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Using Bayesian network-based TOPSIS to aid dynamic Port State Control detention risk control decision

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Abstract

Port State Control (PSC) inspections have been implemented as an administrative measure to detect and detain substandard ships and thus to ensure maritime safety. Advanced risk models were developed to investigate the impact of factors influencing ship detention. Although showing much attractiveness, current studies still reveal a key challenge on how such analysis can improve the ship performance in PSC inspections and aid PSC detention risk control decision. By incorporating a data-driven Bayesian network (BN) into the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method, this paper proposes a new ship detention risk control methodology, in which the decision criteria are generated from the root risk variables, and the alternatives refer to the established strategies adopted by ship-owners in their practical ship detention risk control. Along with the new methodology, the main technical novelty of this paper lies in the quantitative measurement of the effectiveness of each strategy in terms of the reduction of detention rate in a dynamic manner. Its practical contributions are seen, from both ship owner and port authority perspectives, through the provisions of useful insights on dynamic evaluation of rational control strategies to reduce ship detention risk under various PSC inspection scenarios.

Keywords: *Port state control, Bayesian network, TOPSIS, detention risk, maritime safety, maritime risk*

1. Introduction

Traditional flag state control has its limits in ensuring the implementation of maritime safety regulations, particularly when ship owners choose open registration. Port State Control (PSC), which renders port authorities the ability to inspect foreign vessels in their own ports, was set up in 1982 as an effective complementation of flag state control, to avoid the entries of sub-standard ships into their waters and prevent the occurrence of maritime accidents. Since its implementation, PSC has been gradually viewed as one of the important safety lines of defending sub-standard vessels and improving maritime safety. As a result, PSC effectively reduces the appearance of the vessels that are not obeying the relevant maritime safety regulations to a satisfactory level.

Practical lessons, in the meantime, reveal the shortcomings of PSC in its practical applications such as no risk stake on the involved ship management companies. Every year there are still a large number of vessels that do not comply with the inspection regulations and fail to pass the inspection, according to the Paris MoU detention records (Paris MoU inspection database, https://www.parismou.org). In the old PSC inspection system, ship management companies are third-party managers who, for a negotiated fee and with no shareholding ties with their clients, undertake the responsibility of managing vessels in which they have no financial stake (Mitroussi, 2003). They accepted and managed ships on behalf of ship owners without much concern on their technical soundness given that they had no responsibility on vessels' failures of passing PSC inspections, which is a big issue in supervising vessel quality (Yang et al., 2018b).

To improve the PSC inspection efficiency, New Inspection Regime (NIR) was launched in 2011 by Paris Memorandum of Understanding (MoU). It is so far viewed as the most significant change that transforms and modernizes the PSC inspection mechanism in recent years (Paris MoU, 2011). Under the NIR, a foreign vessel visiting a port will be attributed with a ship risk profile (SRP) through a risk associated information system containing some essential factors such as vessel age, vessel type, and flag state performance (Xiao et al., 2020), which is used to determine the priority of ship inspections, the intervals between the inspections of a ship and the type of the inspections. Based on the feedback from the information system, port authorities will assign PSC Officers (PSCOs) to inspect those vessels with high priority or having overriding or unexpected factors that may pose threats to maritime safety (Wan et al., 2019b). Once the inspection is completed, an inspection report including the detected deficiencies, detention results, and detention periods is issued. The vessels are required to rectify their deficiencies in different time periods according to their status (https://www.parismou.org/). The Paris MoU expected that the implementation of NIR could efficiently improve the performance of PSC inspection system and the overall vessel quality of the shipping industry. In fact, through the analysis on the statistics provided by the Paris MoU annual reports, the implementation of NIR indeed improves the PSC system, which is reflected from the aspects such as the reduction of detention rate, deficiencies per inspection, detainable deficiencies per inspection, and the detainable deficiency rate (Yang et al., 2020).

Since the implementation of PSC inspection, several revisions and improvements have been undertaken to make the rules stricter, leading to various concerns posing on different perspectives. However, the issue on how to strike a balance by rational ship detention control strategies remains to be further addressed in both academic and industrial communities. A high number of ship detention means the existence of a large substandard ship fleet sailing at sea, not only bringing potential hazards to maritime safety, but also causing huge losses and negative impacts on shipping productivity. For port authorities, they need to allocate more resources to monitor these poor-quality vessels until the identified deficiencies are rectified to a satisfactory level under the NIR, as the inspection intervals for high-risk vessels are between 5-6 months, much shorter than standard (within 10-12 months) and low-risk vessels (within 24-36 months). Such condition poses high pressures and inspection burdens on port authorities within the Paris MoU region. Furthermore, an international shipping management company becomes a key stakeholder under the NIR. When a ship is detained, the delay puts a high cost on the company, and the punishment helps raise its attention on ship quality under its management. Moreover, a high rate of ship detention will also weaken the competitiveness of a shipping company in the international market, and even seriously affected the reputation of shipping companies and flag states. Therefore, studies on rational detention risk control measures will essentially be highly valuable to address the above concerns practically and trigger the thoughts on new risk control frameworks that enables the evaluation of risk control measure(s) based on dynamic risk scenarios.

The aim of this paper is to establish a new risk decision tool to aid the evaluation and selection of PSC detention risk control strategies (DRCSs) to reduce the detention risk of ships under the NIR of PSC. The findings can contribute to the current research in the following ways. Firstly, it proposes a novel evaluation tool to aid the evaluation of DRCSs in dynamic PSC scenarios, which can be easily tailored and adopted by a shipping company facing high ship detention risk. Secondly, it supports rational shipping safety decision-making through a new theoretical risk control methodology by incorporating BNs and TOPSIS. Thirdly, it indicates that arranging shipping routes based on ship risk condition could effectively reduce the detention probability among possible risk control measures. Fourthly, it provides useful insights for port authorities when formulating and improving corresponding inspection regulations in terms of the reduction of detention risk, as well as for ship owners to support their decisions as it provides a way for comparing the performance of different DRCSs in a quantitative manner.

The rest of the paper is organized as follows. Section 2 gives an overview of the existing risk-based PSC research. Section 3 introduces the main methods used to develop the novel PSC risk control decision-making model. Section 4 illustrates the proposed method by conducting a case study, before the conclusion in Section 5.

2. Literature review

Since PSC inspections play an increasingly important role in maritime safety, more and more researchers stepped into this field and conducted works on the risk management of PSC inspections from both qualitative and quantitative perspectives, especially in the past two decades. It is evident by the increasing number of relevant papers since 2011 when NIR was initiated. The PSC related studies are therefore critically analysed below.

In 2014, Li et al. (2015) built a bi-matrix game between the port authorities and ship operators in PSC inspection to quantify the risks existing in PSC inspections to decide on the optimal inspection policy with an aim to save inspection cost whilst keeping deterrence pressure on potential wrongdoers. Through a numerical case study, it was shown that the optimal inspection rate obtained from the model can yield a significant saving, as well as prevent potential violations by ship operators. Knowing that heavy maritime traffic may cause significant navigational challenges in the Istanbul Strait, Kara (2016) applied a weighted point method to assess the risk level of each vessel experiencing the PSC inspection under the Black Sea MoU. However, the weighting and scoring methods adopted in these studies were based on subjective expert judgements, which arguably introduced subjective bias to the obtained results.

Extracted from Tokyo MoU inspection database, Tsou (2018) used association rule mining techniques in big data analysis to examine the relationships between detention deficiencies and external factors as well as between detention deficiencies themselves. The findings provided countermeasures and can be used as a reference by ship management personnel during the corresponding PSC inspection to reduce the detention rate of ships, improve working efficiency of staff members, and reduce the adverse influences brought by substandard vessels. Similarly, Osman et al. (2020) used the same approach to analyse the inspection pattern in Malaysian port and provide a useful rule to help PSC officers in organizing an effective inspection plan.

Realising former risk assessment approaches are not fully competent to tackle dynamic PSC risk (e.g., ship detention probability) in different environments, Yang et al. (2018a) pioneered the development of a BN framework to create a detention rate prediction tool for port authorities. The advantages of BN over other approaches in dynamic prediction are that it provides important insights to seek the optimal inspection policies under different environments in NIR. Furthermore, based on the BN models in this research, Yang et al. (2020) conducted a comparative analysis between 'Pre-NIR' period and 'Post-NIR' period from both qualitative and quantitative perspectives. The results revealed that it is beneficial to implement NIR for PSC inspection system, vessel quality and maritime safety.

Following Yang et al. in 2018a, Wang et al. (2019) developed a new Tree Augmented Naïve (TAN) Classifier to identify high-risk foreign vessels coming to the Hong Kong port. Compared with the Ship Risk Profile selection scheme currently used 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. Later in 2021, to solve the imbalanced inspection records issue, Yan et al. (2021) proposes a classification model called balanced random forest (BRF) to predict ship detention by using 1,600 inspection records at the Hong Kong port for three years. Compared with the current selection regime at the Hong Kong port, the BRF model is much more efficient and can achieve an average improvement of 73.72% in detained ship identification.

Understanding the current PSC research and practice are not able to incorporate deficiency records into detention analysis, Wang et al. (2021) utilize a Bayesian Information Criteria (BIC) approach to construct a PSC risk probabilistic model to analyse the dependency and interdependency among the factors influencing detention. The results reveal that safety condition and technical features are the most influential factors concerning ship detention.

Focusing on the factors behind the detention of vessels, Chen et al. (2019) proposed a grey rational analysis (GRA) model with improved entropy weights to understand how much the varied factors influence the decision of ship detention, and identify key factors of detainment to guarantee shipping safety and environmental protection. The results could be used by port authorities to develop the suggestions and countermeasures of reducing ship detention.

Another popular method in PSC inspection model development is support vector machine (SVM). Back to 2007, Xu et al. (2007) presented a risk model based on SVM to estimate the risk state of vessels before conducting on-board inspection. Recently, Wu et al. (2021) proposed a SVM based framework to exploit crucial ship deficiencies and forecast the probability of ship detention. The findings could help port authorities easily identify fatal ship deficiencies to make more reasonable ship detention decision.

Other applied methods like Bayesian search algorithm (Fan et al., 2020) and binary logistic regression (Xiao et al., 2020) also play important roles in risk-based PSC inspection studies.

In light of the above analysis, it is obvious that previous studies are mainly conducted for the identification, analysis and assessment of the risks associated with PSC inspections, leaving the issues on the management of detention risk under PSC inspection unaddressed. To fill the research gap, this study proposed a BN-based TOPSIS method to develop rational DRCSs under dynamic PSC inspection scenarios.

3. Methodology

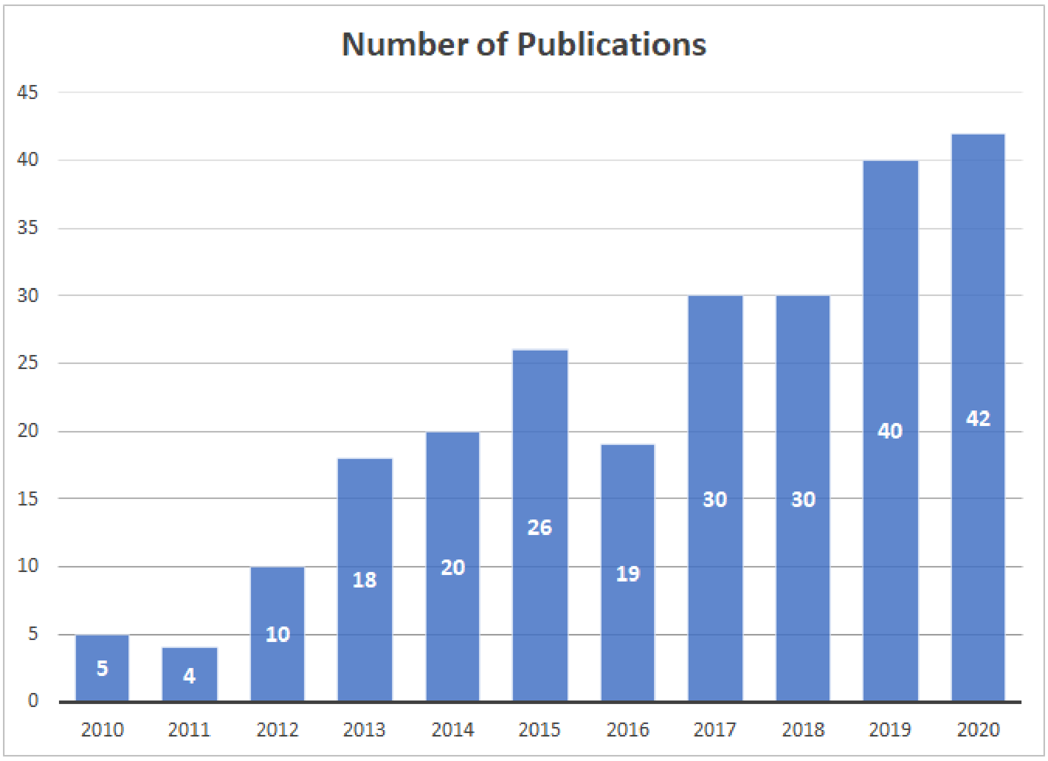
3.1 BNs in maritime risk

The BN method was developed based on the well-defined Bayesian probability theory and networking technique. A BN is a graphical presentation of probability combined with a mathematical inference calculation, which provides a strong framework for representing knowledge. It has a good ability in modelling randomness and capturing non-linear causal relationships, so that the inference based on imprecise and uncertain information can be achieved (Wan et al., 2019a). Taking advantage of causal inference, BN has been used to analyse the importance degree of risk variables and the relationships between them. Compared to pure Bayesian theory, BN is more visualized, while it has a solid foundation of mathematical knowledge. Because of its advantages, BN has been increasingly applied in various research orientations in risk assessment of maritime related systems, as shown in Table 1. Additionally, a figure illustrating the change of number of core journal publications on BN applications (on Web of Science) in the maritime field in recent years is presented as well, demonstrating the popularity and feasibility of BN applications (see Fig. 1).

Table 1 BN applications in maritime related risk related topics

Research Classification	Relevant Reference
Occurrence of ship-ship collisions	Kujala, et al. (2009); Klanac, et al. (2010); Hänninen & Kujala (2012); Weng, et al. (2012); Hänninen, et al. (2014); Goerlandt & Montewka (2015)
Navigational safety in shipping	Zhang et al. (2013); Banda et al. (2016)
Maritime accident evaluation and prevention	Antao et al. (2009); Hanninen et al. (2014); Li et al. (2014)
Oil spill accidents & recovery in maritime field	Lehikoinen et al. (2013); Goerlandt & Montewka (2014)
Offshore safety analysis	Eleye-Datubo et al. (2008); Ren et al. (2009);
Sea wave overtopping issue	Tolo, et al. (2015)

PSC inspections	Hänninen & Kujala (2014); Hanninen et al. (2014); Yang et al. (2018a); Yang et al. (2018b); Wang et al. (2019)



Source: Web of Science, by authors

Fig 1 - Number of publications of BN in maritime field in the recent decade

Normally, the process of developing a BN model consists of four phases: data acquisition, variable identification, BN construction, and conditional probability distribution and risk prediction (Yang et al., 2018b). Unlike the traditional ways (i.e., human expert knowledge, common sense, historical experience) to develop the structure of BN, the network structure of this research is purely induced from data. This kind of data-driven approaches can avoid common issues in traditional approaches, such as time consuming, heavy burden on experts, and subjective perception (Yang et al., 2018a; Yu et al., 2020). Additionally, the accuracy of model results can be improved when comparing with traditional ways involving subjective judgements. Specifically, various methods for network configuration optimisation were utilised in the literature, including dependency analysis (Thomas, 2005), search and score approach (Cooper et al., 1992), genetic algorithm (Novobilski, 2003), chain genetic algorithm (Kabli et al., 2007). Although BN can be extended into an influential diagram (ID) to incorporate decision and utility nodes for decision making, ID is usually incompetent to deal with multiple decision attributes of different characteristics in maritime risk control studies (Yang et al., 2009).

3.2 TOPSIS in maritime risk analysis

Multi-criteria decision-making (MCDM) problems are frequently encountered in various aspects in maritime operations. TOPSIS (Hwang and Yoon, 1981), as one of the well-established methods for solving MCDM problems, has been widely studied for several decades, and been widely applied in maritime risk management due to its advantages of being intuitive, easy to understand and to implement. Moreover, it is able to manage each kind of variables and each type of criteria with data collected from various sources involving risk, cost, and social benefits. Othman et al. (2015) applied TOPSIS method to ranking the factors that caused psychological problem of distraction of seafarers. Wu et al. (2016) introduced TOPSIS for group decision-making in order to provide a practical decision framework for safety control of ships out of control. Due to high flexibility of TOPSIS, it can accommodate further extension to make better choices in different conditions, including fuzzy environment. Liu et al. (2016) proposed an extend TOPSIS model to facilitate the comparison between fuzzy numbers in the safety assessment of inland waterway transportation with the ability to dealing with expected values of different situations. Yan et al. (2017) introduced the cost-benefit ratio to the fuzzy TOPSIS in order to achieve a rational risk analysis for prioritising congestion risk control options of inland waterway transportation under dynamic risk scenarios. Zhang and Lam (2019) combined fuzzy TOPSIS with Delphi and AHP to identify barriers in emerging technology adoption with a case of maritime organizations. However, TOPSIS and its extensions are rarely used to model the dynamic interdependencies among multiple decision criteria with very few previous studies (e.g. Yang et al., 2009, Fan et al. 2020).

3.3 The proposed method

In this research, a new methodology incorporating BN with TOPSIS is proposed to develop the risk decision tool for the evaluation of DRCSs in PSC inspections. It combines the advantages of both BN and TOPSIS (as mentioned in section 3.1 and 3.2 respectively). Therefore, the holistic approach is superior over either BN or TOPSIS (as standing along methods) in a way of:

1) A BN for predicting the safety of a system cannot be used to make a decision about whether or not an action can improve the system safety, when such a decision have to be made against multiple criteria such as cost and safety. However, the cooperation of TOPSIS can address this BN deficiency, and extend the function and application scope of traditional BN.

2) Compared to the traditional TOPSIS method, the proposed holistic method can first be used to predict safety and the result is integrated into TOPSIS in an objective form. In particular, the outputs of BN (i.e. root variables, mutual information) are used as the inputs of TOPSIS (i.e. criteria, and their weights), reducing the influence of subjective

judgments when making decision. Additionally, the results can be updated accordingly when new information is incorporated, supporting dynamic decision making.

As aforementioned, the process of developing a BN model consists of four phases: data acquisition, variable identification, BN construction, and conditional probability distribution and risk prediction. While the main steps of applying a TOPSIS method include constructing decision-making matrix, weighting and normalizing the decision matrix, calculating the separation measures of the alternatives, determining their relative closeness to the ideal solution, and finally ranking the alternatives. To avoid unnecessary repetitions regarding the construction of data-driven BNs (incl. equations and algorithms) and the application of the TOPSIS method, which are detailed in Yang et al. (2018a) and Yan et al. (2017), respectively, this paper stresses the key steps of combining the two in the context of PSC inspection. By doing this, we can emphasize how the original data-driven BN model and the TOPSIS method can be combined in a complementary manner for decision making of detention risk reduction strategies under PSC inspections.

As the kernel of the proposed method, a risk-based BN for PSC is constructed to capture the relationships among different risk factors and then use their risk contribution to ship detention to calculate their dynamic importance degrees. The risk factors that are identified as root variables in the BN will be transformed as the decision criteria when constructing the decision matrix in TOPSIS, while the weights of the selected criteria will be determined based on their mutual information with the target node, i.e., ‘detention’, in the BN. Fig.2 shows the flow chart of the proposed method. It is worth noting that when the prior probabilities in the BN model are updated to reflect a particular case scenario (e.g. a particular port in a specified timeframe), the weights of the criteria (i.e. root causes) will be changed accordingly to respond to the dynamic feature of PSC to meet a particular ship/ship-owners requirement.

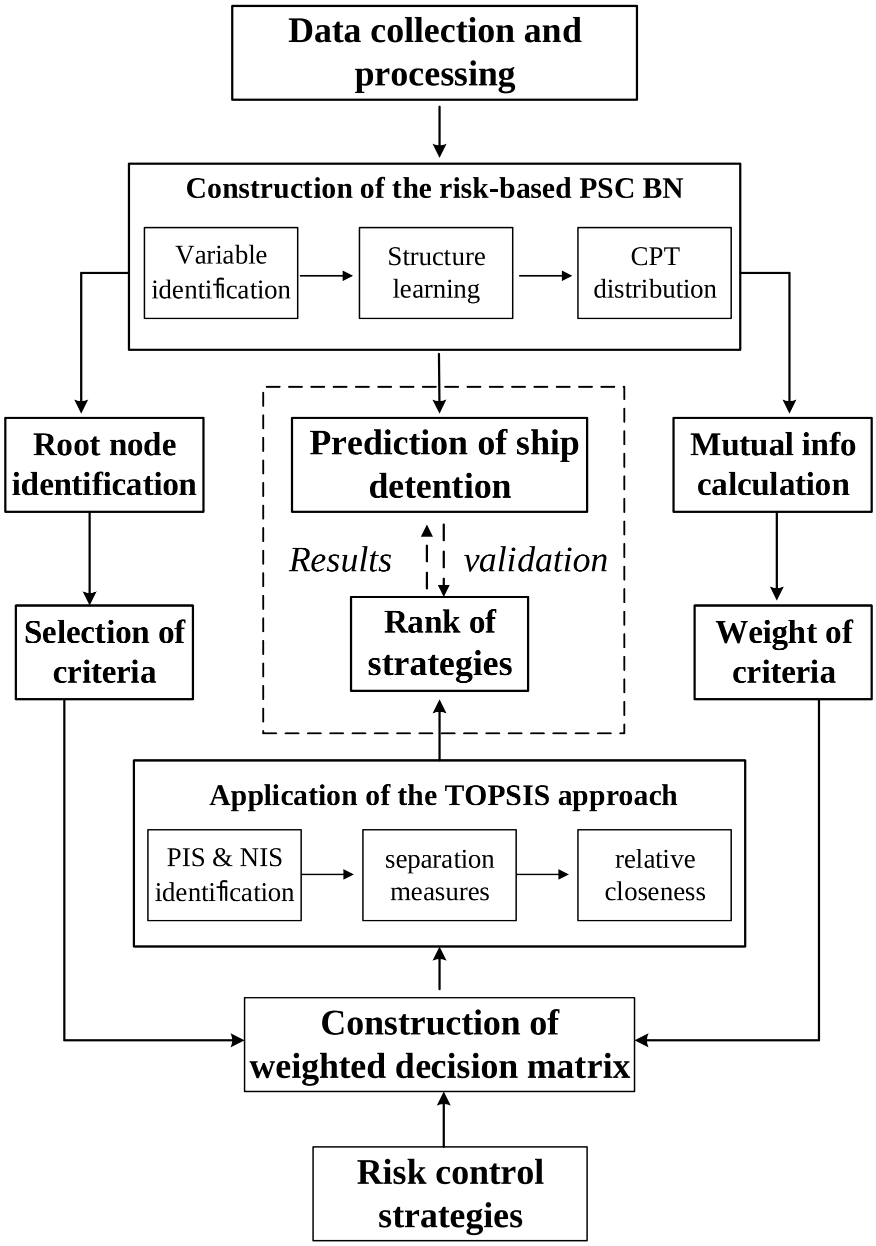


Fig 2 - The flow chart of the proposed method

Source: Authors

The detailed description of the proposed methodology is outlined in the following steps.

Step 1. Data collection and processing

To determine the detention rate of a vessel in a port, it is important to have a list of historical PSC inspection records from the port region (e.g., Paris or Tokyo MoU). Collected from the Paris MoU online inspection database, 49,328 inspection records from 2015-2017 are extracted to form the research database to train the prior probabilities in the PSC risk-based BN. It is noted that the bulk carriers are selected as the research target in this study due to 1) its dominant role in the global maritime market (making up 15% - 17% of the world's merchant fleets), and 2) the detention rate of bulk carriers shows a very similar trajectory to general situations, which is proved in a recent research produced by Yang et al. (2020) through a comprehensive analysis.

Step 2. Construction of the risk-based PSC BN

The construction of the PSC BN consists of variable identification, structure learning, and conditional probability configuration (Yang et al., 2018a).

The variables used in model construction are determined based on the PSC inspection records and previous studies simultaneously. A PSC inspection record contains information in two aspects, vessel-related and inspection-related. It is noteworthy that the factors concerned in this study are those influencing detention (inspection results), instead of inspections, which means the research is conducted on the whole inspection process. Major information in inspection records is valuable and selected as the risk variables in our research, which are vessel flag, vessel age, company performance, type of inspections, port of inspection, number of deficiencies, and detention. These variables have been proved to be important factors influencing inspection results according to previous research, i.e., Yang et al. (2018a). Meanwhile, two intermediate level risk variables, 'vessel group' and 'inspection group', are introduced to avoid enormous conditional probability tables (CPTs) and reduce calculation work based on the principle of divorcing approach (Jensen, 2001). They can be viewed as the overall level of vessel-related risk and inspection-related risk. For the 'vessel group', based on the information provided by Yang et al (2018) and Wang et al. (2019), this variable has two states of 'detention risk higher than 10%' and 'detention risk lower than 10%'. Three parent nodes of 'vessel group' have a number of different combinations, and cases correlated with them can all be found in the PSC inspection database. If we select several cases with different combination of vessel-related nodes and same combination of inspection-related nodes, when inputting them into BN model, the results reveal that most cases resulting in detention has a detention rate more than 10%, and other cases are lower than 10%. In other words, once the detention risk of a vessel is higher than 10%, the inspection records showed it is about to be detained. Therefore, in this study, 10% detention probability is a threshold value of 'vessel group', resulting in two states of this variable 'detention risk higher than 10%' and 'detention risk lower than 10%'. The same distinguish criteria goes to the 'inspection group'. More detailed information can be referenced in Yang et al. (2018a).

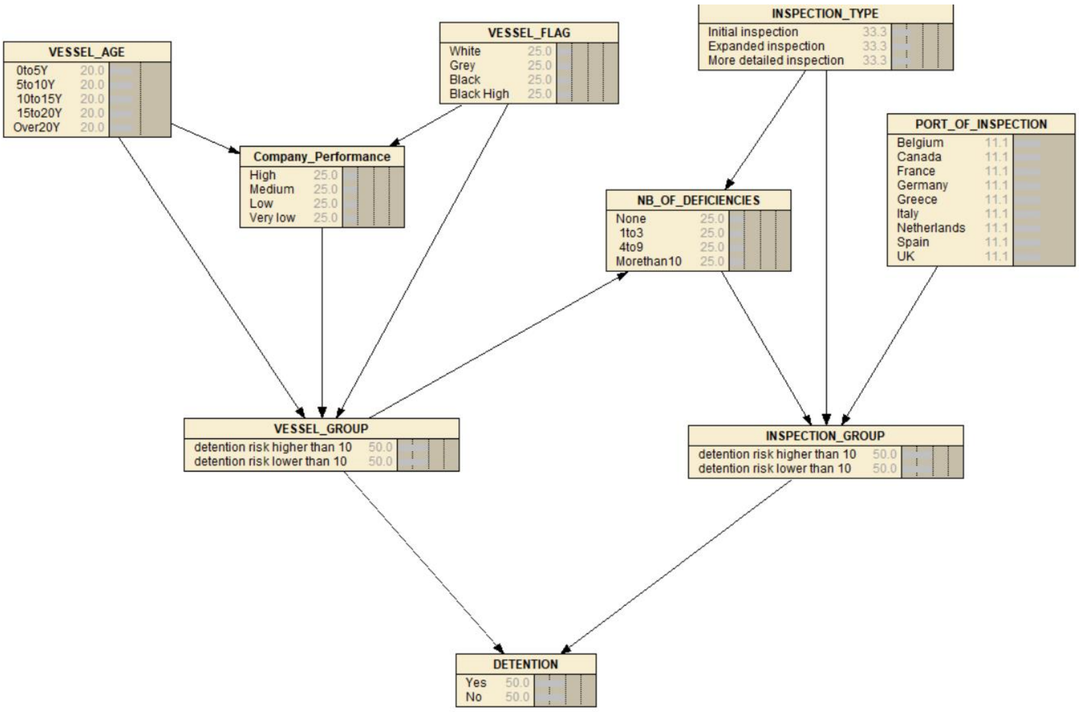


Fig 3 - PSC BN model

The structure of BN in this study is learned via a data-driven approach, called Tree Augmented Naïve (TAN) learning, the essence of which is actually an optimization problem (Friedman et al., 1997). The TAN learning is chosen in this study because it is proved to be more competitive and accurate than other data-driven approaches (Murphy & Aha, 1995). The detailed process of how the network is derived from TAN is found in Yang et al., (2018a). Through the Netica software, the result is presented in Fig. 3.

Once the structure of BN is determined, the conditional probabilities of nodes are required to model the uncertainties of risk variables. To avoid the problems existing in traditional CPT calculation methods (expert judgment) like time-consuming and impractical application in this study, the CPTs are formulated by a gradient descent approach (Bottou, 2010). Its essence is to narrow the distance between the conditional probability and the value of prior information. When the minimum distance is found, the value at this point is selected as the associated conditional probability. The gradient descent approach has good performance when calculating CPTs (Yang et al., 2018a). When the structure and CPTs of BN are properly constructed, the probability of ship detention under the PSC inspections can be predicted by considering different sets of observable evidence.

Step 3. Selection of the criteria for measuring detention DRCSs

Only root variables in the constructed PSC BN model are considered to be the possible criteria for decision-making analysis, as they are derived directly from the PSC inspection database, and can be effectively influenced by the stakeholders from different aspects via appropriate actions. According to Fig 3, they are vessel flag, vessel age, type of inspections and port of inspection. Port of inspection is at large fixed based on the charter party that the ship is engaged with and hence beyond the owner's direct control and removed from the criterion list. Therefore, the retained three root variables are selected as the criteria for measuring and comparing the performance of DRCSs, including vessel flag, vessel age, and type of inspections.

Step 4. Weighting the criteria according to the mutual information

In this research, the weight of each criterion is determined according to the mutual information of each node. Mutual information is the information that two variables share in a BN, which can be used to calculate the strength of the relationships between the target node (i.e. detention) and influencing nodes (i.e. the selected three criteria - vessel age, vessel flag, and type of inspections) in this study. One of the advantages of mutual information is that it can be computed between variables at different layers. The mutual information between 'detention' and other risk variables can be defined as:

$$I(D,\beta) = -\sum_{d,i} P(d,\beta_i) log_b \frac{P(d,\beta_i)}{P(d)P(\beta_i)} \tag{1}$$

Where D represents 'detention', β represents risk variable, β_i represents the ith state of β, $I(D,\beta)$ represents the mutual information between 'detention' and risk variables. The value of $I(D,\beta)$ is only related to the two variables D and β, and it is independent to other mutual information in the model. The larger the value of mutual information is, the stronger relationship which exists between variable 'β' and 'detention'. It is noteworthy that the amount of mutual information represents the degree of influence, not the exact weight of variables.

Then, the weight of each criterion can be calculated using Eq. (2).

$$w_j = I_j / \sum_{j=1}^{n} I_j,\ j = 1, 2, ..., n \tag{2}$$

where, w_j is the weight of jth criterion (or in other words, jth selected risk variable), and I_j is the mutual information between jth risk variable and 'detention'.

Step 5. Construction of the decision matrix of DRCSs

DRCSs are developed from different perspectives based on multiple sources in order to maximally reduce the risk of ship detention, and the performance of each DRCS against each criterion under a specific risk scenario is assessed by expert judgement. For example, under a high-risk scenario, stricter control measures are usually more desirable; while under a low-risk condition, more attention will be paid on the cost of taking countermeasures in order to select a cost-effective one. In this way, the performance of each DRCS against each variable under dynamic situations can be achieved. A questionnaire survey was designed to collect experts' judgements about the performance of DRCSs in terms of each criterion. Experienced staff members who have working experience in relation to the PSC inspections of European ports were selected for the case study. The subjective probability distributions from multiple expert judgments are merged using a weighted average approach (Wan et al., 2018). To facilitate subjective data collection and representation of judgements associated with the performance of DRCSs, a set of linguistic variables are defined. Three grades of performance are considered, and they are described using linguistic variables "*low*", "*medium*", and "*high*". Supposing altogether l variables are used to evaluate the performance of DRCSs, then the score of k^{th} variable (C_k) can be calculated using Eq. (3) (Yang et al., 2014).

$$C_k = 10^{k-1} (k = 1, 2, ...l) \tag{3}$$

k is the order of variables and they are listed in an ascending order, which means a higher value of k represents a better performance in this study. Thus, the scores of "*low*", "*medium*", and "*high*" are 1 (10^0), 10(10^1), 100(10^2), respectively, and then the overall evaluation can be transferred into a numeric value by using the following utility function.

$$u(E) = \sum_{l=1}^{L} \beta_l u(G_l) \tag{4}$$

Where, $u(E)$ is the total score of the performance of a DRCS, l is the number of linguistic variables used to describe the performance of a DRCS (which is three here), $u(G_l)$ is the score of lth grade of performance, and β_l is the subjective probability distributed to lth grade of performance, ranging from 0% to 100%.

Based on the criteria and evaluation on the performance of DRCSs, a decision matrix $D = (x_{mn})$ can be established, and normalized as:

$$r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}, \ i = 1, 2, ..., m; \ j = 1, 2, ..., n \tag{5}$$

Where, x_{ij} in matrix D describes the performance of i^{th} DRCS with respect to j^{th} criterion. m is the total number of DRCS, and n is the number of criteria. r_{ij} denotes the normalised value of x_{ij}.

Multiply the columns of the normalized matrix by the associated weights to obtain the weighted decision matrix $A = (v_{mn})$:

$$v_{ij} = w_j \cdot r_{ij},\ i = 1, 2, ..., m,\ j = 1, 2, ..., n \tag{6}$$

Where, w_j is the weight of jth criterion.

Step 6. Selection of the optimal DRCSs

Once the weighted decision matrix is constructed, the optimal DRCSs can be identified via employing the TOPSIS algorithm. Firstly, the positive ideal and the negative ideal solutions, are denoted by A^+ and A^-, respectively. They are defined as follows:

$$\begin{aligned} A^+ &= (v_1^+, v_2^+, ..., v_n^+) = \left\{ (\max_i \{v_{ij}\} \middle| j \in J_1), (\min_i \{v_{ij}\}) \middle| j \in J_2 \right\}; \\ A^- &= (v_1^-, v_2^-, ..., v_n^-) = \left\{ (\min_i \{v_{ij}\} \middle| j \in J_1), (\max_i \{v_{ij}\}) \middle| j \in J_2 \right\} \end{aligned} \tag{7}$$

Where, J_1 and J_2 represent the set of benefit and cost criteria, respectively.

Secondly, the Euclidean distances of each DRCS from the PIS (d_j^+) and the NIS (d_j^-) can be calculated as:

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{\ +})^2},\ i = 1, 2, ..., m;\ j = 1, 2, ..., n; \\ d_i^- &= \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{\ -})^2},\ i = 1, 2, ..., m;\ j = 1, 2, ..., n \end{aligned} \tag{8}$$

Finally, the relative closeness (S_i) to the ideal solution is calculated as:

$$S_i = \frac{d_i^-}{d_i^+ + d_i^-},\ \ i = 1, 2, ..., m \tag{9}$$

Where, $0 \leq S_i \leq 1$.

After ranking the DRCSs according the relative closeness, the DRCSs with the highest S_i are selected to reduce a ship detention rate.

Step 7. Validation of the proposed method

The validation of the proposed method is conducted through its benchmark with some established methods. In this process, the results from all the investigated methods are compared to check their consistency.

4 Case study

4.1 DRCSs of ship detention

In this study, DRCSs are developed and taken in response to the risk influencing factors (e.g., detainable deficiencies of ships) which are directly and closely related to the ship detention, and will increase the possibility of a ship being detained to a large extent under PSC inspections. From the perspective of system engineering, a system is usually composed of three major parts which are human, machine and environment (Lank et al., 2011). In this study, we substitute management factors for environmental ones considering the special role management plays in the safety of waterway transportation and the fact that environmental factors are usually difficult to control, whether natural environment or political environment. Thus, three main aspects considered here are human (e.g., crew), vessel, and management (e.g., shipping company, maritime safety authority, and port authority). By combing this idea with the existing PSC practice, several generic DRCSs are selected only for the illustrative purpose of the proposed method[1].

DRCS #1. Strengthen the knowledge promotion of PSC inspection

Strengthen the knowledge promotion of PSC inspection for those who work closely related to the maritime shipping such as managers of shipping companies, senior crew, and shore-based personnel. For example, the training of seafarers on PSC inspection can vigorously improve the professional quality of seafarers, and raise the awareness of safety management as well. Maritime shipping safety is closely related to the quality of the crew. Thus, many shipping companies have not only required crew members to conduct performance training, but also developed special training courses for crew based on the company's conditions, in order to improve their competitiveness in the shipping market. It should be ensured that captains are full familiar with the company's Safety Management System (SMS). When PSC officers audit the captain with respect to performance of the monitoring duties, they will pay attention not only to the written records of captains such as Navigation Logs, but also their actual monitoring quality of operation.

DRCS #2. Arrange shipping routes based on ship risk condition

Several amendments to the maritime safety-related conventions have come into effect in the past five years, with many different types of inspection items being involved. Therefore, both management and operation personnel on board should be familiar with the relevant requirements of the amendments in a timely manner, and take effective

[1] It is worth noting that the development of specific DRCSs are very complicated, requiring information on operational environments to make it sensible according to the survey of domain experts in the process of identifying valid DRCSs in this work. For the purpose of illustrating the proposed methodology and not losing the generality of the used DRCSs, the following three generic strategies are put forward in this study.

measures to ensure that ships meet the new requirements of conventions. It is required that more attention should be paid on the ships with a relatively higher risk level with respect to maintenance and shore-based support, in order to reduce risks of ships.

DRCS #3. Self-inspection of ships before sailing

It is required that shipping companies should establish reasonable self-inspection procedures before the sailing of a ship. An individual agency/department is suggested to set up which is responsible for collecting PSC information of the ships abroad. Also, we need to clarify the responsibilities of relevant departments, personnel and ships, eliminate the defects found in time, and improve the technical status of the ship. Every time before the sailing of ships, the crew should conduct self-inspection with respect to ship's technical conditions and cargo loading conditions, and fill out the "Self-inspection checklist" which needs to be signed and confirmed by the captain in responsible before sailing. Shipping companies, regulatory bodies/authorities and classification societies need to work together to develop and implement a tripartite coordination mechanism for PSC inspection, and strengthen the safety management of ships through the implementation of the International Safety Management (ISM) Code.

4.2 Evaluation of the selected DRCSs

First of all, the weights of criteria can be determined based on the mutual information between these nodes and target node, as shown in Table 1. It is noted that the value of mutual information between all nodes and target node 'detention' were calculated, but only that of root nodes is presented. According to the mutual information, the weight of each criteria can then be calculated using Eq. (2), and the results are listed as follows:

Table 2 - Mutual information between root nodes and 'Detention' in 2015-2017

Node	Mutual Information	Percent	Weight
Detention	0.20388	100	-
Vessel age	0.00669	3.28	0.55
Type of inspections	0.00523	2.57	0.43
Vessel flag	0.00025	0.123	0.02

The assessment of the three DRCSs with respect to different risk variables influencing ship detention under PSC inspection was conducted to demonstrate the feasibility of the proposed method in the performance evaluation of DRCSs. A questionnaire was conducted with three senior staff from different organisations working related to the PSC inspection and ship navigation safety. It is worth noting that all these experts have working experience in European countries (or European shipping routes) to ensure that they are familiar with Paris MoU. The qualification of the selected experts is summarized as follows:

- Expert No. 1: Senior Captain, technical safety department; has worked onboard ships on different shipping routes for more than 12 years.
- Expert No. 2: General Manager, marine operations centre; involved in the safety and security management of global ship fleets for more than 12 years.
- Expert No. 3: Senior marine investigator, maritime authority; has worked on maritime safety and accident investigation for more than 13 years.

This study employed a subjective probability method to collect expert opinions. Subjective probability is a probability derived from an expert's judgment about the degrees of a specific assessment level to which one criterion belongs with respect to any DRCS. In the subjective probability method, the performance of each DRCS is estimated and represented using the probability distribution of the linguistic variables (i.e. *Low*, *Medium*, and *High*), provided directly by experts (see an example in Appendix A). Due to the similar seniority of the three experts, equal weight was assigned to each expert when combining their evaluations, and then the total score of each DRCS in terms of each criterion can be calculated by using Eq. (4). The results are summarised in Table 3.

Table 3 - Summary of the evaluation results from different experts

RCS	**Criteria**	**Evaluation of DRCSs**			**Total score**
		Low	*medium*	*High*	
No.1	Vessel age	63%	37%		4.3
	Type of inspections	40%	60%		6.4
	Vessel flag	67%	33%		4.0
No.2	Vessel age		17%	83%	85.0
	Type of inspections	17%	47%	36%	41.5
	Vessel flag	17%	57%	26%	32.5
No.3	Vessel age	63%	37%		4.3
	Type of inspections		40%	60%	64.0
	Vessel flag		43%	57%	61.0

Based on the above information, the weighted normalized decision matrix for the evaluation of DRCSs can be constructed using Eq. (5) and (6), which is shown as follows.

$$D = \begin{pmatrix} 0.0257 & 0.0385 & 0.0017 \\ 0.5087 & 0.2494 & 0.0141 \\ 0.0257 & 0.3846 & 0.0264 \end{pmatrix}$$

Finally, the DRCSs can be ranked according to the value of relative closeness, as shown in Table 4.

Table 4 - Ranking of the DRCSs

	d^+	d^-	S_j	Rank
DRCS 1	0.613	0	0	3
DRCS 2	0.127	0.557	0.815	1
DRCS 3	0.521	0.324	0.383	2

As aforementioned, the results from Table 4 indicate the preference of each DRCS with respect to the overall dry bulk ship detention data of MoU Paris in the period of 2015-2017. Due to the difficulty of accessing individual port/ship company level information on the operational environment, the DRCS ranking and functionality analysis are kept at the generic level. From the managerial implication perspective, it helps ship owners/management companies to understand that without further specific port level information, they could implement the above three strategies in a sequence to reduce the ship's detention rate in European ports. It also serves as the base line to observe how the methodology can be used to deal with dynamic situations when specific data becomes available.

4.3 Performance of DRCSs under dynamic situations

In this section, the performance of the DRCSs under dynamic situations is demonstrated. To explore this dynamic feature, new evidence is collected and entered into the proposed method. An extended database of over 2000 inspection records in 2018 is collected. Based on the same group of experts, the performance of three DRCSs under new environment is presented as follows. Table 5 is the updated mutual information between root nodes and 'Detention' in 2018.

Table 5 - Mutual information between root nodes and 'Detention' in 2018

Node	**Mutual Information**	**Percent**	**Weight**
Detention	0.18495	100	-

Vessel age	0.00280	1.51	0.44
Type of inspections	0.00344	1.86	0.54
Vessel flag	0.00017	0.0926	0.02

For illustration purpose only, we use the same evaluation results of each DRCS as presented in Table 2 to reflect the dynamic features of the proposed model in decision-making under a different scenario (for this case, it is a different time period)[2]. Under this situation, the weighted normalized decision matrix for the evaluation of DRCSs in 2018 can be constructed as follows.

$$D = \begin{pmatrix} 0.0156 & 0.0560 & 0.0012 \\ 0.3092 & 0.3632 & 0.0094 \\ 0.0156 & 0.5602 & 0.0176 \end{pmatrix}$$

Finally, the DRCSs can be ranked according to the value of their relative closeness

Table 6 - Ranking of the DRCSs in 2018

	d^+	d^-	S_j	Rank
DRCS 1	0.582	0	0	3
DRCS 2	0.159	0.485	0.753	1
DRCS 3	0.417	0.407	0.494	2

It can be seen from the above results that although the same order of ranking of DRCSs are obtained in 2018, the numerical gap (S_j value) between DRCS 2 and DRCS 3 is much reduced, which indicates that the performance of these two strategies tend to be similar under this circumstance. It is believed that with more PSC inspection data derived from other time periods, the changing trend of the role that these DRCSs play in different time periods can be revealed.

4.4 Validation and analysis of the results

Since the criteria in the decision matrix are generated from risk variables in the PSC BN, the evaluation of the DRCSs with respect to each criterion from expert judgement can also be explained as the effects of DRCSs on the mitigation of each risk factor. Thus, the performance of the DRCSs in terms of each criterion will be transformed into the reduction of probability of relevant risk factors in the BN model. This kind of transformation is achieved according to the total score that a DRCS obtained. For example, the total score of DRCS #1 in terms of vessel flag is 4.0, it means that a share of probability of 4.0% is reassigned in node "vessel flag" moving toward the maximal

[2] It is worth noting that the proposed model is able to deal with both dynamic weights and evaluations under different scenarios when more evaluation results from experts are collected.

decrement of detention risk (from status "black high" to "white"). In this way, the performance of DRCSs can be reflected in the form of variation of detention rate of individual vessels in the BN model, and then the DRCSs can be ranked according to their effects on reducing the ship detention rate under PSC inspections.

Figure 4 shows the result of detention analysis based on the BN model. It indicates that the detention rate of a bulk carrier is estimated to be 3.19% given the input data covering the period of 2015-2017. If we calculate the detention rate from the database directly, it is 3.23%, which shows a harmony with the result delivered by the model (a similarity of 98.8%). The model is verified in terms of prediction of detention rate of bulk carriers.

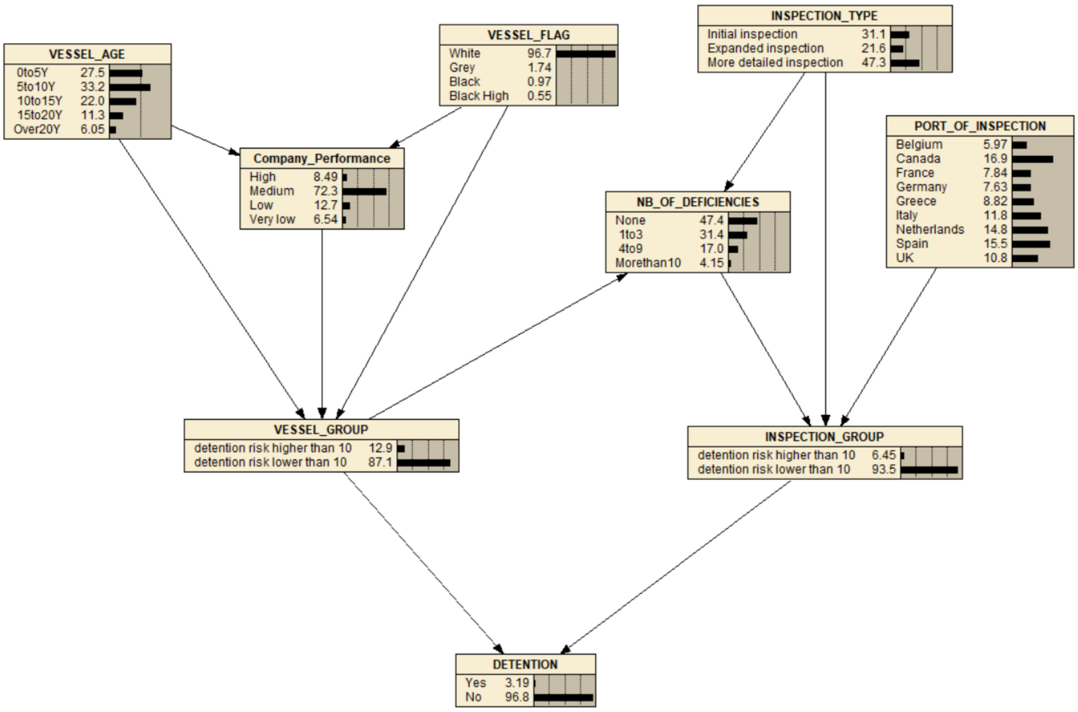


Fig 4 - Results of BN model

Source: Author

Taking DRCS #1 as an illustration, the total scores of it in terms of criterion vessel age, type of inspections, vessel flag are 4.3, 6.4, 4.0 respectively, which means that the probability reassigned in node "vessel age", "type of inspections", "vessel flag" are 4.3%, 6.4%, and 4.0% respectively, moving towards the maximal decrement of detention risk. For example, in node "vessel age", the probability of "over 20 years" will be decreased from 6.05% to 1.75%, while that of "0 to 5 years" will be increased from 27.5% to 31.8% accordingly. In a similar way, the effect of each DRCS on the reduction of ship detention risk can be calculated according to the BN model, as shown in Fig 5, 6, and 7, respectively.

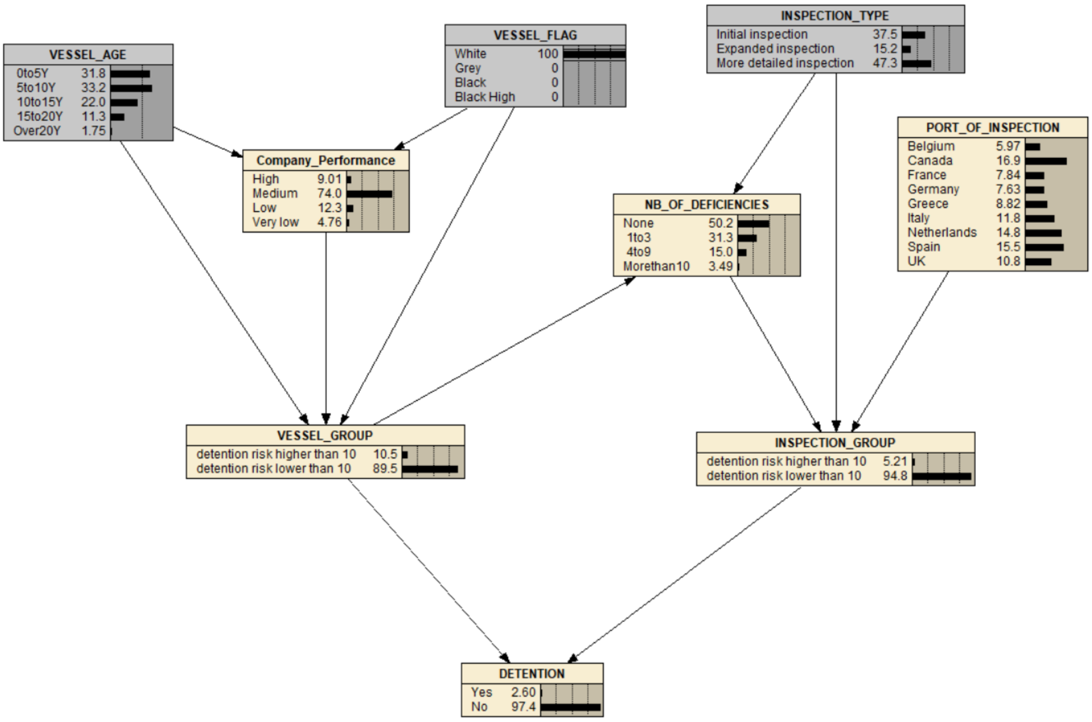


Fig 5 - Risk of ship detention under DRCS #1

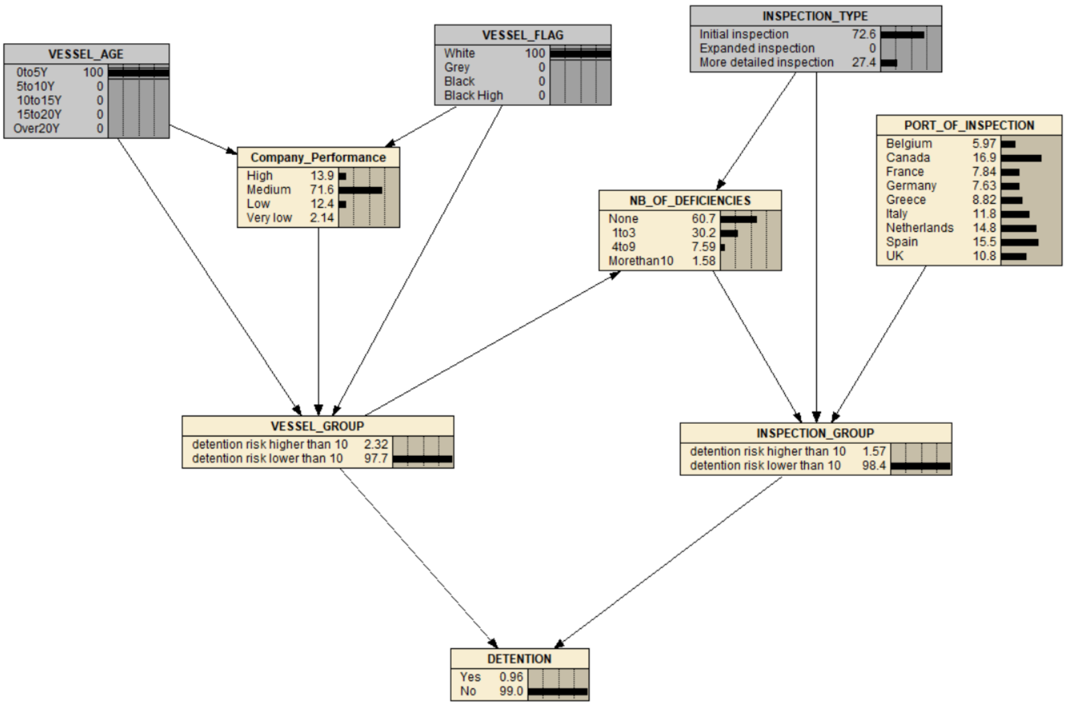


Fig 6 - Risk of ship detention under DRCS #2

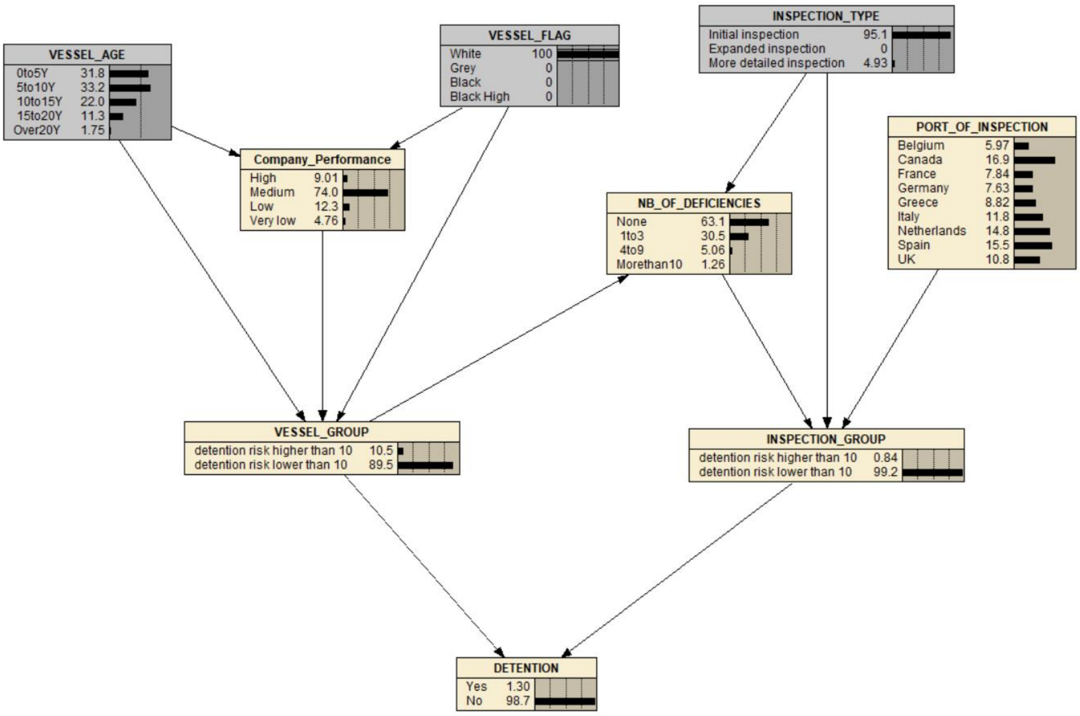


Fig 7 - Risk of ship detention under DRCS #3

It can be seen from the BN results that, after the implementation of these DRCSs individually, the detention rate of a bulk carrier is reduced to 2.60%, 0.96%, and 1.30% respectively. The results reveal that DRCS #2 performs the best in in this case, followed by DRCS #3 and #1. This is consistent with the results obtained from the proposed method, validating the model to a certain degree.

4.5 Managerial insights

4.5.1 Perspective from the port authorities

Port authorities usually aim to regulate the behaviour of ship owners in order to avoid potential accidents and ensure ship safety through their PSC inspections. Vessels with different risk levels will be provided with different safety-improve suggestions. According to the results of the proposed models, the DRCSs which show better performance in terms of the reduction of detention risk of ships can be collected and taken as a reference for port authorities when formulating and improving corresponding inspection regulations. This in turn will also improve the overall quality of ships to be inspected, and thus enhance the safety of maritime transportation.

4.5.2 Perspective of the shipping companies

Once a vessel was detained, all the identified deficiencies need to be fully addressed as required. Different from port authorities, shipping companies care more on profits and are more likely to know whether the implementation of a DRCS could help them to reduce detention cost, and how effective it is. In this regard, the proposed model is helpful to support their decisions as it provides a way for comparing the performance of different DRCSs in a quantitative manner, making it possible to carry out cost-effective analysis of DRCSs if needed. Furthermore, the effectiveness of one DRCS on different ships can also be calculated so that DRCSs can match different ships under different conditions more appropriately.

5 Conclusion

Although BNs have proven to be a powerful technique for reasoning under uncertainty and have been widely applied in the prediction of ship detention risk under PSC inspection, they cannot be used directly to make a decision in terms of the selection of the most effective countermeasures since such a decision are usually based on some certain criteria other than a single goal of safety. To solve this problem, this paper proposes a novel method by incorporating a data-driven BN with the TOPSIS method in a complementary manner for selecting risk control options of ship detention under PSC inspections.

The proposed model in this research is proved to be able to deal with both dynamic weights and evaluations when more evaluation results from experts are collected. The novel method can be used to quantitatively analyse the performance of different risk control strategies under PSC inspections, so as to provide stakeholders with helpful reference on the evaluation of DRCSs from different aspects and identify the most effective one under different situations. Moreover, the proposed model has the potential to be adapted to different application scenarios. On one hand, it helps collect and analyse the current information of ships under PSC inspection to model the relationships between different variables; On the other hand, based on the results of analysis, it can evaluate how much one DRCS can reduce the detention probabilities after being applied to reduce future detention risk. It is well reflected by the BN ability of supporting forward risk prediction and backward risk diagnosis.

It is worth noting that the ranking of DRCSs is mainly used to show the feasibility of the proposed model and methodology. When port/management company level data becomes available, the methodology can be tailored and applied to evaluate more specific DRCSs. The findings from the case should be further interpreted to meet the individual stakeholder requirements. Any implications from the discussed DRCSs should be carefully reviewed to avoid any misleading insights being disseminated inappropriately. In future research, with the proposed method being gradually applied in real world and more detailed information of the detainable deficiencies from PSC inspections being collected, more specific stakeholder-related DRCSs can be developed accordingly to guide the action of shipping companies, so that the safety of maritime shipping can be improved. Besides, the performance of these DRCSs can also be evaluated and compared to further validate and improve the proposed method.

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Appendix A

Questionnaire Survey

Three grades (using linguistic variables "*low*", "*medium*", and "*high*".) of performance of DRCSs are considered in terms of their influence on each detention risk parameter (or criteria). Linguistic grade *Low* means the investigated DRCS has a slight impact on the selected criteria, *Medium* indicates a moderate impact, and *High* indicates a strong impact.

The performance of each DRCS is estimated using the probability distribution of the linguistic variables provided directly by experts. For example, if an expert thinks that DRCS #1 has a slight impact on the vessel age with a belief degree of 20%, and a moderate impact on the vessel age with a belief degree of 80%. Then the performance of DRCS #1 with respect to vessel age will be 0.2 *Low* and 0.8 *Medium*. An example of the judgement on DRCS #1 with respect to each criterion is show in Table A1.

In a similar way, performance evaluation results of DRCSs from different experts can be obtained and merged together for case study.

Table A1 Example of judgement from an expert

DRCS	**Criteria**	**Performance of DRCSs**		
		Low	*medium*	*High*
No.1	Vessel age	20%	80%	
	Type of inspections		50%	50%
	Vessel flag	90%	10%	
No.2	Vessel age			
	Type of inspections			
	Vessel flag			
No.3	Vessel age			
	Type of inspections			
	Vessel flag			