bar{s}})}{P^{I+1,L}(a_{\pi^L(i),s^{(\pi^L(i))}}\,|\,c_{\bar{s}})}}_{AA}\times\frac{P^{I+1,L}(a_{I+1,s^{(I+1)}},a_{\pi^L(I+1),s^{(\pi^L(I+1))}}\,|\,c_{\bar{s}})}{P^{I+1,L}(a_{\pi^L(I+1),s^{(\pi^L(I+1))}}\,|\,c_{\bar{s}})}, \\
&\bar{s}=1,\ldots,N_C
\end{aligned}
\tag{C5}
$$

It should be noted that AA in Eq. (C5) is actually the value $\tilde{P}(a_{1,s^{(1)}},\ldots,a_{I,s^{(I)}},c_{\bar{s}})$ for the TAN classifier with I attribute variables and root attribute variable $A_{i_0^L}$ in Figure C-2(a).

There are two cases of the right classifier. In Case (i), as shown in Figure C-2(b), the root node $A_{i_0^R}$ is not A_{I+1}. Then, similar to Eq. (C5), we have

$$
\begin{aligned}
&\tilde{P}^{I+1,R}(c_{\bar{s}}\,|\,a_{1,s^{(1)}},\ldots,a_{I,s^{(I)}},a_{I,s^{(I+1)}}) \\
&= \underbrace{P^{I+1,R}(c_{\bar{s}})\times P^{I+1,R}(a_{i_0^R,s^{(i_0^R)}}\,|\,c_{\bar{s}})\times \prod_{i=1,i\neq i_0}^{I} \frac{P^{I+1,R}(a_{i,s^{(i)}},a_{\pi^R(i),s^{(\pi^R(i))}}\,|\,c_{\bar{s}})}{P^{I+1,R}(a_{\pi^R(i),s^{(\pi^R(i))}}\,|\,c_{\bar{s}})}}_{BB}\times\frac{P^{I+1,R}(a_{I+1,s^{(I+1)}},a_{\pi^R(I+1),s^{(\pi^R(I+1))}}\,|\,c_{\bar{s}})}{P^{I+1,R}(a_{\pi^R(I+1),s^{(\pi^R(I+1))}}\,|\,c_{\bar{s}})}, \\
&\bar{s}=1,\ldots,N_C
\end{aligned}
\tag{C6}
$$

Note that BB in Eq. (C6) is actually the value $\tilde{P}(a_{1,s^{(1)}},\ldots,a_{I,s^{(I)}},c_{\bar{s}})$ for the TAN classifier with I attribute variables and root attribute variable $A_{i_0^R}$ in Figure C-2(b). Based on the precondition of the induction, we have $AA=BB$. Since A_{I+1} is connected to exactly one other node in the tree, we have $\pi^L(I+1)=\pi^R(I+1)$ and therefore

$$
\frac{P^{I+1,L}(a_{I+1,s^{(I+1)}},a_{\pi^L(I+1),s^{(\pi^L(I+1))}}\,|\,c_{\bar{s}})}{P^{I+1,L}(a_{\pi^L(I+1),s^{(\pi^L(I+1))}}\,|\,c_{\bar{s}})}=\frac{P^{I+1,R}(a_{I+1,s^{(I+1)}},a_{\pi^R(I+1),s^{(\pi^R(I+1))}}\,|\,c_{\bar{s}})}{P^{I+1,R}(a_{\pi^R(I+1),s^{(\pi^R(I+1))}}\,|\,c_{\bar{s}})}.
\tag{C7}
$$

Hence, for Case (i),

$$
\tilde{P}^{I+1,L}(c_{\bar{s}}\,|\,a_{1,s^{(1)}},\ldots,a_{I,s^{(I)}},a_{I,s^{(I+1)}})=\tilde{P}^{I+1,R}(c_{\bar{s}}\,|\,a_{1,s^{(1)}},\ldots,a_{I,s^{(I)}},a_{I,s^{(I+1)}}).
\tag{C8}
$$

In Case (ii), as shown in Figure C-2(c), the root node $A_{i_0^R}$ is A_{I+1}. Then since A_{I+1} is connected to exactly one other node in the tree, we have $\pi^R(\pi^L(I+1))=I+1$, that is, the parent attribute variable of $A_{\pi^L(I+1)}$ as the parent of A_{I+1}. Moreover, $\pi^R(i)\neq I+1, i=1,\ldots,I, i\neq\pi^L(I+1)$, that is, no attribute variable other than $A_{\pi^L(I+1)}$ has parent A_{I+1}. Therefore, in the right classifier,

$$
\begin{aligned}
&\tilde{P}^{I+1,R}(a_{1,s^{(1)}},\dots,a_{I,s^{(I)}},a_{I+1,s^{(I+1)}},c_{\bar{s}})\\
&= P^{I+1,R}(c_{\bar{s}})\times P^{I+1,R}(a_{I+1,s^{(I+1)}}\mid c_{\bar{s}})\times\prod_{i=1,I\neq\pi^{L}(I+1)}^{I} P^{I+1,R}(a_{i,s^{(i)}}\mid a_{\pi^{R}(i),s^{(\pi^{R}(i))}},c_{\bar{s}})\times P^{I+1,R}(a_{\pi^{L}(I+1),s^{(\pi^{L}(I+1))}}\mid a_{I+1,s^{(I+1)}},c_{\bar{s}})\\
&= P^{I+1,R}(c_{\bar{s}})\times P^{I+1,R}(a_{I+1,s^{(I+1)}}\mid c_{\bar{s}})\times\prod_{i=1,I\neq\pi^{L}(I+1)}^{I}\frac{P^{I+1,R}(a_{i,s^{(i)}},a_{\pi^{R}(i),s^{(\pi^{R}(i))}}\mid c_{\bar{s}})}{P^{I+1,R}(a_{\pi^{R}(i),s^{(\pi^{R}(i))}}\mid c_{\bar{s}})}\times\frac{P^{I+1,R}(a_{\pi^{L}(I+1),s^{(\pi^{L}(I+1))}},a_{I+1,s^{(I+1)}}\mid c_{\bar{s}})}{P^{I+1,R}(a_{I+1,s^{(I+1)}}\mid c_{\bar{s}})}\\
&= P^{I+1,R}(c_{\bar{s}})\times\prod_{i=1,I\neq\pi^{L}(I+1)}^{I}\frac{P^{I+1,R}(a_{i,s^{(i)}},a_{\pi^{R}(i),s^{(\pi^{R}(i))}}\mid c_{\bar{s}})}{P^{I+1,R}(a_{\pi^{R}(i),s^{(\pi^{R}(i))}}\mid c_{\bar{s}})}\times P^{I+1,R}(a_{\pi^{L}(I+1),s^{(\pi^{L}(I+1))}},a_{I+1,s^{(I+1)}}\mid c_{\bar{s}})\\
&= \underbrace{P^{I+1,R}(c_{\bar{s}})\times P^{I+1,R}(a_{\pi^{L}(I+1),s^{(\pi^{L}(I+1))}}\mid c_{\bar{s}})\times\prod_{i=1,I\neq\pi^{L}(I+1)}^{I}\frac{P^{I+1,R}(a_{i,s^{(i)}},a_{\pi^{R}(i),s^{(\pi^{R}(i))}}\mid c_{\bar{s}})}{P^{I+1,R}(a_{\pi^{R}(i),s^{(\pi^{R}(i))}}\mid c_{\bar{s}})}}_{CC}\times\frac{P^{I+1,R}(a_{\pi^{L}(I+1),s^{(\pi^{L}(I+1))}},a_{I+1,s^{(I+1)}}\mid c_{\bar{s}})}{P^{I+1,R}(a_{\pi^{L}(I+1),s^{(\pi^{L}(I+1))}}\mid c_{\bar{s}})}\\
&\bar{s}=1,\dots,N_C
\end{aligned}
\tag{C9}
$$

Then, CC in Eq. (C9) is actually the value $\tilde{P}(a_{1,s^{(1)}},\dots,a_{I,s^{(I)}},c_{\bar{s}})$ for the TAN classifier with I attribute variables and $A_{\pi^{L}(I+1)}$ as the root attribute variable, as shown in Figure C-2(c). Based on the precondition of the induction, we have $AA = CC$. Therefore, for Case (ii),

$$\tilde{P}^{I+1,L}(c_{\bar{s}}\mid a_{1,s^{(1)}},\dots,a_{I,s^{(I)}},a_{I,s^{(I+1)}}) = \tilde{P}^{I+1,R}(c_{\bar{s}}\mid a_{1,s^{(1)}},\dots,a_{I,s^{(I)}},a_{I,s^{(I+1)}})\,. \tag{C10}$$

This concludes the proof of the theorem. □

Appendix D

Method used to calculate the CPTs in Chapter 3

The CPT of a variable in the BN contains the probabilities of each state of the variable under the condition of the states of its parent variables. For the class variable (i.e., the node "deficiency_no"), the CPT is reduced to the prior probability distribution of its states as it has no parent variable, as is shown in Table D-1.

Table D-1: CPT of deficiency_no

deficiency_no	prior probability
S1:0to2	35.6%
S2:3to6	32.0%
S3:7+	32.4%

For an attribute variable, the CPT is dependent on the states of its parent variables, which include the class variable and/or another attribute variable. For the root attribute variable "age", whose parent only contains the class variable, the conditions in its CPT only contain three states of the variable "deficiency_no", and the probabilities of different states of "age" under the condition of a specific state of "deficiency_no" are the probabilities of the cases belonging to that state of "deficiency_no" and the state of "age" in the training data set. The sum of each column of the CPT is equal to 100%. The CPT of the root attribute variable "age" is shown in Table D-2.

Table D-2: CPT of age

age	deficiency_no = S1:0to3	deficiency_no = S2:3to6	deficiency_no = S3:7+
S1:0to7	44.56%	36.15%	13.10%
S2:8to12	36.96%	34.94%	26.19%
S3:13+	18.48%	28.91%	60.71%

For the non-root attribute variables, whose parent variables contain the class variable and another attribute variable, the conditions in CPT are the combination of one state of the class variable and one state of the parent attribute variable. An example of the CPT of node "RO" is shown in Table D-3.

Table D-3: CPT of RO

RO(%)	flag											
	S1: white	S2: grey	S3: black	S4: not _listed	S1: white	S2: grey	S3: white	S4: not _listed	S1: white	S2: grey	S3: black	S4: not_ listed
	deficiency_no											
	S1: 0to2	S1: 0to2	S1: 0to2	S1: 0to2	S2: 3to6	S2: 3to6	S2: 3to6	S2: 3to6	S3: 7+	S3: 7+	S3: 7+	S3: 7+
S1:high	93.5	40.0	25.0	25.0	93.9	25.0	25.0	50.0	93.3	66.7	58.9	12.5
S2: medium	1.1	20.0	25.0	25.0	1.2	25.0	25.0	16.7	1.7	16.7	11.7	37.5
S3:low	1.1	20.0	25.0	25.0	1.2	25.0	25.0	16.7	1.7	8.3	11.7	12.5
S4:not_ listed	4.3	20.0	25.0	25.0	3.7	25.0	25.0	16.7	3.3	8.3	17.7	37.5

Appendix E

Procedure 2: Selection of n ships by the SRP selection scheme

Procedure 2. Selection of n ships by the SRP selection scheme.

Step 1: Divide the ships in Ψ' into four categories in sequence: ships without any PSC inspections before, ships whose inspection time windows are closed, ships within the inspection time window, and ships out of (not entering) the time window. Ships in the first category are considered to have equal priority. The priority of ships in the first category is higher than ships in the second, followed by ships in the third and fourth categories. Different ships in the second category have different priorities, so do ships in the third and fourth categories. The priorities of ships in the second, third, and fourth categories are determined in Step 2.

Step 2: Calculate the risk index RI of each ship in Ψ'. Denote the last inspection time for ship i, $i = 1, ..., 50$, as L_i. The risk index RI is used to indicate the relative risk ranking of the ships in their corresponding categories. The method to calculate the ship risk index RI is in Table E-1.

Step 3: Sort the ships in Ψ' to generate the sequence of the inspection list. The sequence of ships is: ships in the first category are randomly sequenced, followed by ships in the second category in descending order of RI, followed by ships in the third category in descending order of RI, and followed by ships in the fourth category in descending order of RI. The first n ships in the inspection list are selected

Table E-1: Calculation of ship risk index

Ship risk profile	Time window (months)	State of time window		
		out of time window	within time window	time window closed
LRS	9 to 18	$RI = \frac{L_i}{9}$	$RI = \frac{L_i - 9}{18 - 9}$	$RI = \frac{L_i}{18}$
SRS	5 to 8	$RI = \frac{L_i}{5}$	$RI = \frac{L_i - 5}{8 - 5}$	$RI = \frac{L_i}{8}$
HRS	2 to 4	$RI = \frac{L_i}{2}$	$RI = \frac{L_i - 2}{4 - 2}$	$RI = \frac{L_i}{4}$

Appendix F

Procedure 3: Selection of n ships by the TAN classifier

Procedure 3: Selection of n ships by the TAN classifier.

Step 1: Train the TAN classifier using data set Ψ. The class variable "deficiency_no" has three states: S1:0to2, S2:3to6 and S3:7+. Calculate the average number of deficiencies of each state of deficiency_no in the 250 cases in Ψ. The results are: ships with 0 to 2 deficiencies on average have 1.00 deficiency, ships with 3 to 6 deficiencies on average have 3.85 deficiencies, and ships with 7+ deficiencies on average have 10.07 deficiencies.

Step 2: Input the states of each ship in Ψ' into the TAN classifier and the probability distribution of deficiency number is shown in the states of deficiency_no. Denote the probability for a ship to have 0 to 2, 3 to 6, or 7+ deficiencies by D_{0to2}, D_{3to6} and D_{7+} respectively.

Step 3: Use the average number of deficiencies of each state of deficiency_no in the 250 cases in Ψ to denote the expected number of deficiencies of that state, and calculate the expected number of deficiencies for every ship in Ψ' by $E(deficiency\_no) = 1.00 \times D_{0to2} + 3.85 \times D_{3to6} + 10.07 \times D_{7+}$.

Step 4: Sort the 50 ships in Ψ' in descending $E(deficiency\_no)$ to generate the sequence of inspection list. The first n ships in the inspection list are selected.