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Realising Advanced Risk-based Port State Control Inspection using Data-Driven Bayesian Networks

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Abstract

In the past decades, maritime transportation not only contributes to economic prosperity, but also renders many threats to the industry, causing huge casualties and losses. As a result, various maritime safety measures have been developed, including Port State Control (PSC) inspections. In this paper, we propose a data-driven Bayesian Network (BN) based approach to analyse risk factors influencing PSC inspections, and predict the probability of vessel detention. To do so, inspection data of bulk carriers in seven major European countries from 2005-2008[2] in Paris MoU is collected to identify the relevant risk factors. Meanwhile, the network structure is constructed via TAN learning and subsequently validated by sensitivity analysis. The results reveal two conclusions: first, the key risk factors influencing PSC inspections include number of deficiencies, type of inspection, Recognised Organisation (RO) and vessel age. Second, the model exploits a novel way to predict the detention probabilities under different situations, which effectively help port authorities to rationalise their inspection regulations as well as allocation of the resources. Further effort will be made to conduct contrastive analysis between 'Pre-NIR' period and 'Post-NIR' period to test the impact of NIR started in 2008.

Key words: Port state control, Bayesian network, maritime risk, maritime safety, TAN network, maritime transport

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[2] In 2008, New Inspection Regime (NIR) was first introduced in Paris MoU port state control. Two sets of data, before and after 2008 are being collected for analysis of the effect of NIR. This paper, as the first phase study, analyses the detention probability before the implementation of NIR.

1. Introduction

The past decades witnessed an unprecedented growing rate on maritime transportation demand, which on one hand contributes to industrial prosperity, but on the other hand renders threats and risks to the maritime industry, including but not limited to ship collisions, stranding, fire, and oil spill causing large property losses, environmental pollution and casualties. For instance, the grounding of the Exxon Valdez, the capsizing of the Herald of Free Enterprise and the Estonia passenger ferry are well-known accidents in maritime transportation. These accidents attracted the attention of the world on maritime safety (Li et al., 2014; Yang et al., 2013; 2014; John et al., 2014; Pristrom et al., 2016; Zhang et al., 2016) and Port State Control (PSC) inspections have been implemented as an administrative measure to reduce the occurrence of maritime accidents and ensure maritime safety (Viladrich-Grau, 2003; Li and Zheng, 2007).

PSC inspections, which render port authorities the ability to inspect vessels in their own ports, are set up in order to prevent illegal actions of ship owners and maritime accidents. The PSC officers select high-risk vessels for inspection according to the risk estimation mechanism suggested by the regional PSC organizations (Xu et al. 2007). If a vessel fails to pass the inspection, it will face a certain level of detention based on its safety status. Actually, PSC inspections are regarded as the last line of defence in coping with substandard vessels that may cause maritime accidents. It is however well noted that although risk analysis approaches, qualitative or quantitative, have been widely used to enhance maritime safety in recent years, they have been insufficiently utilized in the PSC inspection area in the literature.

This study aims to develop a risk assessment model using Bayesian Networks (BNs) to reveal the importance degree of different risk factors influencing PSC inspection results, as well as predict the detention rate of individual vessels under different situations. In order to build the model, the bulk carrier data of seven major European countries from 2005 to 2008 is collected from Paris MoU online inspection database (www.parismou.org/inspection-search/inspection-search). Meanwhile, the casual factors related to PSC inspections are also identified from this database, including vessel flag, vessel age, DWT, classification society, inspection type, inspection port, number of deficiencies and inspection duration. The dependency among these factors and the casual relationships between them are simulated using qualitative diagram in BN while the quantitative configuration of such dependency (i.e. conditional probabilities) is obtained using a gradient descent approach based on the collected dataset (Jensen, 1999).

In this study, BN is constructed through a data-driven approach and it attempts, for the first time (up the authors best knowledge), to use BN in risk analysis and prediction on PSC. The network induced from a data-driven approach reduces the disturbance of experts' judgements on accuracy of the results. Additionally, incorporating BN to PSC inspections enables port authorities to predict the detention probability of vessels under different circumstances. The results of the study will provide important insights 1) for port authorities to ensure that optimal inspection actions are taken to improve safety at sea in a cost effective manner and 2) for ship owners to identify and address the potential deficiencies in advance. Moreover, it is useful for both stakeholders to make decisions in PSC inspections and check whether their actions are beneficial.

The remainder of this paper is organised as follows. Section 2 reviews the current literature relating to risk based PSC and use of BN in maritime risk assessment. Section 3 describes the methodologies and techniques applied in this study, which is followed by the risk based PSC model construction process and result analysis in Section 4. Finally, Section 5 concludes this study with reference to its contributions and implications.

2. Literature review

2.1 Risk studies on PSC inspection

Since PSC inspections play an increasingly important role in maritime safety, more and more researchers have conducted related studies in this area from both qualitative and quantitative perspectives. For example, the introduction and implementation of PSC inspection (Chiu et al. 2008), influence of PSC inspection (Cariou et al. 2011), relationship between maritime management and PSC inspection (Mitroussi, 2015) and game analysis on optimal inspection policies (Li and Yin, 2014). However, use of quantitative risk approaches in PSC is limited to risk diagnosis, waiting new solutions on real time risk prediction to be explored.

Shen (2003) and Yang (2004) both proposed risk assessment PSC systems, which had been proved to have better performance than traditional PSC inspection mechanisms. Knowing that intense maritime traffic may cause significant navigational challenges in Istanbul Strait, Kara (2016) applied weighted points method to assess the risk level of each vessel experiencing the PSC inspection under Black Sea MoU. However, the weighting and scoring methods adopted in these studies are at large based on subjective expert judgements, which may cause arguments on the results.

To address this problem, Xu et al. (2007) presented a risk assessment system based on Support Vector Machine (SVM) to estimate the risk of candidate vessels according to historical data before conducting on-board inspections. Evaluations showed that the proposed system could improve the accuracy of risk assessment. Gao et al. (2008) combined SVM and K-nearest neighbour approaches to facilitate the risk assessment system capable of coping with noisy data. Consequently, this method significantly improved the accuracy of results. Although showing attractiveness, such methods still reveal problems in practical applications in terms of their capability of providing real time risk prediction (e.g. ship detention probability) in dynamic situations.

Based on 183,819 PSC inspection records, Knapp & Franses (2007) applied binary logistic regression to measure the effect of inspections on the probability of casualties, especially for the very serious cases. Meanwhile, the model determined the magnitude of improvement areas for substandard vessels. Later in the same year, they did a further econometric analysis about the influence on the detention probability of different risk factors, and the results indicated only vessel types and PSC regimes were influential elements.

2.2 Bayesian network in maritime risk analysis

Qualitative analysis was largely used to assess maritime safety. For instance, in a score method, the selected evaluation factors are scored according to subjective experience. It provides the basis of the target factor method employed by Paris MOU and Tokyo MOU. However, over the years researchers realized that it is hard to achieve the best risk assessment results by qualitative or quantitative analysis separately. Fuzzy comprehensive evaluation (Pillay and Wang 2002; Akhtar and Utne 2014), grey system theory evaluation (Wu et al. 1997), neutral network evaluation (Li and Zhang 2000) and some other approaches are gradually used to complement qualitative analysis in maritime safety studies. Meanwhile, risk analysis is moving away from accident investigation to the analysis of risk factors, resulting in the creation of advanced methods on risk diagnosis and prediction, such as BN (Eleye-Datubo et al., 2006, Eleye-Datubo et al., 2008, Ren et al. 2008).

Taking advance of casual inference, BN can be used to analyse the importance degree of risk factors and the relationships between them. Compared to pure Bayesian theory, BN is more visualized; while compared to other graphic models, it has a foundation of mathematical knowledge. Because of its advantages, BN has been increasingly applied in maritime safety in the past decade. When summarizing the topics of the publications in this area, it is not surprising to find various aspects are covered. For example, the occurrence of ship-ship collisions (Hänninen & Kujala, 2012; Goerlandt & Montewka, 2015; Zhang et al., 2015), navigational safety (Banda, O.A.V. et al., 2016; Zhang et al., 2013; Hänninen et al., 2014; Wu et al., 2015), maritime accidents analysis and prevention (Hänninen, 2014; Li et al., 2014; Antao et al., 2009), offshore safety mangement (Ren et al., 2008; Eleye-Datubo et al., 2008), risk-based vessel design (Montewka et al., 2017), oil spill in maritime accidents (Goerlandt & Montewka, 2014), oil spill recovery (Lehikoinen et al., 2013) and PSC inspections (Hanninen & Kujala, 2014). The variety of topics indicates the popularity of BN in maritime safety area.

Despite such applications, a common criticism of BN is that it requires too much data in the form of prior probabilities, and such data is hard to collect, even inaccessible sometimes (Yang et al. 2008). Meanwhile, the size of conditional probability table (CPT) grows quickly in size as more parent nodes are added, leading to complexity and difficulty in computation.

Due to lack of empirical data, CPTs are often generated based on experts' judgements in many publications. However, for large-scale BN models, it is time-consuming, impractical and inconsistence (Mkrtchyan et al. 2015).

To address such concern, Li et al. (2014) proposed a solution through logit model and binary logistic regression to gain a large amount of likelihood of accidents as prior probabilities and built a maritime risk BN. However, it is available only when a large dataset is obtained. Another approach is called Noisy-OR. It was originally proposed by Pearl in 1988 and experienced several extensions. Through the Noisy-OR approach, the elicitation of full CPTs is simplified to the assessment of individual parent-child CPDs while the missing relationships are derived by combining the estimated CPDs disjunctively (Pearl 1988). Yang and Ning (2007) proposed non-impeding noisy-AND tree and improved it later in 2012, which enhanced BN's capability of dealing with multi-state and dependent nodes. Yet, its limitations on how to derive the tree topology and the fact that not all causal interactions can be expressed by the method affects its popularity (Yang and Ning 2012, Yang et al. 2012). Through applying ranked nodes to BNs, Norman et al. (2007) presented a novel but effective approach. The approach is based on the doubly truncated Normal distribution with a central tendency that is invariably a weighted function of parent nodes. The results of case studies proved that the elicitation burden is much reduced by using ranked nodes. It is naturally an evolutionary approach of expert judgments. Other approaches, like Monte Carlo Simulation (Min et al. 2011), interpolation of anchor inputs (Cain 2001, Wisse et al. 2008), and function based methods (Vinnem et al. 2012), also provide different ways to cope with the drawbacks of BN in terms of high demand on prior probabilities.

2.3 Data-driven approaches for BN construction

Normally, the structure of a BN is constructed using human expert knowledge or common sense. However, such an approach is time consuming, and heavy emphasis is placed on experts to provide both the local probability parameters and dependency among the parameters. An alternative method for BN construction is to induce the network structure from data, namely the data-driven approach, which can greatly reduce the dependence on human experts and in some cases increase the accuracy of the model. However, a significant drawback of data-driven approach is that the number of possible structures for a given problem grows super-exponentially with the number of employed variables in the problem domain. Therefore, lots of effort has been made from the literatures to reduce such complexity.

Dependency analysis, which is based on conditional independence test, was developed by Spirtes and Glymour (1991) and improved by Cheng et al. (1997) and Thomas (2005). Although there exist several drawbacks, such as extensive testing of independence relations to derive the final network structure (Singh and Valtorta, 1993), it is still recognised as a good attempt to deal with computational complexity problems in network construction.

Unlike the dependency analysis approach, the search and score approach is more popular and presents a better result. It seeks to explore a search space of candidate BN structures for the one that best represents the causality and dependency relationships (Cooper et al. 1992). It is more like an optimization problem in nature. To achieve the objective, a scoring is indispensable. Cooper and Herskovits (1992) derived K2 scoring metric based on Bayes theorem, starting with an empty network and iterating through each node to get the best structure. An order among the variables needs to be assumed in this algorithm, making it hard to determine. In contrast to Cooper and Herskovits, Buntine's 'B' algorithm (1991) does not require a variable order. A link will be added at the end of each iteration if it can maximize the score and does not lead to a cycle, until the score no longer increases. However, once local optima occurs, the algorithm could not give reasonable results. Besides these two algorithms, other algorithms such as conditional independence and Bayesian learning algorithm (Singh and Valtorta 1993), genetic algorithm (GA) (Larra 1996, Novobilski 2003), and ChainGA algorithm (Kabli et al. 2007) present distinctive ideas in optimisation of network construction, respectively.

When applied in risk-based PSC inspection study, according to the reviewed literatures, BN shows its superiority (e.g. bi-directional analysis) over risk assessment approaches, presenting a novel way to analyse PSC inspections for ship owners and port authorities. In other words, whenever the information about a specific ship concerning the defined nodes is obtained, its ship owner/operator or the authority of the port that the ship visit can use the BN based PSC model to analysis the detention probability of the ship in a forward risk prediction. If the ship is detained, the owner/operator can use it again to analyse the most possible causes leading to the detention in a backward risk diagnosis. Furthermore, it combines the visualized graph with mathematical knowledge, enabling it to analyse the inner relationship between different variables influencing PSC inspection results. However, because of the research challenges on CPTs and network construction, BN's advantages in risk-based PSC have not yet been appropriately explored, revealing the major research gap to be fulfilled.

3. Methodology

Normally, the process of developing a data-based BN model consists of four phases: data acquisition, BN structure learning, BN monitoring and analysis, and model validation (Zhang et al. 2013). When applying it in the context of risk-based PSC inspections, a new conceptual methodology to analyse PSC inspections is developed including the following six steps in this study.

3.1 Data acquisition

To determine if a vessel is more likely to be detained, a list of historical PSC inspection records is necessary. The data used in this study is derived from Paris MoU online inspection database (www.parismou.org/inspection-search/inspection-search, 2005-2008), which presents the details of inspections and provides a comprehensive and support dataset for this study.

3.2 Variable identification

Based on the inspection records from Paris MoU database, several variables are identified, including vessel flag, Recognized Organization (RO), dead weight tonnage (DWT), vessel age, type of inspection, port of inspection and number of deficiencies. It is noteworthy that the factors concerned are those influencing detention, rather than inspections. In this study, the risk variables are set as the 'root variables', or 'first level risk variables' influencing detention rates of vessels. However, the size of the relevant CPT table would have been enormous if all root variables are defined as the parent nodes of inspection results in terms of 'detention'. To solve this issue, two intermediate level risk variables are introduced based on the principal of divorcing approach (Jensen, 2001), one is 'vessel group', and the other is 'inspection group'. Vessel-related root variables (i.e. vessel age, flag, RO, DWT) and inspection-related root variables (i.e. type of inspection, port of inspection, and number of deficiencies) are connected as the parent node of the two intermediate level variables, respectively. Then the two intermediate level risk variables will act as the parents of the node 'detention'. In fact, they are two dummy variables to help reduce CPT calculation work. 'Vessel group' is the child node of vessel-related variables, while 'Inspection group' is the child node of inspection-related variables. They are at the same level in network and jointly act as the parent nodes of 'Detention'. The hierarchical BN structure can significantly reduce the CPT calculation work (Huang et al. 2006).

3.3 Structure learning through data-driven approach

After identifying risk variables in the second step, a qualitative BN representing their interactive dependencies can be constructed through a data-driven approach, called TAN learning (Friedman et al, 1997).

3.3.1 TAN learning

The essence of TAN learning is actually an optimization problem. Let $A_1 \ldots A_n$ be the attribute variables (e.g. the first level root variables) and C be the class variable (e.g. 'Vessel group') in PSC inspection. Π_C represents the parent variables of C. B is defined as a TAN model if $\Pi_C = \emptyset$ and there is a function π that defines a tree over $A_1, \ldots, A_n$ such that $\Pi_{A_i} = \{C, A_{\pi(i)}\}$ if $\pi(i) > 0$, and $\Pi_{A_i} = \{C\}$ if $\pi(i) = 0$. The optimization problem consists on finding a tree defining function π over $A_1 \ldots A_n$ such that the log likelihood is maximized, and the TAN model under this function is the structure of the target BN model. One difference between BN model and TAN model lies in class variables. Class variables in BN model always have at least one parent node. However, since we will do Bayesian inference on the results, it is accepted for links to go in either direction to best fit the result reflecting the reality. In other words, we can change the directions of links in TAN model appropriately to fit the demand of BN.

The procedure called Construct-TAN can solve this optimization problem. This procedure follows the general outline proposed by Chow and Liu (1968), except that instead of using the mutual information between two attributes, it uses conditional mutual information between attributes given the class variable. This function is defined as

$$I_P(\boldsymbol{A_i}; \boldsymbol{A_j}|\boldsymbol{C}) = \sum_{\boldsymbol{a_{ii}},\boldsymbol{a_{ji}},\boldsymbol{c_i}} P(\boldsymbol{a_{ii}}, \boldsymbol{a_{ji}}, \boldsymbol{c_i}) log \frac{P(\boldsymbol{a_{ii}}, \boldsymbol{a_{ji}}|\boldsymbol{c_i})}{P(\boldsymbol{a_{ii}}|\boldsymbol{c_i})P(\boldsymbol{a_{ji}}|\boldsymbol{c_i})} \tag{1}$$

where I_P represents the conditional mutual information, $\boldsymbol{a_{ii}}$ is the *i*th state of attribute variable $\boldsymbol{A_i}$**,** $\boldsymbol{a_{ji}}$ is the *i*th state of attribute variable $\boldsymbol{A_j}$, $\boldsymbol{c_i}$ is the *i*th state of class variable $\boldsymbol{C_i}$**.**

This function measures the information that $\boldsymbol{A_i}$**,** $\boldsymbol{A_j}$ both have when the value of $\boldsymbol{C}$ is known.

The Construct-TAN procedure of PSC inspection consists of five main steps:

a) Compute $I_P(A_i, A_j|\ C)$ between each pair of attribute variables in PSC inspection, $i \neq j$.
   Attribute variables in PSC inspection: vessel flag, Recognized Organization (RO), dead weight tonnage (DWT), vessel age, type of inspection, port of inspection and number of deficiencies.
   Class variables in PSC inspection: vessel group, inspection group
b) Build a complete undirected graph in which the vertices are the attributes A_1,..., A_n. Annotate the weight of an edge connecting A_i to A_j by $I_P(A_i, A_j|\ C)$.
c) Build a maximum weighted spanning tree.
   Spanning tree: A spanning tree is a connected subgraph containing no cycles.
   Maximum weighted spanning tree: The maximum weight spanning tree is a spanning tree that no other spanning tree has a larger sum of weights on its edges.
   Therefore, the maximum weighted spanning tree in our study is the tree that has a maximum sum of $I_P(A_i, A_j|\ C)$.
d) Transform the resulting undirected tree to a directed one by choosing a root variable from the attribute variables and setting the direction of all edges to be outward from it.
e) Construct a TAN model by adding a vertex labeled by class variable *C* and adding an arc from *C* to each A_i.

Compared to other data-driven network construction approaches, like naive BN (Langley et al., 1992) and C4.5 (Quinlan, 1993), TAN is proved to be more competitive and accurate (Murphy et al. 1995).

3.3.2 Construction of BN for risk-based PSC

To reduce the size of the CPT of the node 'detention', the BN construction process is conducted as follows:

a) Divide the risk variables into two groups, 'vessel group' and 'inspection group'

   Vessel group

   The first level variables are vessel age, vessel flag, classification society, and DWT
   The intermediate level variable is vessel group.

   Inspection group

   The first level variables are port of inspection, type of inspection, number of deficiencies.
   The intermediate level variable is inspection group.

b) The structure of each group is established via the TAN learning approach in Section 3.3.1. 'Vessel group' and 'Inspection group' are set as the target node of each group respectively.

c) Combine two group structures and 'detention' together to obtain the final BN structure.

3.4 CPT distribution of the risk-based PSC BN

When the structure of the PSC BN is confirmed, the conditional probabilities of the nodes are required to model the uncertainties of risk variables. In this paper, the CPTs are formulated by using a gradient descent approach.

In the developed PSC BN, there is an existing evidence *e*, for example, the inspection database from 2005-2008. For a particular variable *V,* take 'Vessel age' as an example*,* we have $\boldsymbol{x} = P(V \mid e) = (x_1, \dots, x_n)$, which reflects the conditional probabilities of different states of 'Vessel age'. Meanwhile, we have a prior request $\boldsymbol{y} = (y_1, \dots, y_n)$ for $P(V \mid e)$. If the structure of BN is determined, the conditional probabilities associated with 'vessel age' are described by a set $\boldsymbol{t} = (t_1, \dots, t_m)$, for example, $P(vessel\ group =' high\ detention\ risk' | V = 'morethan20')$. Set $\boldsymbol{t}$ has an initial value $\boldsymbol{t}_0$, which based on the estimation or related experience. According to Bayes' rules, the conditional probability of 'vessel age' can be calculated as a function of set $\boldsymbol{t}$**,** denoted as $\boldsymbol{x} = P(V \mid e) = F(\boldsymbol{t})$. The objective of gradient descent approach is to adjust the conditional probability set $\boldsymbol{t}$ so that $P(V \mid e)$ is sufficiently close to $\boldsymbol{y}$**.** Once this objective is satisfied, the value of set ***t*** at this time is the corresponding conditional probabilities in the BN model of PSC.

A distance measure approach is introduced, called *Euclidean* distance ($dist_E$):

$$dist_E(\boldsymbol{x}, \boldsymbol{y}) = \sum_i (x_i - y_i)^2 \tag{2}$$

It is a metric, having the following characteristics:

1. $dist_E(\boldsymbol{x}, \boldsymbol{y}) = 0$ if and only if **x** = **y**
2. $dist_E(\boldsymbol{x}, \boldsymbol{y}) \leq dist_E(\boldsymbol{x}, \boldsymbol{z}) + dist_E(\boldsymbol{z}, \boldsymbol{y})$
3. $dist_E(\boldsymbol{x}, \boldsymbol{y}) = dist_E(\boldsymbol{y}, \boldsymbol{x})$

The task is to set the conditional probability set $\boldsymbol{t}$ such that the distance is as small as possible. If it is possible to determine $dist_E(\boldsymbol{x}, \boldsymbol{y})$ as a function of $\boldsymbol{t}$, then the problem can be solved directly. However, usually the problem cannot be solved directly even when the function is known, and a gradient descent method can be used:

a) Calculate **grad** $dist_E(\boldsymbol{x}, \boldsymbol{y})$ with respect to set $\boldsymbol{t}$.
b) Give $\boldsymbol{t}_0$ a displacement $\Delta\boldsymbol{t}$ in the direction opposite to the direction of the **grad** $dist_E(\boldsymbol{x}, \boldsymbol{y})(\boldsymbol{t}_0)$, which is denoted as:
$$\Delta\boldsymbol{t} = -\alpha\, \mathbf{grad}\, dist_E(\boldsymbol{x}, \boldsymbol{y})(\boldsymbol{t}_0)$$
Where the step size $\alpha > 0$.
c) Iterate this procedure until the gradient is close to 0.

From the definition above, that the following is obtained:

$$\mathbf{grad}\, dist_E(\boldsymbol{x}, \boldsymbol{y})(\boldsymbol{t}) = \sum_i 2(x_i - y_i)\mathbf{grad}\boldsymbol{x_i}(\boldsymbol{t}) \tag{3}$$

Once the adjustment process stops, the latest values of set $\boldsymbol{t}$ are defined as the conditional probabilities in BN model of PSC.

3.5 Generation of posterior probabilities and risk prediction

Once the BN structure and CPTs are properly constructed, the unobservable situations associated with PSC inspection can be predicted through the generated posterior probabilities when observable evidence is provided. Bayes' rule is applied to obtain the posterior probabilities in this study illustrated as follows:

Imagine there are only two variables 'vessel age' and 'vessel group', and 'vessel age' is the parent node of 'vessel group'. Set 'vessel age' as *M*, 'vessel group' as *N*, '$M = M_i$' means the vessel is at its *i*th 'vessel age' state, and the same goes to '$N = N_j$'.

According to Bayes' rule, the joint probability

$$P(M = M_i, N = N_j) = P(M = M_i) \times P(N = N_j | M = M_i)$$

Where: $P(M = M_i, N = N_j)$ represents the joint probability that events '$M = M_i$' and '$N = N_j$' both occur, $P(M = M_i)$ denotes the prior probability of the *i*th 'vessel age' state,

$P(N = N_j | M = M_i)$ denotes the conditional probability of the occurrence of *i*th 'vessel age' state given that *j*th 'vessel group' state occurs.

If the state of 'vessel group' is locked and the state of 'vessel age' is changed to different states, the sum of joint probabilities is known as the probability of *i*th 'vessel group' state described as follows:

$$P(N = N_j) = \sum_i P(M = M_i) \times P(N = N_j | M = M_i) \tag{4}$$

Further, when the variable *N* has more than one parent node, the probability of *i*th 'vessel group' state can also be calculated through equation (4) as it is a special case of binary variables.

Imagine $M^0, M^1, M^2, \ldots, M^n$ are parent nodes of N, and the ith state of kth parent nodes are represented as '$M^k = M^k_{i(k)}$' . Through applying equation (4), the probability of jth 'vessel group' state described as follows:

$$P(N = N_j) = \sum_{i(k)} P\left(M^1 = M^1_{i(1)}, M^2 = M^2_{i(2)}, \ldots, M^k = M^k_{i(k)}\right) \\ \times P\left(N = N_j | M^1 = M^1_{i(1)}, M^2 = M^2_{i(2)}, \ldots, M^k = M^k_{i(k)}\right)$$

Where *i (k)*, *k*= 1, 2... n, are independent numbers.

3.6 Sensitivity analysis, scenario simulation and model validation

Sensitivity analysis is known as a way to determine how the uncertainty in the output of a model can be influenced by the different sources of uncertainty in its input. In this particular study, a two-step sensitivity analysis has been developed to not only determine the influence degree of risk variables, but also validate the proposed model.

3.6.1 Mutual information calculation

Entropy is described as a value that, when increased, can be interpreted as increase in uncertainty of a dataset which would then require more information in order to describe that data. Consider a discrete random variable $\boldsymbol{\alpha}$ with possible values $\{\alpha_1, \alpha_2, \ldots, \alpha_i\}$ and probability mass function $P(\boldsymbol{\alpha})$, then the entropy can be explicitly written as:

$$H(\boldsymbol{\alpha}) = -\sum_i P(\alpha_i) log_b P(\alpha_i)$$

Where b is the base of the logarithm used. Normally, the value of b is 2.

Based on entropy theory, mutual information (entropy reduction) is introduced in this paper to measure the mutual dependence of different variables. Since our objective is to find the relationship between risk variables and 'detention', 'detention' is chosen as a fixed variable in mutual information calculation. Therefore, the mutual information between ‘detention’ and other risk variables can be defined as:

$$I(D,\beta) = -\sum_{d,i} P(d,\beta_i) log_b \frac{P(d,\beta_i)}{P(d)P(\beta_i)} \quad (5)$$

Where D represents ‘detention’, β represents risk variables, β_i represents the ith state of β, $I(D,\beta)$ represents the mutual information between ‘detention’ and risk variables.

The larger the value of mutual information is, the stronger relationship exists between variable ‘β’ and ‘detention’.

Moreover, the results of mutual information can help filter out insignificant variables in our model to avoid unnecessary work.

3.6.2 Scenario simulation - the effects of different variables

Once the variables are selected from mutual information calculation, scenario simulation, another form of sensitivity analysis, are needed to determine the effects of these variables. The classical way to set a scenario is to lock all the other nodes and change the target node gradually, for example, 10% as a step for up and down, and the changes rate can be used to analyse the effect of this variable. However, this approach has an obvious drawback that it is only suitable for variables having two states. For those who have more than two states, the classical way is not workable. Take the variable ‘vessel age’ in this study as an example, it has five states ‘0 to 5 years’, ‘5 to10 years’, ’10 to15 years’, ’15 to 20 years’ and ‘over 20 years’ (the reason for the classification is in section 4). If we increase the state ‘over 20 years’ from 0% to 10%, the overall value of other states will decrease from 100% to 90% accordingly. Actually, the combinations of in this case are innumerable, and it is impossible to decide which one should be applied. Therefore, the traditional scenario simulation (sensitivity analysis) is inappropriate to our study.

To overcome the difficulties, a new method (Alyami et al. 2016) is applied in this study. First, increase the probability of the state that can generate the highest detention rate to 100% to obtain the High Risk Inference (HRI). Secondly, increase the probability of the state that can generate the lowest detention rate to 100% to obtain the Low Risk Inference (LRI). Finally, the average value of HRI and LRI will show the True Risk Influence (TRI) of each risk variable in the entire PSC inspection system, and it is described as follows:

$$TRI = \frac{\mathrm{HRI} + \mathrm{LRI}}{2} \quad (6)$$

The sensitivity analysis results, or in other words, the influence degree on ‘detention’ of different risk variables, can therefore be ranked according to the value of TRI.

Through this approach, the downside of classical scenario simulation (sensitivity analysis) can be overcome.

3.6.3 Model validation

If the methodology and method in our study is reasonable and logical, then the sensitivity analysis must at least satisfy the following two axioms (Yang et al., 2009; Jones et al., 2010; Li, K.X. et al., 2014):

Axiom 1. A slight increase/decrease in the prior probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of the child node.

Axiom 2. The total influence magnitudes of the combination of the probability variations from x attributes (evidence) on the values should be always greater than the one from the set of x-y $(y \in x)$ attributes (sub-evidence).

4. BN model for PSC inspection before the implementation of NIR in 2008

4.1 Data

A database containing more than 80000 inspection records before the implementation of New Inspection Regime (NIR) from 2005 to 2008 is established and named as ‘Pre-NIR’ database. Data after this period is also under collection for a comparative study to investigate the impact of NIR in the next phase of this research project.

A preliminary analysis of the inspection records indicates that bulk carriers play a dominating role, as inspection records of bulk carriers occupies the biggest part, thus are selected as the research target in this paper.

4.2 Risk variables

The risk variables are classified into three levels as mentioned in Section 3.2

Firstly, the root variables influencing detention are explained with a particular reference to their state definitions as follows:

(1) Vessel flag

Each year a new White, Grey and Black list is published in the Paris MoU Annual Report. The “White, Grey and Black (WGB) list” presents the full spectrum, from quality flags to flags with a poor performance that are considered to have a high or very high risk. It is based on the total number of inspections and detentions over a 3-year rolling period for flags with at least 30 inspections.

This variable has four states: ‘White’, ‘Grey’, ‘Black’ and ‘Black (high risk)’, where the performance of each state decreases successively.

(2) Recognized Organization (RO)

The performance of recognized organizations is also summarized into a performance list by Paris MoU. According to Recognised Organisation Performance table published by Paris MoU every year, only those ROs that had 60 or more inspections in a 3-year period are taken into account.

Meanwhile, the RO table provides an official performance level classification: ‘high’, ‘medium’, ‘low’ and ‘very low’.

(3) Dead Weight Tonnage (DWT)

DWT is a measure of a vessel's weight carrying capacity, and does not include the weight of the ship itself. The ‘Review of maritime transport’ of United Nations Conference on Trade and Development (UNCTAD) classified bulk carriers into five categories according to DWT: ‘Small’, ‘Handysize’, ‘Handymax’, ‘Panamax’ and ‘Capesize’.

Dry bulk and ore carriers	
Capesize bulk carrier	100,000 dwt plus
Panamax bulk carrier	65,000–99,999 dwt
Handymax bulk carrier	40,000–64,999 dwt
Handysize bulk carrier	10,000–39,999 dwt

Figure 1 – Bulk carrier categories

(Source: UNCTAD Review of Maritime Transport, 2016)

(4) Vessel age

Vessel age is another important factor influencing inspection results. Old vessels are more likely to suffer detention. In UNCTAD reports, vessel age is categorized in Figure 2.

Table 2.2. Age distribution of world merchant fleet by vessel type, 2016

		Years					Average age		Percentage change, 2015–2016
		0–4	5–9	10–14	15–19	20+	2015	2016	
World									
Bulk carriers	Percentage of total ships	42.83	25.46	11.97	9.86	9.89	9.04	8.83	-0.21
	Percentage of dead-weight tonnage	46.40	25.95	11.48	8.14	8.04	8.06	7.95	-0.11
	Average vessel size (dwt)	78 988	74 330	69 988	60 182	59 281			

Figure 2 – Categorized Vessel age

(Source: UNCTAD Review of Maritime Transport 2016)

Refer to this table, vessel age has 5 states of ‘0 to 5 years’, ‘5 to10 years’, ’10 to15 years’, ’15 to 20 years’ and ‘over 20 years’, where ‘0 to 5 years’ means $0 \leq x < 5$, and so as others.

(5) Type of inspection

A PSC officer visiting a ship will conduct a general inspection of several areas to verify that the overall condition of the ship complies with the requirements by PSC.

If the ship is of full compliance, the PSC Officer will issue a 'clean' inspection report (Form A) to the master of the ship. In case that any deficiency is identified, the inspection report will include a deficiency-found report (Form B) indicating any follow-up actions to be taken to rectify the deficiencies indicated. Furthermore, control on compliance with on-board operational requirements may be included in the control procedures, particularly if an officer has a reason to believe that the crew demonstrates insufficient proficiency in that area.

This variable therefore has the three states of 'Initial inspection', 'More detailed inspection' and 'Expanded inspection'.

(6) Port of Inspection
Paris MoU consists of 27 participating maritime administrations and covers the waters of the European Coastal States and the North Atlantic basin from North America to Europe.

Seven major countries investigated in the research are Belgium, France, Germany, Italy, Netherlands, Spain and UK, which occupy 6913 cases in 11000 inspection records.

(7) Number of deficiencies (Nb of deficiencies)
During an inspection, a vessel may face detention if it is detected with deficiencies. There are different types of deficiencies, such as alarms, cargo operations, fire safety, navigation safety, ISPS. These deficiency types can be divided into two groups: major deficiencies and minor deficiencies. Major deficiencies can lead to direct detention regardless of its combination with other deficiencies.

From the inspection records, the detention rate increases dramatically between the following states: '0', '1 to 3', '4 to 9' and 'more than 10' (the number of inspected deficiencies are integer, e.g. '0' means 0 deficiency in inspection, '1 to 3' means the number of deficiencies are 1, 2 or 3). Hence, these four states are applied to node 'number of deficiencies'.

Secondly, the intermediate level risk variables are explained with a particular reference to their state definitions as:

(1) Vessel group
The variable 'vessel group', which presents the overall risk level of a vessel, is added to the network having connections with 'detention' and inspection-related variables. It has four parent variables, 'vessel flag', 'DWT', 'vessel age' and 'RO'. Meanwhile, it is the parent node of 'inspection type' because port authorities will choose inspection types according to the type (i.e. high or low risk) of the inspected vessel.

Four 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, the result reveals that most cases resulting in detention has a detention rate more than 10%, and other cases are lower than 10%.

(The selected combination of inspection-related nodes are under general conditions)

Therefore, in this study, this variable has two states of ‘High detention risk vessel’ and ‘Low detention risk vessel’.

(2) Inspection group

The ‘inspection group’ is set as the risk level of the inspection considering all inspection-related risk factors. Similar to ‘vessel group’, it also connects the inspection-related variables with ‘detention’. It has three parent variables, ‘type of inspection’, ‘port of inspection’ and ‘number of deficiencies’.

This variable has two states of ‘High detention risk’ and ‘Low detention risk’, and the distinguish criteria is also 10% detention rate as ‘Vessel group’.

Finally, a third level variable ‘Detention’ is determined by the two intermediate level variables, ‘Vessel group’ and ‘Inspection group’. It describes the results of an inspection given the application of the vessel group and the inspection group. This variable has two states, i.e. ‘Yes’ and ‘No’.

4.3 A new risk analysis model for PSC

The model for analysing PSC inspections is developed by considering the risk variables at different levels and their relationships mentioned in section 4.2. Because of the complexity and difficulty to construct BN model by TAN learning manually, Netica software package is used to assist the calculation. It has a ‘learning network’ function that can develop the TAN network based on Equation (1). The structure of BN is presented in Figure 3.

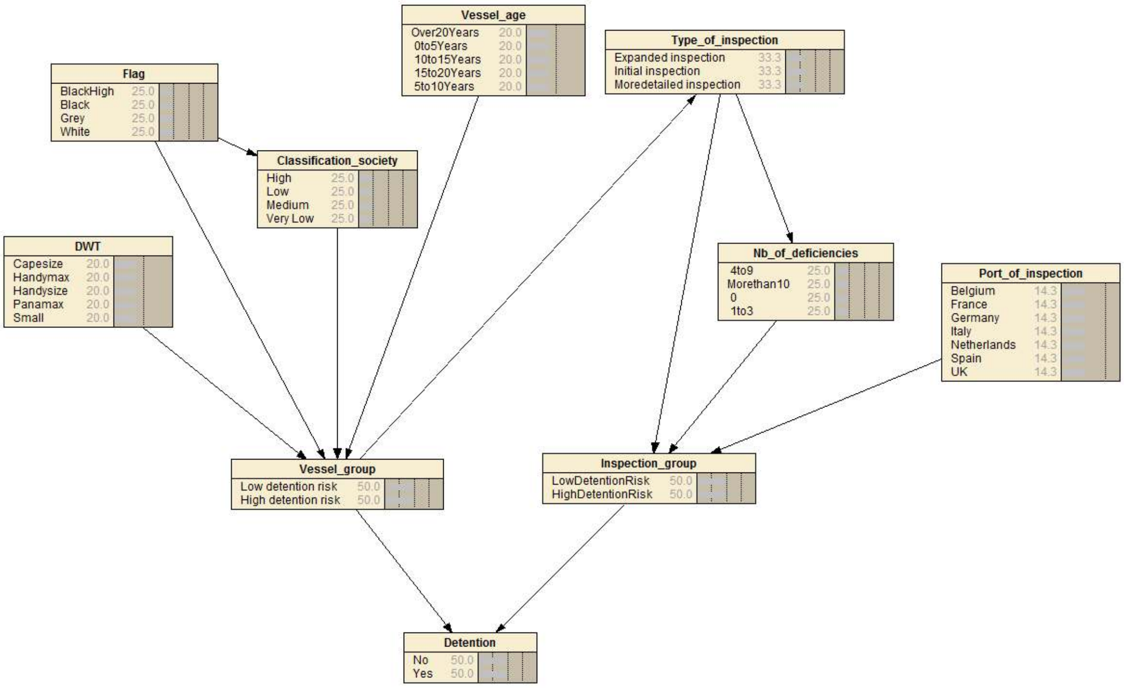

Figure 3 – Proposed BN for PSC inspection

4.4 CPT and prior probabilities for each node

Once the model is developed, the next step is to establish the CPT table of each node. When executing the BN model, the conditional probabilities of each node will be calculated through Equation (2) and (3) mentioned in gradient descent section.

Specifically, it is a three-step calculation process:

(1) With regard to the root nodes, the proportion of each defined state is used as the prior probabilities.

For instance, over the 6913 inspection records, 926 vessels are 0-5 years old, 962 vessels are 5-10 years old, 1050 vessels are 10-15 years old, 520 vessels are 15-20 years old, 3455 vessels are over 20 years old. Therefore, the calculation provides the prior probabilities of vessel age as

0 - 5 years: 926/6913= 0.1340 **5 - 10 years**: 962/6913= 0.1392
10 - 15 years: 1050/6913= 0.1519 **15 - 20 years**: 520/6913= 0.0752
Over 20 years: 3455/6913= 0.4998

In a similar way, the prior probabilities of other root variables are obtained and presented in Table 1.

Table 1 – The prior probability of each root node

DWT						
Capesize	Handymax	Handysize	Panamax	Small		
0.0073	0.1284	0.5949	0.0094	0.2600		
Flag						
Black (High)	Black	Grey	White			
0.0103	0.2218	0.0671	0.7008			
Vessel age						
0to5Years	5to10Years	10to15Years	15to20Years	Over20Years		
0.1340	0.1392	0.1519	0.0752	0.4998		
Port of inspection						
Belgium	France	Germany	Italy	Netherlands	Spain	UK
0.1297	0.1360	0.0866	0.1564	0.1243	0.2356	0.1315

(2) Once prior probabilities of root variables are determined, they are served as the prior request for the subsequent gradient descent calculation for other first level and intermediate-level risk variables.

(3) Similar to step 2, the conditional probabilities obtained in step 2 are set as the prior request for further calculation of third-level risk variable ‘detention’.

Tables 2 – 6 list the relevant conditional probabilities in this model.

Table 2 – CPT of RO

RO / Vessel flag	High	Low	Medium	Very Low
Black (High)	0.5819	0.2467	0.0565	0.1149
Black	0.9740	0.0044	0.0154	0.0063
Grey	0.8113	0.0316	0.0604	0.0967
White	0.9890	0.0036	0.0037	0.0036

Table 3 – CPT of ‘type of inspection’

Type of inspection / Vessel group	Expanded Inspection	Initial Inspection	More detailed Inspection
Low Detention Risk	0.2769	0.3305	0.3926
High Detention Risk	0.5701	0.1021	0.3278

Table 4 – CPT of 'number of deficiencies'

Nb of deficiencies / Type of inspection	4 to 10	More than 10	0 to 1	1 to 4
Expanded Inspection	0.3136	0.2079	0.2273	0.2512
Initial Inspection	0.1052	0.0093	0.6035	0.2820
More detailed Inspection	0.2807	0.0973	0.3322	0.2898

Table 5 – CPT of 'Vessel group'

Vessel age	Flag	RO	DWT	Low Detention Risk	High Detention Risk
Over20Years	Black (High)	High	Capesize	0.5062	0.4938
Over20Years	Black (High)	High	Handymax	0.4364	0.5636
Over20Years	Black (High)	High	Handysize	0.0012	0.9988
Over20Years	Black (High)	High	Panamax	0.5109	0.4891
Over20Years	Black (High)	High	Small	0.0014	0.9986
…	…	…	…	…	…
…	…	…	…	…	…
…	…	…	…	…	…
5to10years	White	Very Low	Capesize	0.5508	0.4492
5to10years	White	Very Low	Handymax	0.4492	0.5508
5to10years	White	Very Low	Handysize	0.4691	0.5309
5to10years	White	Very Low	Panamax	0.4704	0.5296
5to10years	White	Very Low	Small	0.5111	0.4889

Table 6 – CPT of 'Inspection group'

			Inspection group	
Port of inspection	Type of inspection	Nb of deficiencies	Low	High
Belgium	Expanded	4 to 10	0.9987	0.0013
Belgium	Expanded	More than 10	0.0015	0.9985
Belgium	Expanded	0 to 1	0.9986	0.0014
Belgium	Expanded	1 to 4	0.9987	0.0013
Belgium	Initial	4 to 10	0.9989	0.0011
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...
UK	Initial	1 to 4	0.9987	0.0013
UK	More Detailed	4 to 10	0.9986	0.0014
UK	More Detailed	More than 10	0.0013	0.9987
UK	More Detailed	0 to 1	0.9990	0.0010
UK	More Detailed	1 to 4	0.9985	0.0015

Table 7 – CPT of 'Detention'

		Detention	
Vessel group	Inspection group	No	Yes
Low Detention Risk	Low	0.9909	0.0091
Low Detention Risk	High	0.6471	0.3529
High Detention Risk	Low	0.9674	0.0326
High Detention Risk	High	0.5976	0.4024

4.5 Model result

Based on the CPT of each node, the marginal probability of each child node can be obtained using Equation (4). Figure 4 shows the result of the BN model using Netica. It indicates that the detention rate of a bulk carrier under inspection is estimated to be 4.52% given the input data covering the period of 2005-2008. If we calculate the detention rate from database directly, it is 4.57%, which shows a harmony with the result delivered by the model. The model is verified in terms of prediction of detention rate of bulk carriers.

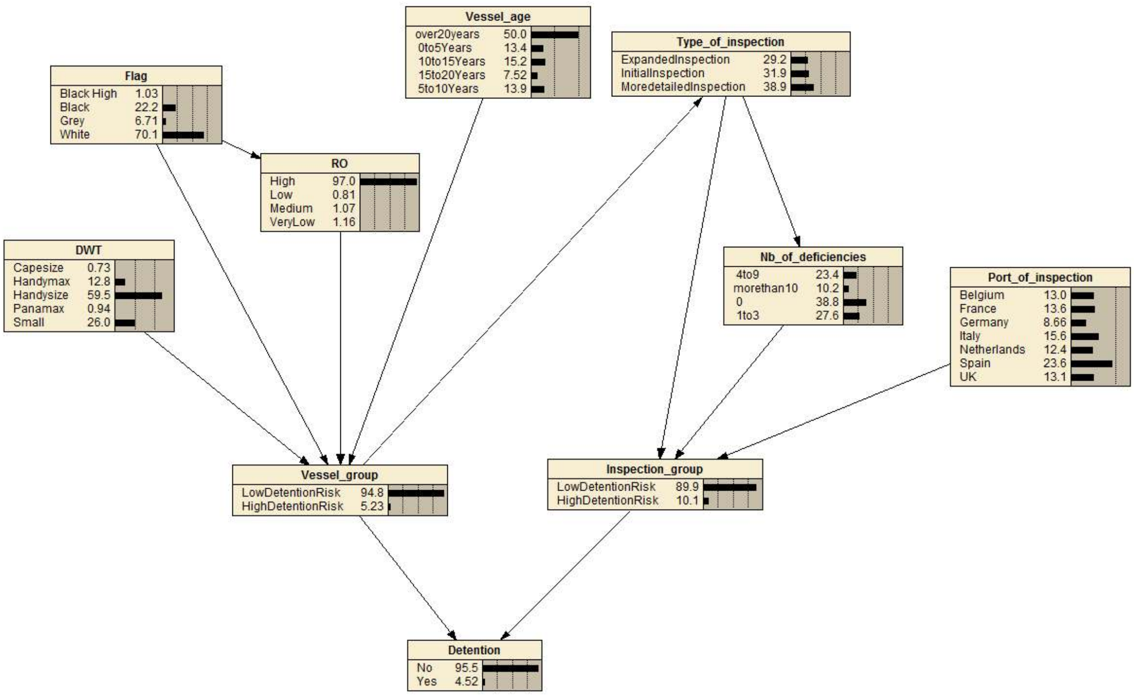

Figure 4 – Results of BN model

4.6 Sensitivity analysis and model validation

A sensitivity analysis is conducted to analyse influencing degree of risk variables and validate the model to prove its capability of realizing real-time risk prediction in dynamic environments.

4.6.1 Mutual information calculation

According to Equation (5) shown in 3.6, mutual information between 'detention' and other risk variables is obtained, which is shown in Table 8.

Table 8 – Sensitivity of 'Detention'

Sensitivity analysis			
Node	**Mutual Info**	**Percent**	**Variance of Beliefs**
Detention	0.26555	100	0.0431370
Inspection group	0.09654	36.4	0.0108729
Number of deficiencies	0.09386	35.3	0.0105047
Type of inspection	0.01464	5.51	0.0008056
Vessel group	0.00140	0.527	0.0001046
RO	0.00025	0.0933	0.0000171
Vessel flag	0.00025	0.0929	0.0000161
DWT	0.00009	0.0331	0.0000053
Vessel age	0.00003	0.0131	0.0000021
Port of inspection	0	0.0007	0.0000001

From Table 8, it is concluded that:

Firstly, inspection-related risk factors have stronger relationship with 'detention' than vessel-related variables in general, except 'port of inspection'. Port of inspection almost has no influence on final inspection results.

Secondly, the most significant node is therefore the variable 'Inspection group'. Mainly responsible for this impact is its parent nodes 'Number of deficiencies' and 'Type of inspection' can change the detention probability more significantly than other first level nodes.

Meanwhile, from Table 8, 'Inspection group', 'Number of deficiencies', 'Type of inspection', 'Vessel group', 'RO' and 'Vessel flag' are selected to do further analysis.

4.6.2 Scenario simulation - the effects of different variables

Table 9 and Table 10 shows the TRI value of selected nodes under different scenarios through Equation (6).

Specifically, the first row of each variable represents the normal scenario, and the following rows represent the different scenarios when each state of the variable reaches 100% occurrence probability respectively. The comparison between TRI of different variables indicates the results of sensitivity analysis – the influence degree of different risk variables.

Here 'Number of deficiencies' is selected to illustrate the process of scenario simulation.

Table 9 – TRI of risk variables (1)

Inspection group

High	Low	Detention rate	HRI	LRI	TRI
-	-	4.52%	31.18%	3.49%	17.34%
100%	0	35.7%			
0	100%	1.03%			

Number of deficiencies

0 to 1	1 to 4	4 to 10	More than 10	Detention rate	HRI	LRI	TRI
-	-	-	-	4.52%	30.48%	3.47%	16.98%
100%	0	0	0	1.05%			
0	100%	0	0	1.07%			
0	0	100%	0	1.10%			
0	0	0	100%	35%			

Type of inspection

Initial	Expanded	More detailed	Detention rate	HRI	LRI	TRI
-	-	-	4.52%	3.86%	3.41%	7.27%
100%	0	0	1.11%			
0	100%	0	8.38%			
0	0	100%	4.41%			

Vessel group

High	Low	Detention rate	HRI	LRI	TRI
-	-	4.52%	4.35%	0.24%	4.59%
100%	0	8.87%			
0	100%	4.28%			

Table 10 – TRI of risk variables (2)

RO

High	Medium	Low	Very low	Detention rate	HRI	LRI	TRI
-	-	-	-	4.52%	2.79%	0.07%	2.86%
100%	0	0	0	4.45%			
0	100%	0	0	5.95%			
0	0	100%	0	7.11%			
0	0	0	100%	7.31%			

Vessel age

0 to 5	5 to 10	10to15	15to20	over20	Detention rate	HRI	LRI	TRI
-	-	-	-	-	4.52%	0.14%	0.16%	0.3%
100%	0	0	0	0	4.36%			
0	100%	0	0	0	4.37%			
0	0	100%	0	0	4.36%			
0	0	0	100%	0	4.43%			
0	0	0	0	100%	4.66%			

Accordingly, based on the results obtained in Table 4.8, the most important variables can be listed as follows:

Inspection group > Number of deficiencies > Type of inspection > Vessel group > RO > Vessel age

As ‘inspection group’ and ‘vessel group’ are class variables which are not existed in PSC inspection records, ‘Number of deficiencies’ is in fact the most important risk factor, followed by ‘type of inspection’, ‘RO’ and ‘Vessel age’. This result indicates sub-standard performance of inspection-related items (Number of deficiencies, type of inspection, etc.) is more likely to lead to detention than unqualified intrinsic attributes of vessels (vessel age, dwt, RO, etc.).

Meanwhile, the BN model in this study can be used to calculate detention rate of bulk carriers under different situations, serving as real-time prediction tool. Such a tool not only helps port authorities to test their policies, but also urges ship owners to improve their vessels accordingly.

In addition, the floating range of different variables on detention rate can also be obtained from this table.

4.6.3 Model validation

To validate the model, another sensitivity analysis is carried out by investigating the detention rate of the minor change given different risk variables. By selecting ‘Inspection group’ as the first node, the state generating highest detention rate is increased by 10%, while the state generating lowest detention rate is decrease by 10%. This change is denoted as ‘~10%’ in this study. Once the updated detention rate is obtained, same change is applied to next node and the combined detention rate is calculated. The sensitivity analysis continues in the same manner until all nodes are included. The following Table 11 presents the results of this sensitivity analysis.

Table 11 – Detention rate of minor change in variables

Inspection group	Number of deficiencies	Type of inspection	Vessel group	RO	Vessel age	Detention rate
-	-	-	-	-	-	4.52%
~10%	-	-	-	-	-	7.98%
~10%	~10%	-	-	-	-	7.99%
~10%	~10%	~10%	-	-	-	8.55%
~10%	~10%	~10%	~10%	-	-	9.14%
~10%	~10%	~10%	~10%	~10%	-	9.59%
~10%	~10%	~10%	~10%	~10%	~10%	9.71%

The first row shows the original detention rate and the rest of the table presents the updated detention rates by changing risk variables continuously. Through comparing the updated results with the initial detention rates, it is claimed that the model is proved to be in line with Axiom 1.

As to Axiom 2, it can be examined by comparing the initial detention rate with reassigned detention rates, in which can be regarded as the evidence and sub-evidence. From Table 11, the detention rate is gradually increasing along with the continuous variation of risk variables, which proves the model is sound in line with Axiom 2.

In general, the model developed is proved reasonable and reliable. It can be used to predict the detention rate of PSC inspection of Paris MoU when any new evidence is entered. Meanwhile, the results of the model, as well as the variation law of detention rate, can be used by port authorities to improve their policies and ship owners to increase their passing rate.

4.7 Research implications - model applications in real cases

In this section, some real cases are simulated to illustrate how the proposed model can help both port authorities and ship owners in PSC inspections. The information in the cases is set based on the real inspection records in Paris MoU online database.

4.7.1 Case I

A bulk carrier was inspected at Port of Immingham in 2008, and the information of this inspection is shown as follows:

1. Vessel age: 2 years
2. Vessel flag: Singapore (White list)
3. DWT: 45223 dwt (Handysize)
4. RO: NKK (High)
5. Inspection: initial inspection
6. Port: Immingham (UK)
7. Number of deficiencies identified: 0

To determine whether this vessel meets the requirement of PSC regulations, port authority of Immingham should input the information of this inspection into the proposed BN model. The result indicated the detention rate was 0.95%, demonstrating this vessel was standard and should not be detained.

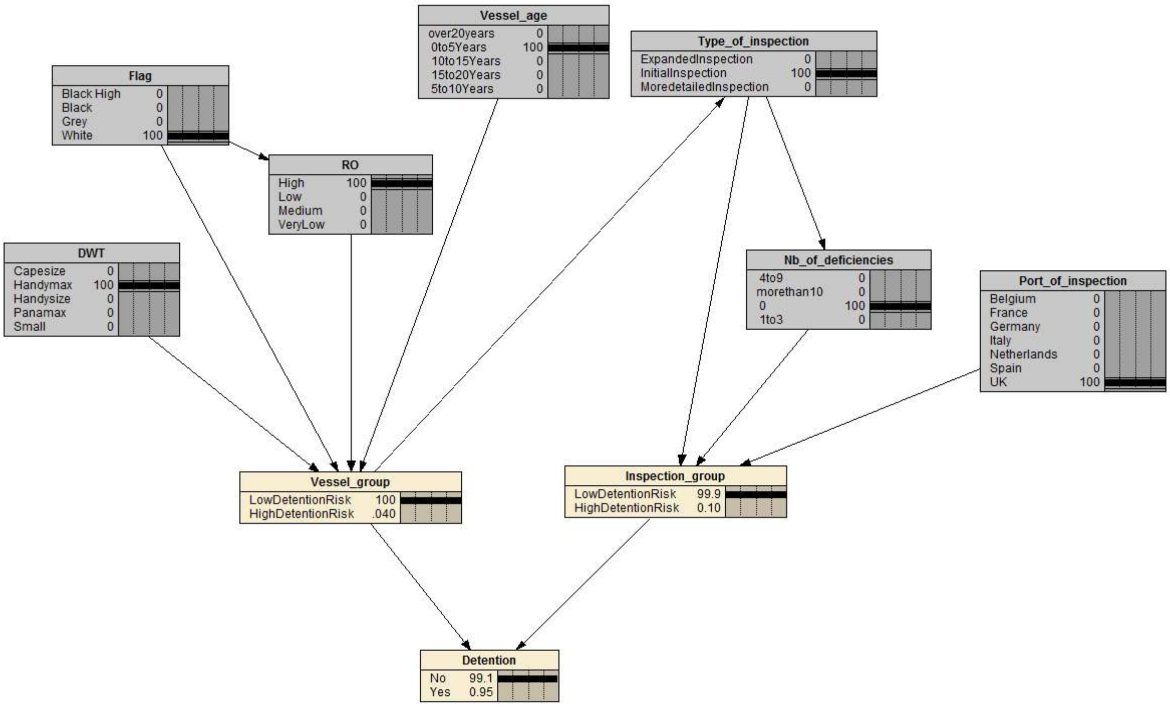

Figure 5 – model prediction of inspection result

In fact, the inspection record of *case I* in Paris MoU online database showed this vessel passed the inspection, which coincides with the model result, illustrating the effectiveness of the model in PSC inspections.

4.7.2 Case II

The relevant information gathered from a bulk carrier that was to be inspected at Port of Hull in England in Year 2008 was:

1. Vessel age: 23 years
2. Vessel flag: Panama (Black list)
3. DWT: 13685 dwt (Handymax)
4. RO: NKK (High)
5. Inspection: Expanded inspection
6. Port: Hull (UK)
7. Number of deficiencies identified: 18

Perspective from the port authority of Hull

Port authorities aims at regulate the behaviour of ship owners to avoid potential accidents and ensure ship safety through their PSC inspections. The vessels at high risk need to be identified and detained. In this case, the port authority of Hull could input the relevant information related to this inspection into the proposed BN model, the result indicated the detention rate was 35.3% under this condition in Figure 5. Compared to the normal detention rate 4.57%, the detention rate of this vessel was almost 8 times higher. Meanwhile, it was 36 times higher than the detention rate of standard vessel in Case I (0.95%). Therefore, this vessel was sub-standard and port authority of Hull needed to detain this vessel to avoid potential accidents at sea.

In fact, if we check the result of this inspection from Paris MoU database, this vessel is indeed detained, proving the effectiveness and accuracy of the model when making decisions for port authorities.

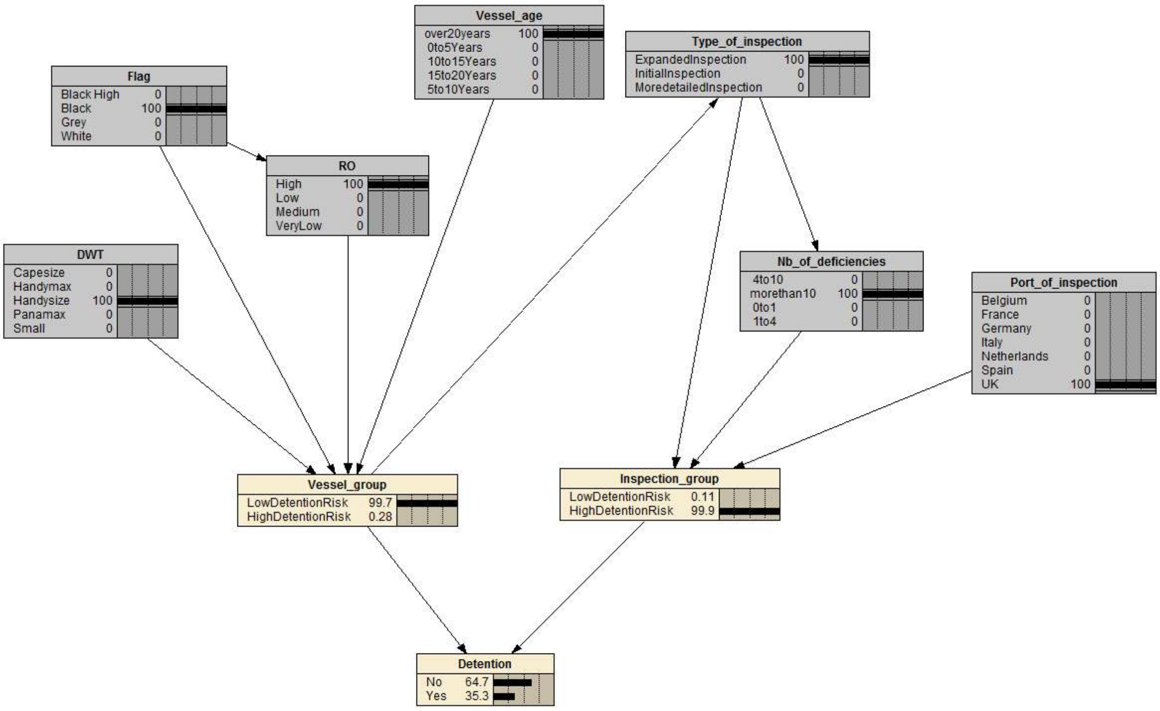

Figure 6 – Perspective of Hull Port authority

Perspective of the ship owner

Once this ship owner was informed that his/her vessel was detained, he/she needed to address all the identified deficiencies. If the vessel were detained in succession, it would have a very high probability to be banned by Paris MoU. Different from port authorities, ship owners cared more on profits and thus evaluated whether the investment on repair/maintenance could help them avoid detention next time. In this regard, the BN model is helpful for rationalize their decisions.

When the ship owner fixed the deficiencies according to the detention report and remains the vessel at a high quality status by reducing the number of deficiencies to less than 10. When it was inspected in Port of Hull in this case, even under the worst situation where the expanded inspection was conducted, the likelihood for its detention was only 0.97% shown in Figure 6.

Therefore, it would strongly motivate the owner to rectify the deficiencies given it was proved to be beneficial.

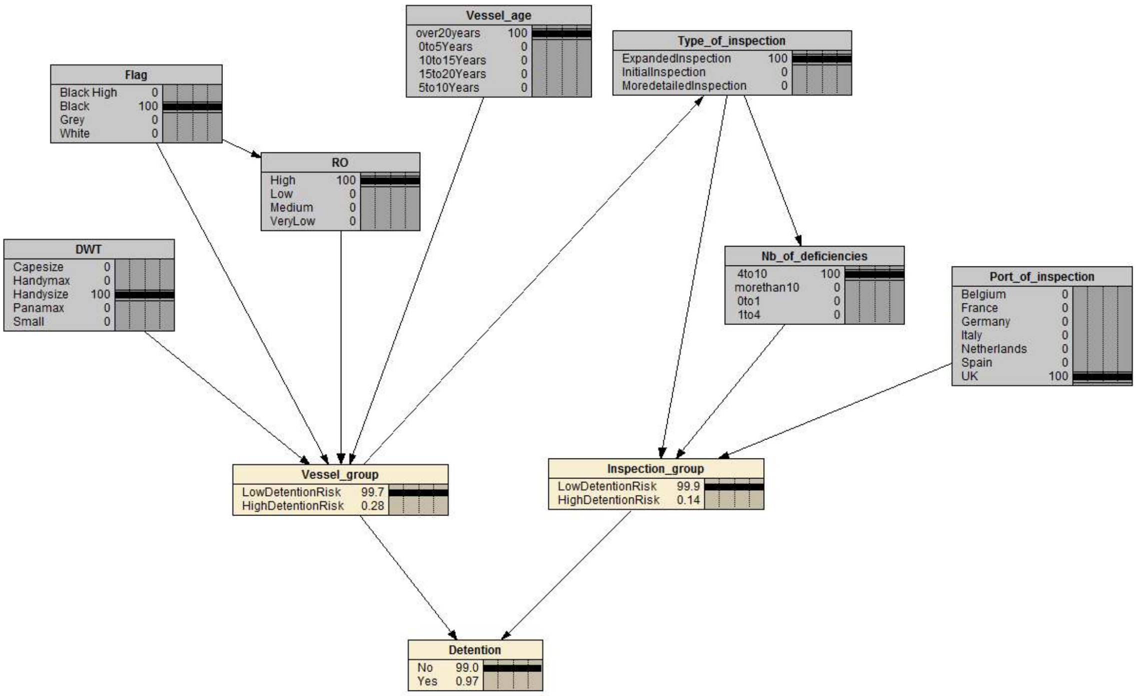

Figure 7 – Perspective of the ship owner

5. Conclusion

PSC inspection is set as an effective way to prevent maritime accidents and illegal actions of ship owners. Previous studies on PSC inspection are mostly based on qualitative analysis for the development of PSC policies.

In this paper, BN, along with the data-driven structure learning approach, are applied to analyse PSC inspections in the context of Paris MoU. In order to facilitate the study, the data relating to bulker carriers of seven major countries in Europe at the 'Pre-NIR' time is collected by a web crawler program from online inspection database of Paris MoU. Meanwhile, the risk factors are identified using the inspection records. Through TAN learning, the data-driven approach, a risk-based BN for PSC is constructed to serve as a real time risk analysis and prediction tool. CPT is calculated through a gradient descent approach, and sensitivity analysis is implemented at last to validate the model.

The results of analysis reveal the important risk factors in PSC inspection are Inspection group, Number of deficiencies, Type of inspection, Vessel group, RO, Vessel age in order. As inspection group and vessel group are intermediate level variables that are not existed in PSC inspection records, 'Number of deficiencies' is in fact the most important risk factor, followed by ‘type of inspection’, ‘RO’ and ‘Vessel age’. Meanwhile, the real-time risk prediction function of BN model in this study can be used to calculate detention rate of bulk carriers under different situations. It can effectively help port authorities to improve their inspection regulations and policies.

In general, the findings from the BN presents the overall picture of PSC detention of Paris MoU before 2008, which forms the first part of our PSC inspection study. New data in the duration of 2009-2017 is being collected to conduct a comparative study to demonstrate the effectiveness of NIR since 2008. Additionally, further effort should also consider ‘detention time’, which is the punishment intensity for vessels that fail to pass the inspection.

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