Bayesian Network modelling of Port State Control Inspections

Antonios Bastoulis

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Supervisor: Prof. Ângelo Manuel Palos Teixeira

Examination Committee
Chairperson: Prof. Carlos António Pancada Guedes Soares
Members of the Committee:
Prof. Ângelo Manuel Palos Teixeira
Dr. Pedro Manuel de Araújo Antão

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Abstract

The Port State Control (PSC) regimes have been developed after several important maritime accidents allowing countries to inspect foreign-registered ships in port other than those of the flag state and take action against ships that are not in compliance with international rules. In the present research, the risk influencing factors adopted in the definition of the Ship Risk Profile used for selecting ships for inspections under the New Inspection Regime of the Paris Memorandum of Understanding (MoU) on Port the State Control are characterized. Moreover, the PSC inspections at two ports, Thessaloniki and Liverpool ports, are analyzed in terms of type and age of ships and other factors influencing the ships' risk. In addition, the results of inspections in terms of detentions and number and type of deficiencies found at the two ports are analyzed. Finally, four Bayesian network models are developed using the data from Port State Control inspections. Two models are used to analyze the Thessaloniki port and two models the Liverpool port. The first two Bayesian network models, one for each port, are used to assess how risk factors such as the flag, the age, the recognized organization among others, influence the number of deficiencies and the detention of the ship. The other two models focus on the categories of deficiencies and how the risk factors influence specific deficiencies.

Key-words: Port state Control, Ship Risk Profile, Inspection data; Bayesian Network, Risk factors.

Resumo

Os regimes de Controlo pelo Estado do Porto (Port State Control - PSC) foram desenvolvidos após vários acidentes marítimos importantes, permitindo aos países inspecionar navios registrados em portos diferentes daqueles do estado de bandeira e tomar medidas contra navios que não estão em conformidade com as regulamentos internacionais. Na presente dissertação são caracterizados os fatores de risco adotados na definição do Perfil do Risco do Navio utilizado para seleção de navios para inspeções no âmbito do Novo Regime de Inspeção do MoU (Memorandum of Understanding) de Paris de Controlo pelo Estado do Porto. Além disso, são analisadas as inspeções do PSC em dois portos, o porto de Salónica e porto de Liverpool, em termos de tipo e idade dos navios e outros fatores que influenciam o risco do navio. Além disso, os resultados das inspeções também são analisados em termos de detenções e número e tipo de deficiências encontradas nos dois portos. Finalmente, quatro modelos de redes Bayesiana são desenvolvidos usando os dados das inspeções do Controlo pelo Estado do Porto. Dois dos modelos são utilizados para analisar o porto de Salónica e dois modelos para o porto de Liverpool. Os dois primeiros modelos de redes Bayesianas, um para cada porto, são usados para analisar como fatores de risco como a bandeira, a idade, a sociedade classificadora, etc. influenciam o número de deficiências e a detenção dos navios. Os outros dois modelos incidem nas categorias de deficiências, e como os fatores de risco influenciam deficiências específicas dos navios.

Palavras-chave: Controle pelo Estado do Porto, Perfil de Risco do Navio, Registos de Inspeções; Rede Bayesiana, Fatores de risco.

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List of Acronyms

BN: Bayesian Network

CIC: Concentrated Inspection Campaign

CPT: Conditional Probability Table

EMSA: European Maritime Safety Agency

HRS: High Risk Ship

IMO: International Maritime Organization

ISM: International Shipping Management

KPI: Key Performance Indicator

LRS: Low Risk Ship

MoU: Memorandum of Understanding

NIR: New Inspection Regime

PSC: Port State Control

RO: Recognized Organization

SRS: Standard Risk Ship

1. Introduction

1.1 Problem

Shipping is a very dynamic sector of global transportation as over 90% of international trade is carried by the sea due to its cost-effectiveness. For example, the ports of the European Union handle around 3.5 billion tons of goods and transport over 350 million passengers on thousands of ship journeys.

However, the occurrence of some important maritime accidents such as the grounding of the Exxon Valdez, the capsizing of the Herald of Free Enterprise and the foundering of Estonia passenger ferry attracted the attention of the world on maritime safety. The common causes of these accidents include, insufficient monitoring of the ship's technical condition, inadequate training of the crew and deficiencies in the safety management on board.

In the past, ship owners, masters and the flag states were the main responsibles for ensuring the vessels comply with the provisions of national and international rules. However, some flag states failed to fulfil their commitments agreed in international legal instruments, and subsequently, some vessels sailed in an unsafe condition, threatening the lifes of the crew as well as the marine environment. The Port state control (PSC) regimes have been developed in response to this situation, as ''second line of defense'' allowing countries to inspect foreign-registered ships in port other than those of the flag state and take action against ships that are not in compliance with international rules.

1.1.1 PSC and Paris MOU

The history of port state control begins in Europe. In March 1978 the Liberian-flagged oil tanker ''Amoco Cadiz'' ran aground off the coast of Brittany/France. The tanker broke into three parts, as shown in Figure 1.1. More than 220.000 tons of crude oil spilled out into the sea, thousands of seabirds perished. The accident was caused by a breakdown of the tanker's steering gear, insufficient monitoring of the ship's technical condition, inadequate training of the crew and deficiencies in the safety management on board.

Figure 1.1 ''Amoco Cadiz'' accident (Marine Insight)

This was the beginning of port state control. 14 European states agreed to join forces against unsafe ships, poorly trained crews and irresponsible ship owners. Since then, the Paris Memorandum of Understanding - Paris MoU on port state control has provided the basis to perform unannounced surveys of foreign-flagged merchant ships calling at ports of the member states of the Paris MoU.

The organization 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.

The current member States of the Paris MoU are: Belgium, Bulgaria, Canada, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, the Netherlands, Norway, Poland, Portugal, Romania, the Russian Federation, Slovenia, Spain, Sweden and the United Kingdom (www.parismou.org).

After Paris MOU in 1982, other regional MOU have also been signed. Some of the prominent ones are as follows such as:

- Tokyo MOU
- United States Coast Guard (USCG)

- Vina-Del-Mar Agreement (Latin America)
- Caribbean MOU
- Mediterranean Sea MOU
- Indian Ocean MOU

1.1.2 New Inspection Regime / Ship Risk Profile

On the 1 January 2011 the Paris Memorandum of Understanding on Port State Control (Paris MoU) implemented the European Union Directive 2009/16/EC introducing a New Inspection Regime (NIR).

With the introduction of the NIR, the initially defined 25% quota for inspections to be performed by each individual Member State was abandoned. As an alternative, a 'fair share' scheme was developed. The fair share scheme takes account of individual ship calls in a Member State versus the individual ship calls of all Member States. The Port call information must be provided by the Member States through SafeSeaNet and will then be transferred to the information system for Port State Control. SafeSeaNet is a system developed by EMSA which enables Member States to provide and receive information on ships and their hazardous cargoes. It provides, among others, the identification, position and status of a ship; times of departure and arrival; incidents reports, details on hazardous cargoes.

Moreover, under this New Inspection Regime the old Target Factor system is replaced by a risk-based one, the Ship Risk Profile. The new approach to inspections has been designed to reward quality shipping with a reduced inspection burden, whereas ships considered to be high risk will be subject to more frequent in-depth inspections.

Several factors are used in order to calculate Ship Risk Profile such as the type of ship, age of ship, flag, company performance and others. In this system ships are described as High Risk Ships (HRS), Low Risk Ships (LRS) or Standard Risk Ships (SRS). The ship’s priority for inspection, the interval between inspections and the scope of the inspection are determined according to Ship Risk Profile.

1.1.3 PSC inspection data

Data on PSC inspections are collected and analyzed to assess the risk influencing factors adopted in the NIR, such as the flag, Recognized Organization, company history, vessel history, etc.

Moreover, Port State Control inspection data are available at the Paris MOU website of all ships inspected in the ports of the current member states of Paris MOU along with the results of the inspection in terms of number of detentions and type of deficiencies found.

The data on Port State Control inspections are currently used to rank flag, Recognized Organization and company performance, factors used to calculate the risk profile. However, the data also provide a means to characterize the deficiencies identified in different ports and how the number and type of these deficiencies relate with the risk profile of the ships visiting the different ports. This can provide some indications on the inspection process in different countries.

Moreover, data on Port State Control inspections can be used to characterize probabilistically the influence of the risk factors adopted in the definition of the Ship Risk Profile on the risk of the ship and the type of deficiencies expected on a specific ship in a particular port.

Finally, inspection data can provide some indications for a better characterization of the risk profiles of the ships that are currently classified as low, standard and high risk ships.

1.1.4 Risk modelling by Bayesian Networks

Bayesian Belief Networks (BBNs) is a common tool used in several research works to develop frameworks for risk assessment. The capability of representing rather complex, not necessarily causal but uncertain relationships makes Bayesian Networks a powerful tool for risk modelling.

Bayesian Network models can be developed directly from data via expert elicitation or a combination of both. The data-driven approach reduces the dependence on human experts and in some cases increases the accuracy of the model.

Data based Bayesian Networks models will be developed in the present dissertation to analyze probabilistically the above issues using PSC inspection data from two different ports of Paris MoU region.

1.2 Objectives

To characterize the risk influencing factors adopted in the definition of the Ship Risk Profile used for selecting ships for inspections under the New Inspection Regime of the Paris MoU on Port the State Control.

To analysis the PSC inspections at two ports, port of Thessaloniki and Liverpool port, in terms of type and age of ships and other factors influencing the ship's risk.

To analysis the results of inspections in terms of detentions and number and type of deficiencies found at the two ports.

To develop Bayesian Network models to characterize the influence of the risk influencing factors on the Ship Risk Profiles and on the deficiencies identified in the inspection at the two ports.

To characterize probabilistically the main differences in the inspection practice at the ports of Thessaloniki and Liverpool.

To better characterize the risk profile of the ships by analyzing the relationship between the risk influencing factors of the ship and the observed risk reflected by the deficiencies found.

1.3 Work Structure

Chapter 1 introduces the problem along with the objectives of the current dissertation and a description of its structure. A brief introduction to the history of Port State Control and to Bayesian Network as a risk modelling tool is provided.

Chapter 2 reviews studies related to the topic of this dissertation. Early researches on maritime transportation and safety are presented. Moreover, studies on various aspects of Port State Control are reviewed too. Finally, studies that have developed Bayesian Network models and frameworks are presented in order to analyze different modelling approaches.

Chapter 3 describes the methodology used in the dissertation. Firstly, a detailed description of Paris MoU on Port State Control, including the New Inspection Regime (NIR) is presented. A detailed description of how Ship Risk Profile is calculated and how vessels are selected for inspection, along with information about categories of deficiencies and Concentrated Inspection Campaigns (CICs) are provided. Moreover, statistics on Port State Control inspections are analyzed in order to draw useful conclusion. Finally, an introduction to the theoretical background of the probability theory and Bayesian Networks is presented.

Chapter 4 address the Bayesian Network models developed and the results obtained in the present dissertation. Firstly, the two ports selected and how the inspection data was collected are presented. After that, an in depth analysis of the inspection data including important parameters such as risk factors, detention rate and deficiencies is provided. The Bayesian Network models developed, including variables used, topology and parameters are described. Finally, the results of the models are presented along with some scenarios in which evidences are included with an objective of identifying differences in the risk of the ships inspected and differences on the inspection practices in the two ports.

Chapter 5 presents the conclusions drawn and suggestions of improvements in future works.

2. Literature Review

Studies related to the research topic of the present dissertation are reviewed in this chapter. Firstly, early efforts and studies on safety maritime transportation are reviewed. After that, research works focusing on different aspects of Port State Control are analyzed. Finally, Bayesian Network applications and frameworks developed for maritime safety modelling are described and analyzed.

2.1 Studies on maritime transportation and safety

Due to the importance of maritime transportation and the variety of hazards there is an extensive research effort on maritime safety. According to Biobaku et al. (2018), the first notable study on Maritime Risk Analysis (MRA) was conducted in 1986 but only after 2000 a significant increase in the number of studies published every year is observed. Figure 2.1 shows the number of publications on MRA as function of time.

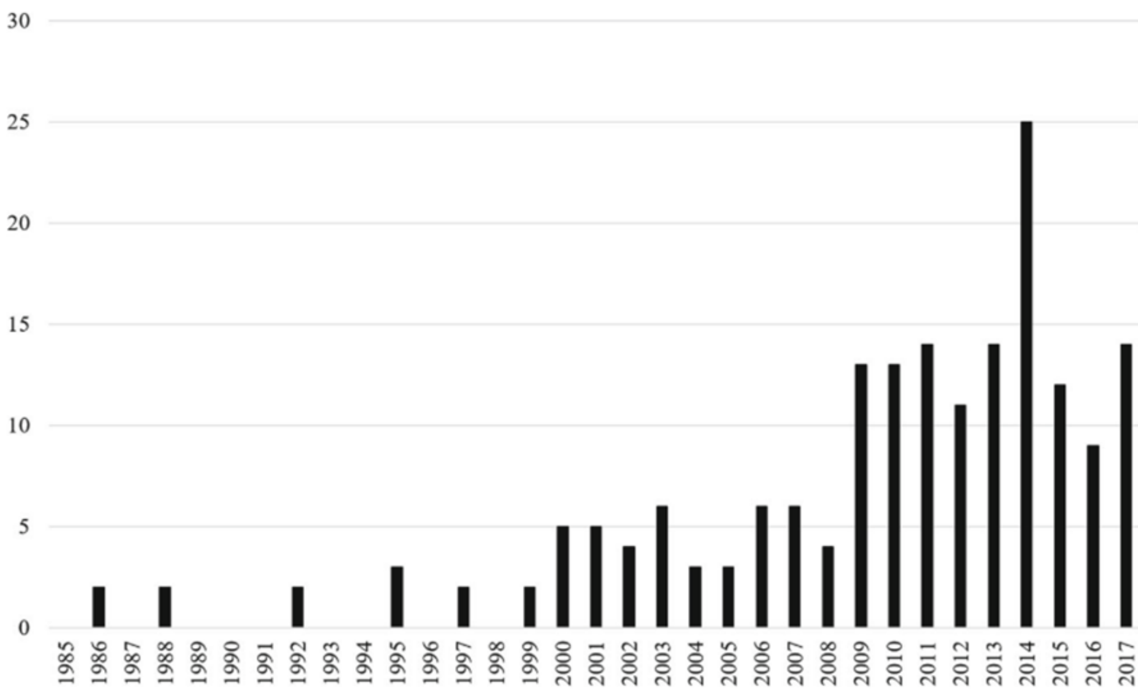


Figure 2.1 Number of publications on MRA (Biobaku et al., 2018)

Goerlandt and Montewka (2015) presented a review of risk definitions, perspectives and scientific approaches to risk analysis found in the maritime application area. Risk definitions are classified in nine categories. The most common is category D1 that defines the risk as the expected value of the probability of an event occurrence and the utility of the consequences. A risk perspective is a way to describe risk, a systematic manner to analyze and make statements about risk. Concerning risk perspectives, three aspects are considered. The measurement tools (probabilities, indicators, fuzzy numbers…), the scope of the analysis (events or events and consequences) and the tools applied to convey information regarding the confidence in the analysis (uncertainty and basis measures).

Among the early research studies on Maritime Risk Analysis, qualitative analysis was more common. Moreover, most studies were based on the accident statistics.

Guedes Soares & Teixeira (2001) have reviewed some applications of quantified risk assessment within the maritime transportation sector and identified early studies on the probability of ship loss by foundering and capsizing. They also addressed approaches used to assess the safety of marine structures.

Many frameworks have been developed for assessing risks in maritime industry with both quantitative and qualitative approaches.

Montewka et al. (2014) introduced a systematic, transferable and proactive framework estimating the risk for maritime transportation systems. Their framework is developed with the use of Bayesian Belief Networks and combines discrete and continuous variables. Moreover, they used the framework for a case study for ships collision in the Gulf of Finland (GoF).

Chai, Weng and De-qi (2017) developed a Quantitative Risk Assessment (QRA) model in order to evaluate the risk of ship collisions. The QRA technique is used to estimate the likelihood and the consequences of hazardous events. In order to test their model, they created a case study using one month's real-time ship motion data in Singapore.

2.2 Studies on PSC inspections

Since PSC is the main strategy to eliminate substandard ships, more and more research works have addressed this subject.

The main reason to develop regional cooperation for Port State Control is to avoid checking the same ship in every port and to have a common way for the inspections.

The literature on Port State Control is broad and covers many aspects such as elements of law, effectiveness, targeting, and discrepancies in implementation among others.

The factors used for targeting vessels for inspection are different between the MOUs. However, there is a relative consensus amongst the various MOUs. Three main categories play a vital role for the selection of the ship. Firstly, the vessel's characteristics such as the type and the age, secondly the performance of the flag, the classification society and the company and finally historic data from previous inspections.

Sage (2005) proposed a criterion for the identification of 'High Risk Vessels' (HRV) in European waters that would allow coastal States to monitor the movements of ships posing significant risk. The idea was to develop a risk index, which could be calculated and attached to ships individually. This index would identify High Risk Vessels and could include important criteria to assess the risk posed by vessels, such as their flag State, results of inspections, age, classification society, etc. Finally, the combination of a risk index attached to ships individually with dynamic factors, such as the weather, sea condition and environmental sensitivity, should determine the monitoring capability of coastal States for ships in waters under their jurisdiction.

Cariou, Mejia and Wolff (2009) investigated how the different target factors contribute to deficiencies and detentions of the vessel. They used data on 26.515 PSC inspections that took place within the Indian Ocean MoU region from 2002 to 2006. According to their results, the age of the ship, the classification society and the port where inspection occurs are the main contributing factors.

Cariou and Wolff (2015) proposed a methodology to complement existing practices focusing on detention with the objective to improve the selection process. They concluded that current practices should still rely on detention statistics when determining target factors but could be improved through a combination of quintile regressions for count data and Probit models, both applied to the number of deficiencies detected through. Such a method could be cost saving.

Graziano et al (2017) conducted a study to determine the factors leading to differences in treatment during the Port State Control inspection process among EU Member States. Data from 14 elite interviews, including policy makers, seafarers' and ship-owners was used and analyzed in this study. According to them, Paris MOU is the most effective of the regional agreements. However, a single training policy for Port State Control Officers will reduce the differences from country to country during the inspection.

Graziano et al. (2018) analyzed 25 inspection reports prepared by EMSA to monitor the level of implementation and enforcement of the Directive 2009/16/EC on Port State Control. They concluded that while the Directive has been properly implemented by the Member States, harmonization is yet to be achieved in order to have common standards in the region.

Chen et al. (2019) analyzed the factors behind the detention of ships using ship detention 2008–2017 data from port states in the Asia-Pacific Region collected by Tokyo MOU. The nine typical factors in the detention cases are selected and the correlation degree of each factor to the detention of ship port state is obtained using improved entropy weight Grey Rational Analysis (GRA) model. The factors considered are not ship-related (type, age, flag etc) but the types of deficiencies obtained from Tokyo MOU annual reports. The results obtained showed that the greatest factors in ship detention are ISM, Emergency Systems and Firesafety Measures. They are followed by factors including Water/Weathertight Conditions, Pollution Prevention and Life-saving Equipment, with moderately relevance. The remaining three factors, Safety of Navigation, Crew Certificates and Radio Communication have the lowest implication on the detentions.

2.3 Application of Bayesian Belief Networks

Bayesian Networks (BNs) is a common tool used in several research works to develop frameworks for risk assessment.

Hänninen (2014) used Bayesian networks for maritime safety modelling. They showed that the capability of representing rather complex, not necessarily causal but uncertain relationships makes BNs a powerful tool for modelling. The most important advantages of BNs are the easy combination of data with expert knowledge and the capability of updating the model with new information and of propagating evidences related to specific scenarios. However, as the model becomes more complex the utilization of several data sources is difficult.

One of the disadvantages of the Bayesian approach is that it requires too much information in the form of prior probabilities, and such information is often difficult to be obtained in risk assessment.

Wang et al. (2012) presented an innovative approach towards integrating logistic regression and a BN. In their model they used a binary logistic regression method of providing input for a BN, making use of different maritime accident data resources. All the conditional probabilities and prior probabilities of the nodes of the BN are obtained through the application of a binary logistic regression. Finally, they applied their approach to a case study in order to define how different factors contribute into ship total loss risk.

Hänninen and Kujala (2014) explored the dependencies of deficiencies and detentions of the ship and ship's involvement in accidents and incidents. They used Bayesian networks with the method of learning from the inspection, accident and incident data. The resulted models can be used for examining e.g. how numbers of different types of deficiencies, detention from an inspection, accident involvement and the ship age, type and flag are dependent and how observing the true states of network variables affect the probabilities of other variable states.

Sotiralis et al. (2016) presented an approach that more adequately incorporates human factors considerations into quantitative risk analysis of ship operation. The approach is based on the development of a Bayesian Network model that take into account the human performance and calculates the collision accidental probability due to human error.

Yang et al. (2018a) proposed a data-driven Bayesian Network (BN) based approach to analyze risk factors influencing PSC inspections, and predict the probability of vessel detention. Data related to bulker carriers of seven major countries in Europe at the 'Pre-NIR' time, from 2005 to 2008 in Paris MoU were used to identify the relevant risk factors. The results of analysis revealed that the important risk factors in PSC inspection are Inspection group, Number of deficiencies, Type of inspection, Vessel group, RO and Vessel age.

Yang et al. (2018b) presented a Bayesian Network model to determine vessel detention rates, emphasizing on company performance as a risk factor. The network was developed based on inspection data of bulk carriers in 2015–2017 involving nine major countries from the Paris MoU. A strategic game model was formulated by incorporating the BN model outcomes to assess the optimal inspection rates of bulk carriers. This can be used as a real-time decision tool for port authorities to respond to ships of different risk profiles under various dynamic situations.

3. Methodology

The methodology used for this dissertation is described in this chapter. The first part is about Paris MoU on Port State Control and covers various aspects such as the implementation of New Inspection Regime, Ship Risk Profile, target system, categories of deficiencies and Concentrated Inspection Campaigns. In the second part, statistics on Paris MoU are analyzed in order to have a better picture of the progress made recently. Finally, the third part introduces the theoretical background of the probability theory and Bayesian Networks which is necessary to understand better the models developed in Chapter 4.

3.1 Paris MoU on Port State Control

3.1.1 New Inspection Regime (NIR)

Every day around 55 ships are selected for a port State control inspection throughout the region of Paris MOU, according to Paris MOU website. To select the ships for inspection, Port State Control Officers (PSCOs) use an information system, known as 'THETIS', that supports the new Port State Control inspection regime (NIR). THETIS indicates which ships have priority for inspection, depending on Ship Risk Profile and allows the results of inspections to be recorded. Via THETIS these reports are made available to all Port State Control authorities in the Paris MOU. Data on ships particulars and reports of previous inspections carried out within the Paris MoU region are provided by the information system as well.

Every ship in the information system will be attributed a ship risk profile (SRP), according to Annex 7 of Paris MOU (Paris MoU on Port State Control, 2014). This SRP will determine the ships priority for inspection. Ships can be "high risk", "standard risk" or "low risk". The profile is calculated using generic and historic factors. A ship's risk profile is recalculated daily taking into account changes in more dynamic parameters such as age, the 36 month inspection history and company performance. Recalculation also occurs after every inspection and when the applicable performance tables for flag and ROs are changed.

Annex 7 of Paris MOU defines the factors and their weighting on the overall risk of the ship. High Risk Ships (HRS) are ships with 5 or more points in the risk profile point system. Low Risk Ships (LRS) are ships which meet all the criteria of the Low Risk Parameters and have had at least one inspection in the previous 36 months. Standard Risk Ships (SRS) are ships that are neither HRS nor LRS.

3.1.2 Ship Risk Profile

Risk Factors

Risk factors used for defining Ship Risk Profile are generic and historical as shown in Figure 3.1.

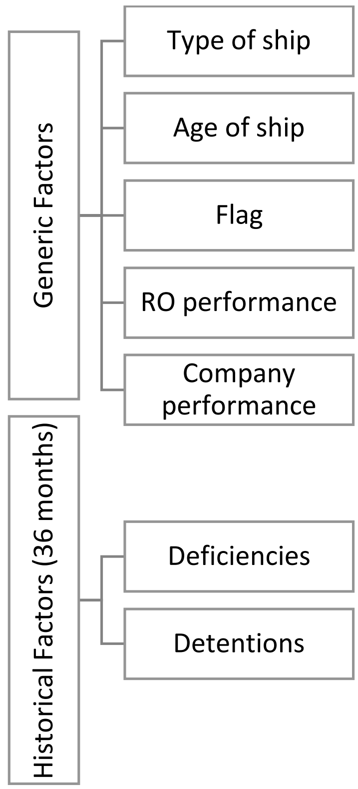


Figure 3.1 Risk Factors used to define Ship Risk Profile

Generic Factors

•Type of ship

The ship type denomination is as per a list adopted by the Paris MoU Committee. If a ship is a Chemical tanker, a Gas Carrier, an Oil tanker, a Bulk carrier or Passenger ship, it has 2 weighting points in the ship risk profile while all other types do not have points.

•Age of ship

The age of the ship is determined by the keel-laying date in dd/mm/yyyy format in the information system. If the ship is more than 12 years old, as calculated above, it has 1 weighting point in the ship risk profile system.

A ship reaches more than 12 years on dd/mm/yyyy+12. If only the year of keel-laying is available in the information system then the ship reaches more than 12 years on 31/12/yyyy+12.

•Flag

Every year Paris MOU organization publishes a new list with White, Grey and Black flags. The "White, Grey and Black (WGB) list" presents all the flags, from flags with high performance to flags with a poor performance that are considered high or very high risk. The flag ranking is based on the total number of inspections and detentions over a 3-year rolling period for flags with at least 30 inspections in the period. The most recent list is effective from 1 July in any year till 30 June the next year and can be found in Paris MOU website.

Flags that are in the Black flag list in the categories of Very High Risk (VHR), High Risk (HR) and Medium to High Risk (MtoHR) take 2 weighting points in the system. Black flags in the category of Medium Risk (MR) take 1 point.

•Recognized Organization Performance

Every year Paris MOU organization publishes a list with the performance of all Recognized Organizations taking into account of the inspection and detention history over the preceding three calendar years. To qualify for the criterion recognized by the Paris MoU the organization must be recognized by one or more Paris MoU Member States.

ROs whose total number of inspections over a 3-years rolling period does not meet the minimum of 60 are not included in the Paris MoU RO performance list.

Recognized Organizations rated as low or very low performance have 1 weighting point on Ship Risk Profile point system.

•Company Performance

Company's performance is calculated taking into account the detention and deficiency history of all ships in a company's fleet while that company was the ISM Company for the ship. Companies are ranked as having a "very low", "low", "medium" or "high" performance. The calculation is made daily on the basis of a running 36-month period. There is no lower limit for the number of inspections needed to qualify except a company with no inspections in the last 36 months will be given a "medium performance".

Company performance ranking consists of two parts, the detention and deficiency index as described below.

Deficiency Index

A point system is also used to calculate deficiency index. ISM related deficiencies are weighted at 5 points while other deficiencies are valued at 1 point. The Deficiency Index is the ratio of the total points of all deficiencies of all ships in a company's fleet to the number of inspections of all ships in the company's fleet within the last 36 months. This ratio is compared with the average for all ships inspected in the Paris MoU over the last 3 calendar years to determine whether the index is average, above average or below average as show in Table 3.1.

Deficiency index	Deficiency points per inspection
Above average	> 2 above PMoU average
Average	PMoU average ± 2
Below average	> 2 below PMoU average

Table 3.1 Deficiency Index calculation

Detention Index

The Detention Index is the ratio of the number of detentions of all ships in a company's fleet to the number of inspections of all the ships in the company's fleet within the last 36 months. This ratio is compared with the average for all ships inspected in the Paris MoU over the last 3 calendar years to determine whether the index is on the average, above average or below average as shown in table 3.2.

Detention index	Detention rate
Above average	> 2 above PMoU average
Average	PMoU average ± 2%
Below average	> 2 below PMoU average

Table 3.2 Detention Index calculation

Finally, Company Performance is calculated based on deficiency and detention index as shown in table 3.3.

Detention Index	Deficiency Index	Company Performance
Above average	Above average	Very low
Above average	Average	Low
Above average	Below average	
Average	Above average	
Below average	Above average	
Average	Average	Medium
Average	Below average	
Below average	Average	
Below average	Below average	High

Table 3.3 Company Performance calculation

Historical Factors

The number of deficiencies recorded in each inspection within the previous 36 months along with the detentions at the same period are two factors used for calculating Ship Risk Profile. As mentioned above, all inspection reports are stored in Paris MOU information system called Thetis and are available to the Port State Control Officers.

Two or more detentions in the previous 36 months add 1 point in the risk profile point system.

Ship Risk Profile

A ship risk profile is attributed to every ship using the risk factors we analyzed above. So a ship can be High Risk (HRS), Standard Risk (SRS) or Low Risk (LRS).

Ships which have 5 or more weighting points in the system, as described above, are defined as High Risk Ships (HRS).

The criteria for a ship to be defined as Low Risk (LRS) are the following.

- "White" flag in flag's performance list
- Recognized Organization with "High" performance
- "High" Company Performance
- Less than 5 deficiencies in each inspection during the last 36 months
- No detention during the last 36 months

The ships that are not “HRS” or “LRS” are defined as Standard Risk Ships (SRS).

3.1.3 Selection for inspection

The selection of a ship for a periodic inspection is based on the Ship Risk Profile, according to the following criteria:

- For HRS – between 5-6 months after the last inspection in the Paris MoU region.
- For SRS – between 10-12 months after the last inspection in the Paris MoU region.
- For LRS – between 24-36 months after the last inspection in the Paris MoU region

The selection scheme based on Ship Risk Profile is also divided into two priorities:

- Priority I: ships must be inspected because either the time window has closed or there is an overriding factor.
- Priority II: ships may be inspected because they are within the time window or the port State considers an unexpected factor warrants an inspection.

So depending on Ship Risk Profile the following priority levels for inspection apply:

High Risk Ships (**HRS**)

- Priority II: Between 5 and 6 months since the last inspection the ship can be inspected
- Priority I: After the 6 months since the last inspection the ship must be inspected

Standard Risk Ships (**SRS**)

- Priority II: Between 10 and 12 months since the last inspection the ship can be inspected
- Priority I: After the 12 months since the last inspection the ship must be inspected

Low Risk Ships (**LRS**)

- Priority II: Between 24 and 36 months since the last inspection the ship can be inspected
- Priority I: After the 36 months since the last inspection the ship must be inspected

3.1.4 Categories of deficiencies

During each inspection, one or more deficiencies can be found by the Port State Control inspectors. All these deficiencies are included in the final report of the inspection along with their unique codes. A list with all categories of deficiencies with their codes is published on Paris MOU website (Paris MoU on Port State Control, 2017a).

The inspection report also includes information such as when the deficiency should be corrected and "action taken".

Each category of deficiency has many sub-categories for every single defective item. There is a code for each category followed by more digits for the subcategories and defective items. For example, 01 is the code for Certification and Documentation while 011 is about Ship Certificates and 01101 is for Cargo ship safety equipment.

The main categories of deficiencies along with their unique codes are presented in the Table 3.4.

THETIS Code	Category of Deficiency
01	Certificates & Documentation
02	Structural Condition
03	Water/Waterlight condition
04	Emergency Systems
05	Radio communication
06	Cargo operations including equipment
07	Fire safety
08	Alarms
09	Working and Living Conditions
10	Safety of Navigation
11	Life saving appliances
12	Dangerous Goods
13	Propulsion and auxiliary machinery
14	Pollution Prevention
15	ISM
16	ISPS
18	MLC,2006
99	Other

Table 3.4 Types of deficiencies

The deficiencies leading to detention are mentioned as detainable deficiencies while the others as non-detainable. According to Paris MOU Guidance on Detention and Action Taken (Paris MoU on Port State Control, 2019), Port State Control officer should decide if the deficiencies found in the inspection are ground for detention. This text includes detailed instructions helping Port State Control officers to decide which deficiencies are detainable.

Table 3.5 shows the most common categories of deficiencies found in Port State Control inspection during 2017 at Paris MOU region.

Category	Deficiencies	% of total deficiencies
Safety of Navigation	5.565	13,66
Fire safety	5.320	13,06
Labour conditions	3.401	8,35
Life saving appliances	3.285	8,06
Certificate & Documentation	2.751	6,75

Table 3.5 Top 5 categories of deficiencies 2017 (Paris MoU on Port State Control, 2017b)

3.1.5 Concentrated Inspection Campaigns (CIC)

Concentrated inspection campaigns (CIC) focus on specific categories where many deficiencies have been found by Port State Control officers. Moreover, such campaigns used for areas where new convention requirements have recently entered into force. Concentrated inspection campaigns take place every year from September to November and are combined with a regular inspection. Over the last years the following topics have been the focus of a CIC:

- 2018 MARPOL Annex VI (Regulations for the Prevention of Air Pollution from Ships)
- 2017 Safety of Navigation
- 2016 Maritime Labour Convention,2006 (MLC 2006)
- 2015 Entry into Enclosed Spaces
- 2014 Hours of Rest -Standards of Training, Certification and Watchkeeping for Seafarers (STCW)

3.2 Statistics on Port State Control inspections

This section analyzes some useful statistics on Port State Control inspections in the Paris MOU region. The following figures cover various aspects of PSC such as the number of inspections, the individual vessels inspected, the number of deficiencies, among others.

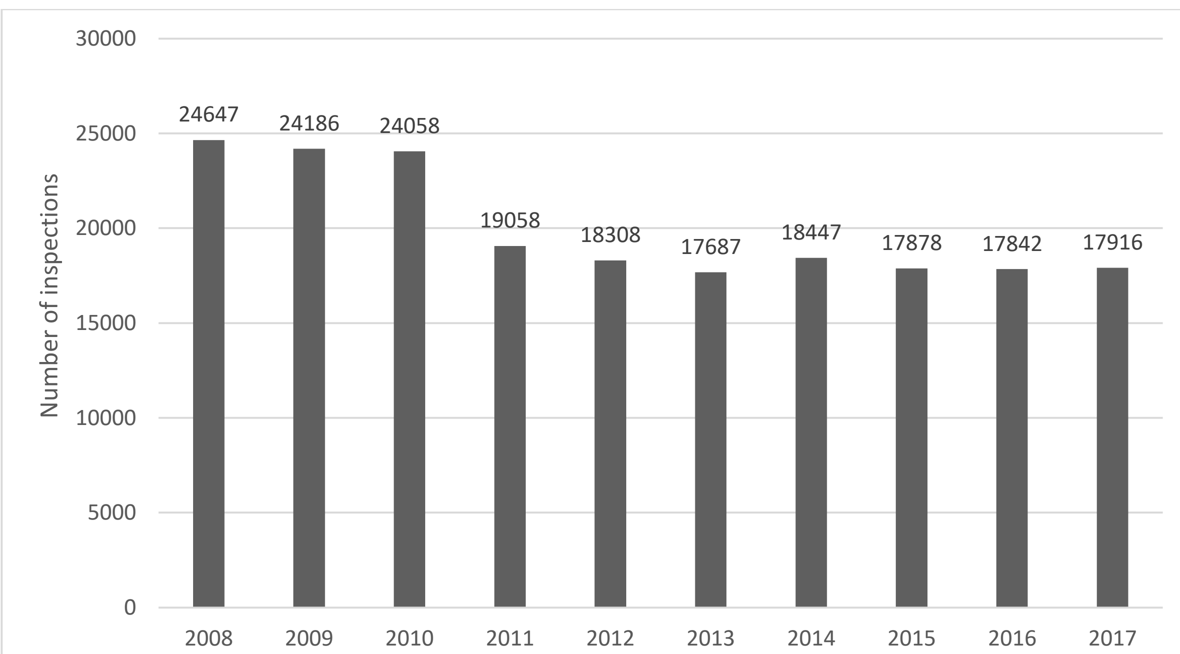
These parameters are called Key Performance Indicators (KPIs). Paris MOU organization publishes statistics in its website along with the annual report[1].

The following statistics cover the period from 2008 to 2017. Special attention is given on how numbers changed after implementation of the New Inspection Regime (NIR) and adoption of Ship Risk Profile to target ships for inspection in 2011.

Number of inspections / inspected vessels

Figure 3.2 and Figure 3.3 show a significant decrease in the number of inspections every year but an increase in the number of individual inspected vessels. This is a result of using Ship Risk Profile for targeting ships as described before. So High Risk Ships are inspected twice a year while Low Risk Ships only once every two or three years. In this way, more vessels are inspected while unnecessary inspections are avoided.

Moreover, after implementation of New Inspection Regime in 2011 the number of individual ships inspected every year remain more or less the same. These numbers indicate the fact that the implementation of New Inspection Regime made the Port State Control system more stable and reliable.



[1] https://www.parismou.org/publications-category/annual-reports

Figure 3.2 Number of inspections at Paris MOU region

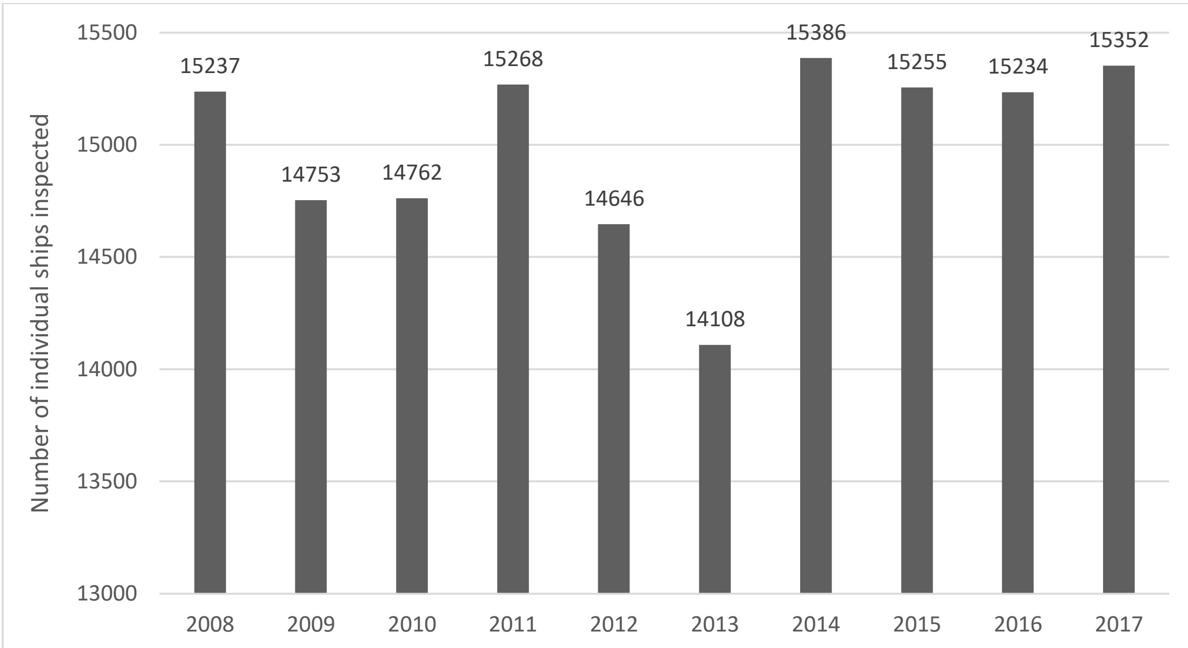


Figure 3.3 Number of individual ships inspected at Paris MOU region

Detention Rate

Another important Key Performance Indicator (KPI) is the detention rate, the number of detentions divided by the number of inspections each year.

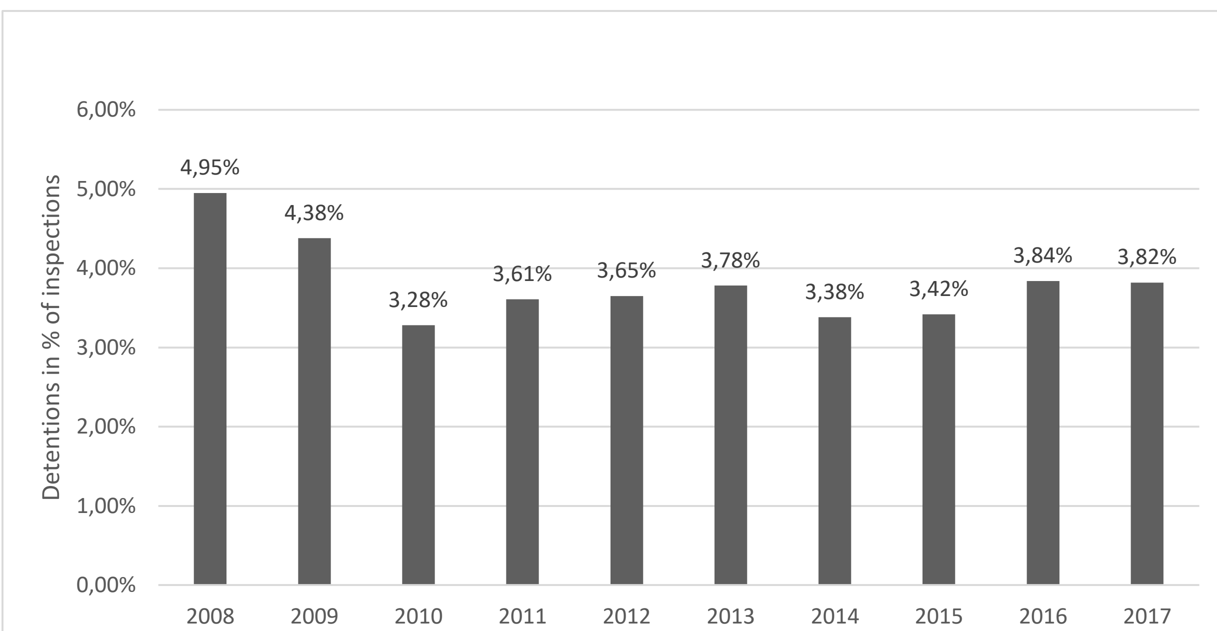


Figure 3.4 Detentions in % of inspections at Paris MOU region

Figure 3.4 indicates that detention rate decreased after implementation of New Inspection Regime (2011) and remained stable the next years. The introduction of New Inspection Regime improved the operation and the quality of Port State Control. Moreover, ship owners invested more money to improve the quality of their vessels to ensure that their ships will not be considered as substandard. As a result, the overall quality of vessels improved and the detention rate dropped.

Inspections per ship type

Figure 3.5 shows the percentage of each ship type inspected in 2016, 2017 and 2018. The data used for the figures are published from Paris MOU organization and the ship types categories are the ones used by the Paris MOU organization.

Most of the ships inspected are General Cargo / Multipurpose followed by Bulk Carriers, Chemical Tankers, Containers and oil tankers. According to Ship Risk Profile, Bulk Carriers, Chemical Tankers and oil tankers are more possible to be High Risk Ships (HRS) so eventually are suffering more inspections. Figure 3.6 shows the number of detentions of each ship type in 2016, 2017 and 2018.

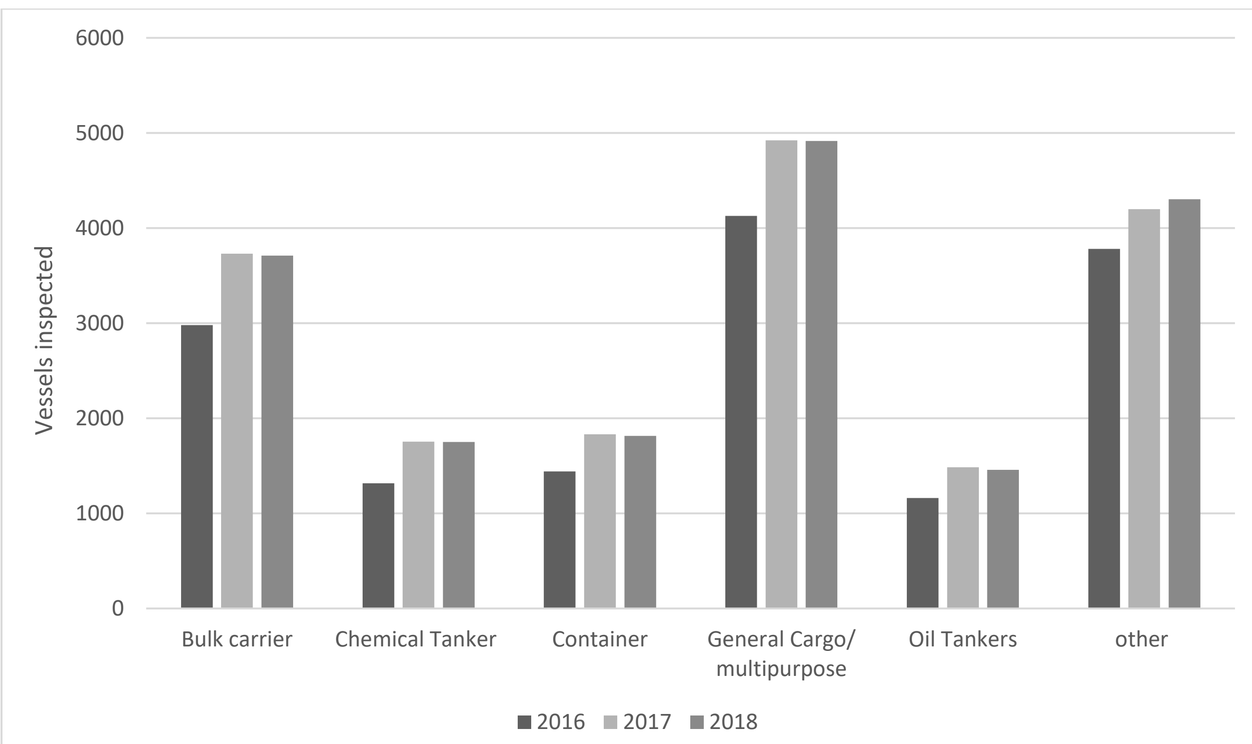


Figure 3.5 Inspections per ship type for years 2016, 2017 and 2018

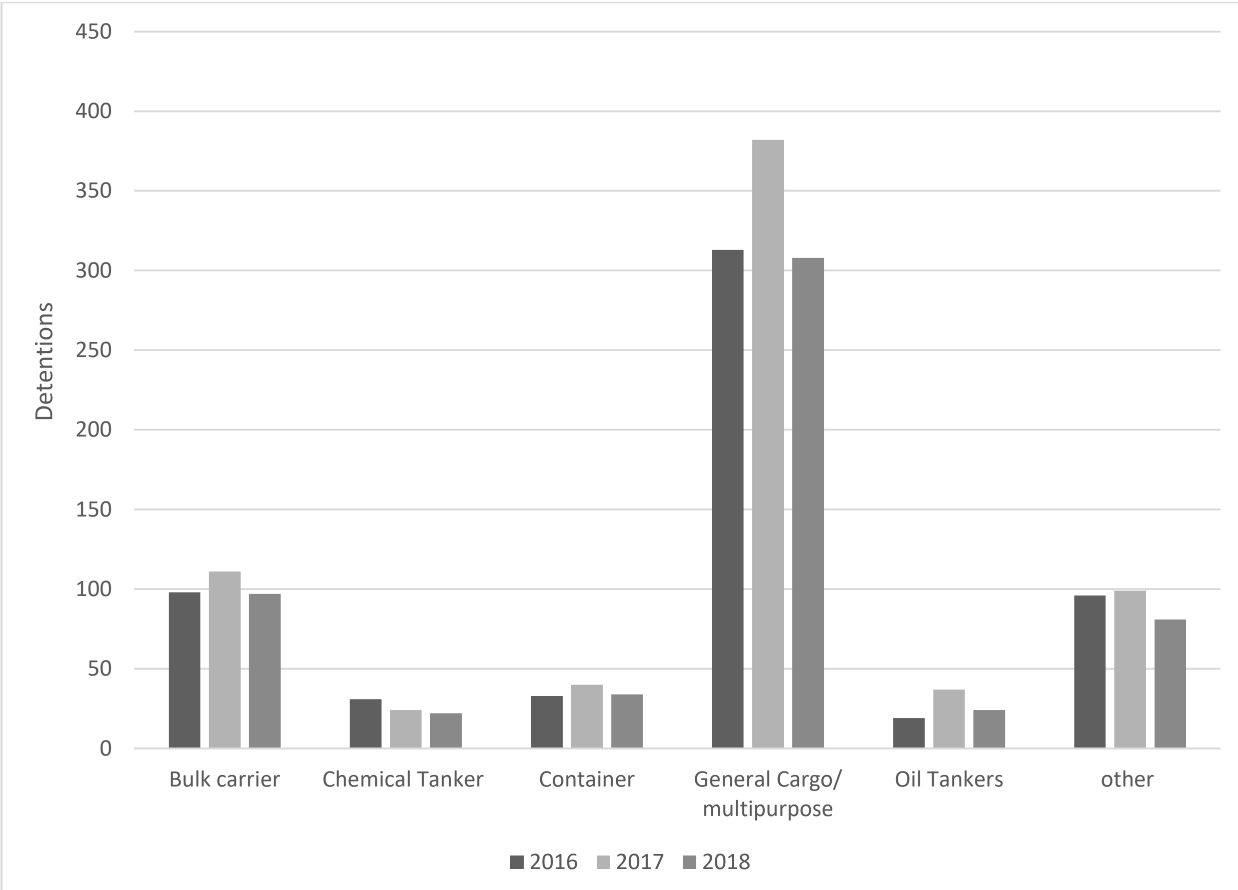


Figure 3.6 Detentions per ship type for 2016, 2017 and 2018

Comparing to previous figures, one can observe that General Cargo/ multipurpose ships have the highest percentage of detentions while oil and chemical tankers the lowest.

A better indicator is the detention rate (detentions/inspections) per ship type (Figure 3.7). General Cargo / multipurpose ships have the highest detention rate by far. This type of ship is not considered as high risk so it is not contributing to Ship Risk Profile. On the other hand, chemical and oil tankers are contributing with 1 weighting point in Ship Risk Profile point system but they have the lowest detention rate. Obviously, owners of tankers invest more money to improve vessel’s quality as their ships are inspected frequently.

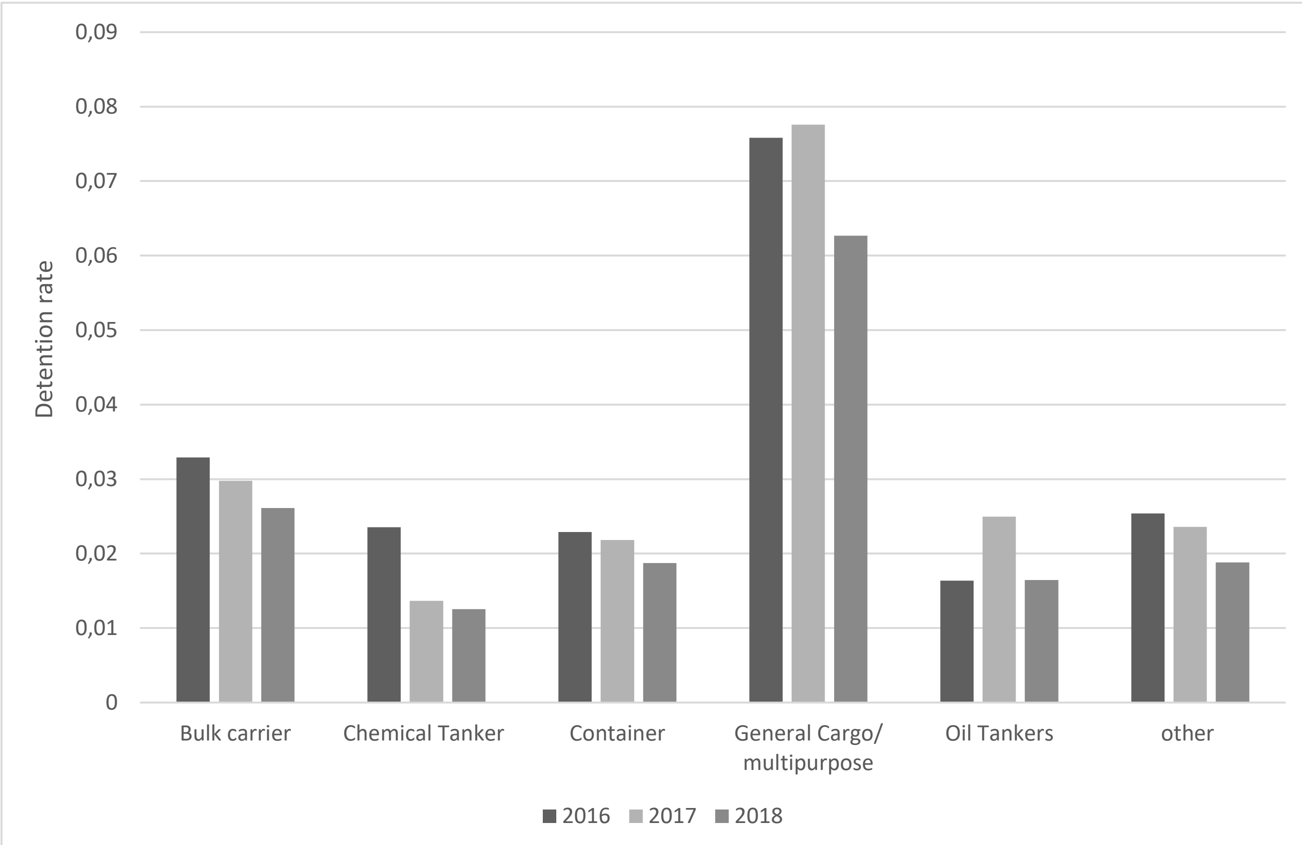


Figure 3.7 Detention rate per ship type for years 2016, 2017 and 2018

Inspections per Ship Risk Profile

Figure 3.8 presents the percentage of inspections of High Risk Ships (HRS), Low Risk Ships (LRS) and Standard Risk Ships (SRS), according to Ship Risk Profile explained before. The statistics used are from 2016 to 2018 and obtained from Paris MOU website[2].

It is clear that most of the vessels inspected are neither "HRS" nor "LRS" so described as "SRS". An extended ship risk profile could help Port State Control officers to target ships for inspection in a more effective way. Using more risk factors could lead to describing ship risk profile better.

Figure 3.9 shows the detention rate (detentions/inspections) for each ship risk profile from 2016 to 2018. High Risk Ships (HRS) have significant higher detention rate comparing to Low

[2] https://www.parismou.org/inspection-search/inspections-results-kpis

Risk Ships and Standard Risk Ships. This fact shows the positive influence of using Ship Risk Profile to target ships for inspection.

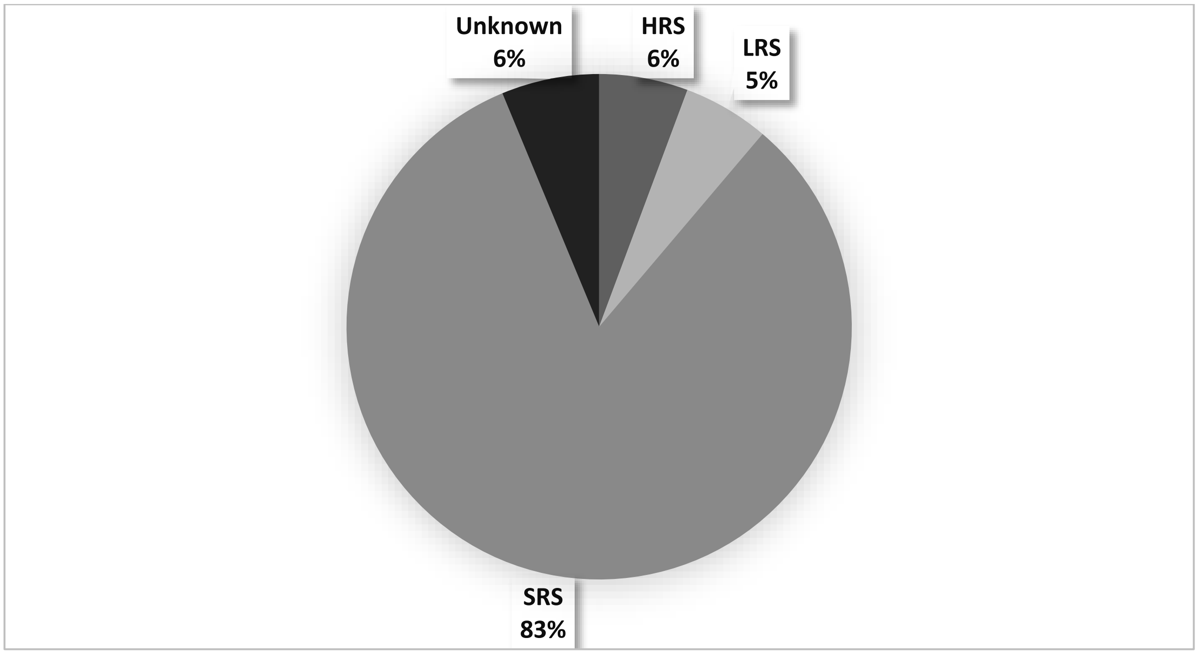


Figure 3.8 Inspections per Ship Risk Profile

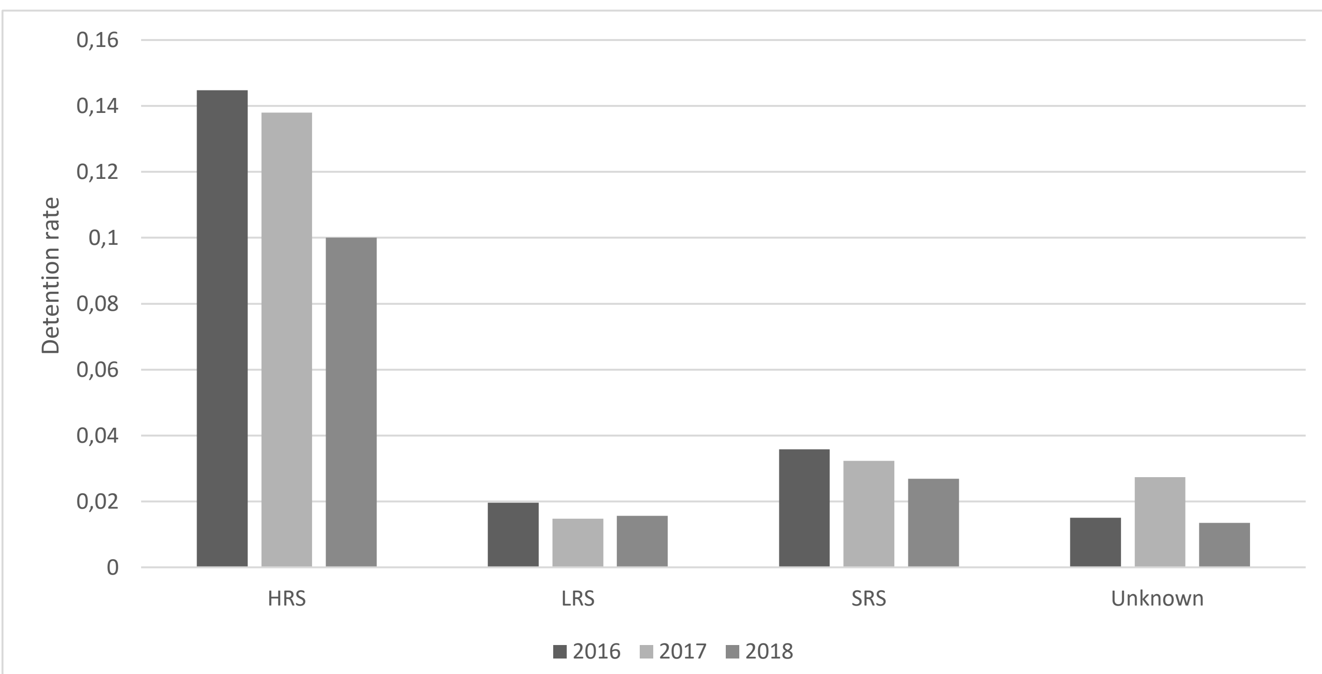


Figure 3.9 Detention rate per Ship Risk Profile

3.3 Theoretical background on Bayesian Networks

Probabilistic networks are graphical models of casual interaction among a set of variables, where the variables are represented as nodes of a graph and the interactions as directed edges between the notes. Any pair of unconnected nodes of such a graph indicates conditional independence between the variables represented by these nodes.

A Bayesian network can be described briefly as an acyclic directed graph (DAG), which defines a more compact factorization of the joint probability distribution over the variables that are represented by the nodes of the DAG, where the factorization is given by the directed links of the DAG.

Generally, a Bayesian network can be described in terms of a qualitative component, consisting of a DAG, and a quantitative component, consisting of a joint probability distribution that factorizes into a set of conditional probability distributions governed by the structure of the DAG.

Below is presented a basic theoretical background about probability theory, Bayesian networks and learning algorithms in order to understand better the Bayesian network models developed in the next chapter. More details on the BN theory can be found in (Kjaerulff & Madsen, 2008).

3.3.1 Probability Theory

As mentioned above, Bayesian networks have qualitative and corresponding quantitative components. The qualitative part consists of the graphical structure made of nodes and arcs in the form of an acyclic, directed graph (DAG). The fact that the structure of a Bayesian network can be characterized as a DAG derives from basic axioms of probability calculus leading to recursive factorization of a joint probability distribution into a product of lower-dimensional conditional probability distributions.

First, any joint probability can be decomposed (or factorized) into a product of conditional distributions of different dimensionality, where the dimensionality of the largest distribution is identical to the dimensionality of the joint distribution.

Second, statements of local conditional independences manifest themselves as reductions of dimensionalities of some of the conditional probability distributions. Most often, these independence statements give rise to dramatic reductions of complexity of the DAG, such that the resulting DAG appears to be quite sparse.

The basic concept in the Bayesian treatment of uncertainty is that of **conditional probability**: Given event β, the conditional probability of event α is x, written as

$$P(a|\beta) = x \tag{3. 1}$$

This means that if β is true and everything else known is irrelevant for α, then the probability of α is x.

There are three axioms that provide the basis for Bayesian probability calculus:

Axiom 1. For any event, α, $0 \leq P(\alpha) \leq 1$, with P (α)=1, if and only if α occurs with certainty.

Axiom 2. For any two mutually exclusive events α and β the probability that either α or β occur is

$$P(a \ or \ \beta) = P(\alpha \cup \beta) = P(a) + P(\beta) \tag{3. 2}$$

In general, if events $\alpha_{1},\ldots,\alpha_{n}$ are pairwise incompatible then

$$P(\cup_i^n a_i) = P(a_1) + \cdots + P(a_n) = \textstyle\sum_i^n P(a_i). \tag{3. 3}$$

Axiom 3. For any two events α and β the probability that both α and β occur is

$$P(\alpha \ and \ \beta) = P(a \cap \beta) = P(\beta|\alpha)P(\alpha) = P(\alpha|\beta)P(\beta) \tag{3. 4}$$

P($\alpha \cap \beta$) is called the joint probability of the events α and β.

The last axiom (Axiom 3) is sometimes referred to as the fundamental rule of probability calculus. The axiom says that the probability of the co-occurrence of the two events, α and β, can be computed as the product of the probability of event α occurring conditional on the fact that event β has already occurred and the probability of event β occurring. The same is right for the event β.

The rule of total probability

Let P(X∩Y) be a joint probability distribution for two variables X and Y with dom(X)={$x_1,\ldots,x_m$} and dom(Y)={$y_1,\ldots,y_n$} . Using the fact that dom(X) and dom(Y) are exhaustive sets of mutually exclusive states of X and Y, respectively, Axiom 2 as shown above give us

$$\forall i: P(x_i) = P(x_i \cap y_1) + \cdots + P(x_i \cap y_n) = \sum_{j=1}^{n} P(x_i \cap y_j) \quad (3.5)$$

The above equitation is the rule of the total probability and helps to calculate P(X) from P(X∩Y).

$$P(X) = \sum_{j=1}^{n} P\left(X \cap y_j\right) = \sum_{Y} P(X \cap Y) \quad (3.6)$$

<u>Fundamental Rule and Bayes' Rule</u>

The fundamental rule of probability calculus is a result of generalizing Axiom 3 shown above:

$$P(X \cap Y) = P(X|Y)P(Y) = P(Y|X)P(X) \quad (3.7)$$

Bayes' rule follows immediately from the above equation:

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} \quad (3.8)$$

Using Axiom 3 and the rule of total probability shown above, Bayes' rule can be rewritten as

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X|Y = y_1)P(Y=y_1)+\cdots+P(X|Y = y_n)P(Y=y_n)} \quad (3.9)$$

<u>Independence</u>

A variable X is independent of another variable Y with respect to a probability distribution P if

$$P(x|y) = P(x) \forall x \in dom(X), \forall y \in dom(Y) \quad (3.10)$$

That means from Bayes' rule shown above:

$$P(x|y) = P(x) = \frac{P(y|x)P(x)}{P(y)} \quad (3.11)$$

Finally, for a probability distribution P(X), over a set of variables $X=(X_1,\ldots,X_n)$ we can use the fundamental rule repetitively to decompose it into product of conditional probability distributions:

$$P(X) = P(X1|X2, \dots, Xn)P(X2, \dots, Xn) = \prod_{i=1}^{n} P(X_i|X_{i+1}, \dots, X_n) \quad (3.12)$$

The above equation is used in Bayesian networks presented below.

3.3.2 Bayesian networks

A discrete Bayesian network, over variables X consists of an acyclic, directed graph ad a set of conditional probability distributions P. Each node in graph corresponds one-to-one with a discreet variable X_n E X with a finite set of mutually exclusive states. The directed links of graph specify assumptions of conditional dependence and independence between the random variables.

There is a conditional probability distribution, $P(X_n|X_{pa(N)})$ for each variable Xn. The set of variables represented by the parents, pa (n), are sometimes called the conditioning variables of X_n – the conditioned variable.

The chain rule from probability theory shown above using the information provided by the BN structure is now given by:

$$P(X) = \prod_{vEV} P(X_v|X_{pa(v)}) \quad (3.13)$$

Figure 3.10 represents the topology of a simple Bayesian network with 3 nodes. X_1 is the parent of X_2 and X_3. For this network the equation of chain rule is the following:

$$P(x_1, x_2, x_3) = P(x_1)P(x_2|x_1)P(x_3|x_1)$$

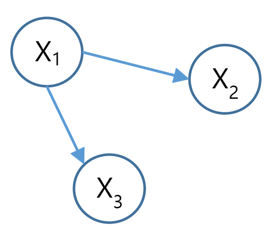


Figure 3.10 Simple Bayesian network

The construction of a Bayesian network thus runs in two phases. First, given the problem at hand, one identifies the relevant variables and the casual relations among them. The resulting graph, called topology, specifies a set of dependence and independence assumptions that will be enforced on the joint probability distribution, which is next to be specified in terms of a set of conditional probability distributions, $P(X_v|X_{pa(v)})$, one for each "family" , $\{v\} \cup pa(v)$ of the topology.

A Bayesian network can be constructed manually, semi-automatically from data or through a combination of a manual and a data driven process, where partial knowledge about structure as well as parameters (conditional probabilities) blend with statistical information extracted from databases.

3.3.3 Learning

Data-driven modeling is the task of identifying a Bayesian network model from a source of data.

Structure learning

Structure learning from data is the task of inducing the structure i.e, the graph, of a Bayesian network from a source data. There exists different classes of algorithms for learning the structure of a Bayesian network such as search-and-score algorithms and constraint-based algorithms as well as combinations of the two. The main part of structure learning is to identify a graph structure that best encodes a set of conditional dependence and independence relations (CIDR's) between the variables.

PC Algorithm

The PC algorithm is a constraint-based algorithm for learning the structure of a Bayesian network (Kjaerulff & Madsen, 2008).The main steps of the PC algorithm are

1. Test for conditional independence between each pair of variables represented in order to derive the sets of conditional dependence and independence relations (CIDR's)
2. Identify the skeleton of the graph
3. Identify colliders
4. Identify derives directions

Parameter learning from data

Parameter estimation in a Bayesian Network is the task of estimating the values of the parameters corresponding to a specific topology and specific distributions P from a database.

The Expectation-Maximization (EM) Algorithm

A widely used algorithm for parameter estimation is Expectation-Maximization (EM) algorithm (Dempster 1977) (Lauritzen 1995) . The EM algorithm proceeds by iterating two steps: the expectation E-step and the maximization M-step.

Let N be a Bayesian network, with a specific topology, for which we would like to estimate the parameters T of P from a database of cases D (datasets). The estimation of the parameters T from D proceeds, as mentioned above, by iterating the E-step and the M-step. Given an initial assignment to the parameters T, the E-step is to compute the expected sufficient statistics under T, while the subsequent M-step is to maximize the log-likelihood of the parameters under the expected sufficient statistics. These two steps are alternated iteratively until a stopping criterion is satisfied.(Kjaerulff & Madsen, 2008)

4. Bayesian Network modeling of Port State Control Inspections

In this chapter, four data-driven Bayesian Networks are developed in order to analyze the factors influencing Port State Control inspections in terms of number of deficiencies and detentions. To do so, inspection data from the Thessaloniki and Liverpool ports are collected from Paris MOU database and processed. Genie software (Druzdzel, 1999) is used for the development of the models.

4.1 Introduction

Bayesian Network is a powerful tool used to create models for risk assessment. An advantage over the simple Bayesian theory is that BNs provide a better graphical representation while comparing to other techniques, BN has a stronger mathematical background. Moreover, taking advantage of casual inference, BN can be used to analyze the importance of different factors influencing ship risk profile and the relationships between them.

The first part of this chapter consists of a brief analysis of the two ports and a detailed description about how the inspection data that will be used to develop the models was collected.

The second part presents the analysis of the data collected. The data are analyzed in terms of risk factors such as age, type, etc. and inspection results such as the number of deficiencies and detention rate.

Finally, the results of the models are presented in the third part of the chapter along with a process of including evidences.

4.2 Data

4.2.1 Ports

The data used for developing the Bayesian Network (BN) models are collected from Paris MOU Inspection Database[3] and processed by the author.

[3] https://www.parismou.org/inspection-search/inspection-search

The data consist of the inspections carried out at two different ports during 2018. The Thessaloniki and the Liverpool ports are selected as case study. The port of Thessaloniki is located on the southern part of Paris MOU community. On the other hand, the port of Liverpool is located on the northern part. Moreover, the number of inspections carried out in these two ports are comparable as in Thessaloniki 75 vessels were inspected during 2018 while in Liverpool 95 inspections were carried out during the same year.

The port of Thessaloniki is the most important port in Macedonia, a region of Greece, and one of the most important ports in Southeast Europe. It occupies a space of 1.5 million square meters. It has 6 piers spreading on a 6200 meter-long quay. It also has open and indoors storage areas that are suitable for all types of cargo and spreading on a total of 600.000 square meters.

During 2018, a total number of 1.929 ships visited the Thessaloniki port. Most of them, 752 ships, arrived at conventional terminal while 492 ships arrived at container terminal. During the same year, 424.500 containers loaded in TEU's while 3.844.522 tons of conventional cargo went in and out. Concerning ship's flag, 659 ships were under Greek flag while 402 were under Malta's flag ("Statistical Data Thessaloniki Port" 2018).

The port of Liverpool is located on both banks of the River Mersey within the North West of the United Kingdom. Commodities at Liverpool port include mainly automotive, containers, dry bulks. Liverpool port is the fourth biggest port in UK, with million tons of cargo loaded and unloaded every year. Moreover, it is the fifth bigger port in UK handling RO-RO main freight, (Department for Transport, 2018).

4.2.2 Data collection

As mentioned above, Paris MOU organization provides access to inspection data through its website[4]. With a custom search for a specific year and location, as shown in Figure 4.1 and Figure 4.2, all inspections at Thessaloniki and Liverpool ports during 2018 can be listed.

[4] https://www.parismou.org/inspection-search/inspection-search

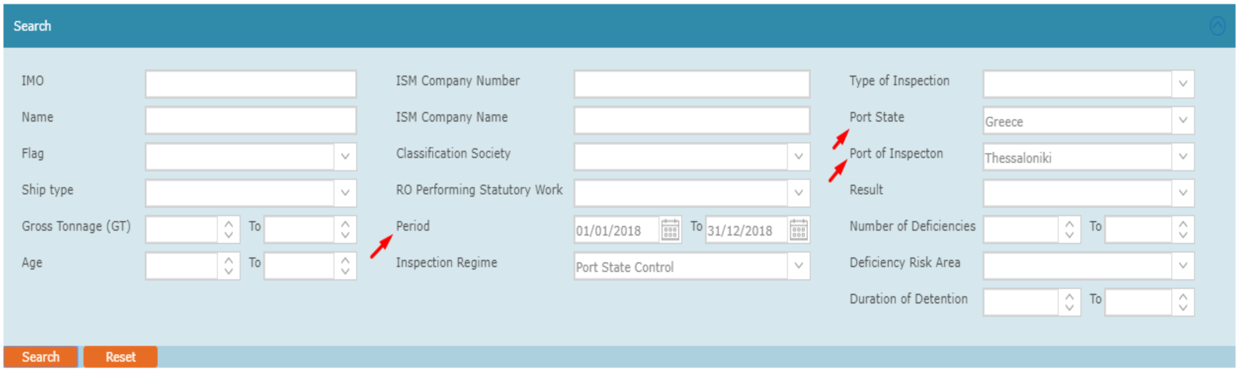


Figure 4.1 Custom search for inspections at Thessaloniki port during 2018 (Paris MOU inspection database)

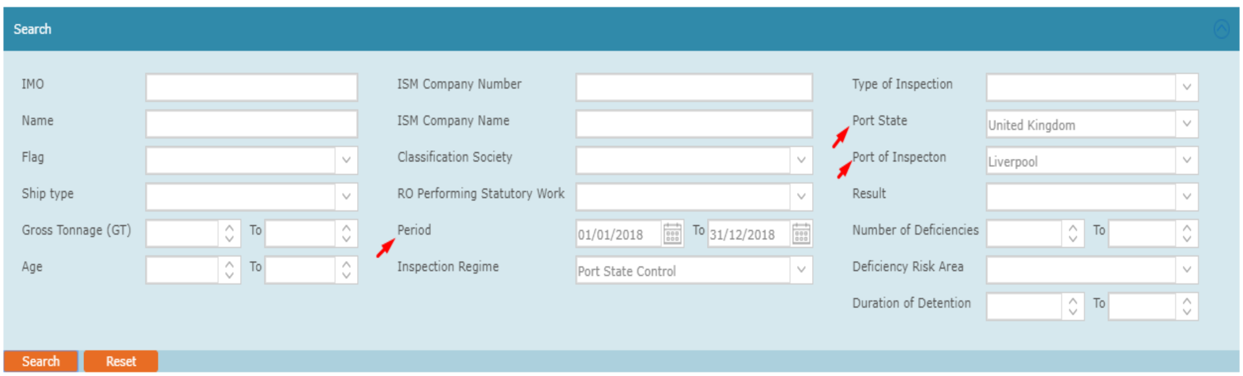
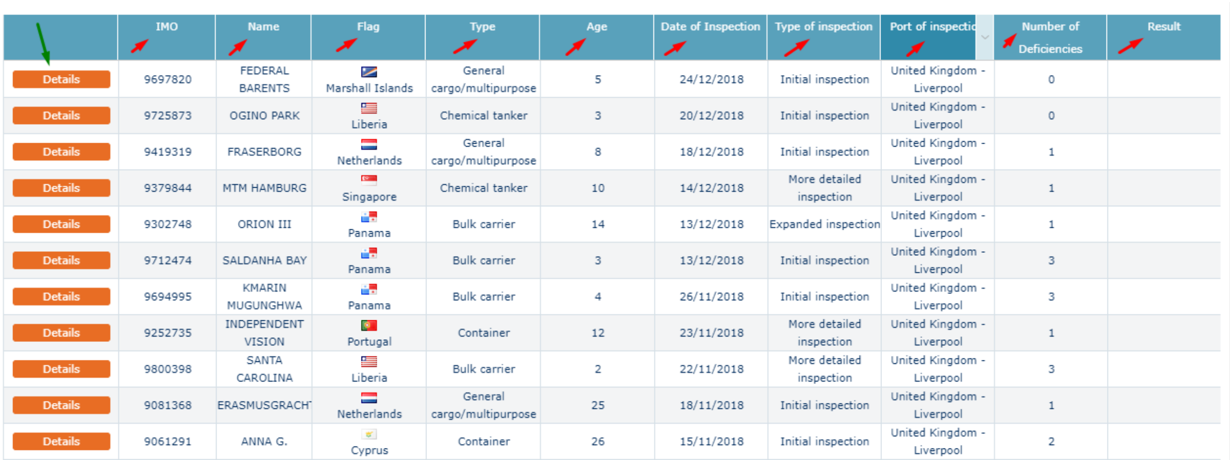


Figure 4.2 Custom search for inspections at Liverpool port during 2018 (Paris MOU inspection database)

The result of the search described above is a list with the ships inspected. The details that are given directly are the vessel's characteristics as the IMO number, name, flag, type and the age and the inspections details as the date, the type and the port of inspection along with the inspection results in terms of number of deficiencies and if the ship is detained or not. An example of such a search result is show in Figure 4.3 where the details mentioned above are marked with the red arrow.

However, all the data required to calculate Ship Risk Profile according to Annex 7 of Paris MOU are not displayed directly in the search result screen. Recognized organization and company information are available at the "Details" page, as shown by the green arrow in Figure 4.3. Moreover, in the "Details" page, information as vessel's tonnage and detailed description of deficiencies are available. These data are also collected for later use in the model.



	IMO	Name	Flag	Type	Age	Date of Inspection	Type of inspection	Port of inspectio	Number of Deficiencies	Result
Details	9697820	FEDERAL BARENTS	Marshall Islands	General cargo/multipurpose	5	24/12/2018	Initial inspection	United Kingdom - Liverpool	0	
Details	9725873	OGINO PARK	Liberia	Chemical tanker	3	20/12/2018	Initial inspection	United Kingdom - Liverpool	0	
Details	9419319	FRASERBORG	Netherlands	General cargo/multipurpose	8	18/12/2018	Initial inspection	United Kingdom - Liverpool	1	
Details	9379844	MTM HAMBURG	Singapore	Chemical tanker	10	14/12/2018	More detailed inspection	United Kingdom - Liverpool	1	
Details	9302748	ORION III	Panama	Bulk carrier	14	13/12/2018	Expanded inspection	United Kingdom - Liverpool	1	
Details	9712474	SALDANHA BAY	Panama	Bulk carrier	3	13/12/2018	Initial inspection	United Kingdom - Liverpool	3	
Details	9694995	KMARIN MUGUNGHWA	Panama	Bulk carrier	4	26/11/2018	Initial inspection	United Kingdom - Liverpool	3	
Details	9252735	INDEPENDENT VISION	Portugal	Container	12	23/11/2018	More detailed inspection	United Kingdom - Liverpool	1	
Details	9800398	SANTA CAROLINA	Liberia	Bulk carrier	2	22/11/2018	More detailed inspection	United Kingdom - Liverpool	3	
Details	9081368	ERASMUSGRACHT	Netherlands	General cargo/multipurpose	25	18/11/2018	Initial inspection	United Kingdom - Liverpool	1	
Details	9061291	ANNA G.	Cyprus	Container	26	15/11/2018	Initial inspection	United Kingdom - Liverpool	2	

Figure 4.3 Search result, Paris MOU inspection database (Paris MOU inspection database)

Another set of data required to calculate Ship Risk Profile according to Annex 7 of Paris MOU are company history and vessel's history. Such data are not available directly from Inspection database but with a custom search similar to the previous one the required information can be obtained manually. Changing "Period" field to cover a 3 years period and specifying the IMO number or ISM company number the historical data about inspections, deficiencies and detentions for every ship or company are obtained. An example of that kind of custom search is shown in Figure 4.4

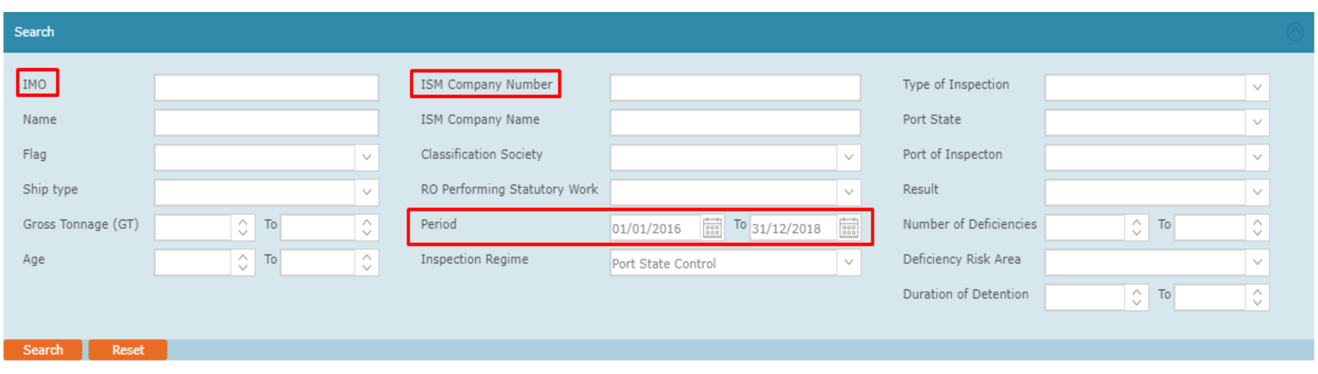


Figure 4.4 Custom search for company or vessel history Paris MOU inspection database)

4.3 Data analysis

The following Figures present the main factors contributing to the ship risk profile. As mentioned above, the data from the two ports are different in many ways. The way the factors are changing and how they affect detention rate or deficiencies found are analyzed as this sample will be used to construct the Bayesian Network models of Liverpool and Thessaloniki ports.

Detention rate/ Deficiencies

Two of the most important indicators are the detention rate and the number of deficiencies found in each inspection. Figure 4.5 shows the number of deficiencies found in each inspection in the two ports. Most of the vessels inspected at Liverpool had under 3 deficiencies while only 1% of them had over 10 deficiencies. On the other hand, the ships inspected at the Thessaloniki had more deficiencies.

Detention rate is defined as the number of detentions divided by the number of inspections. Thessaloniki port had 9.33% detention rate during 2018 while Liverpool port 1.05% during the same year. The higher detention rate at Thessaloniki may be due to the difference in the number of deficiencies found in each inspection as shown above.

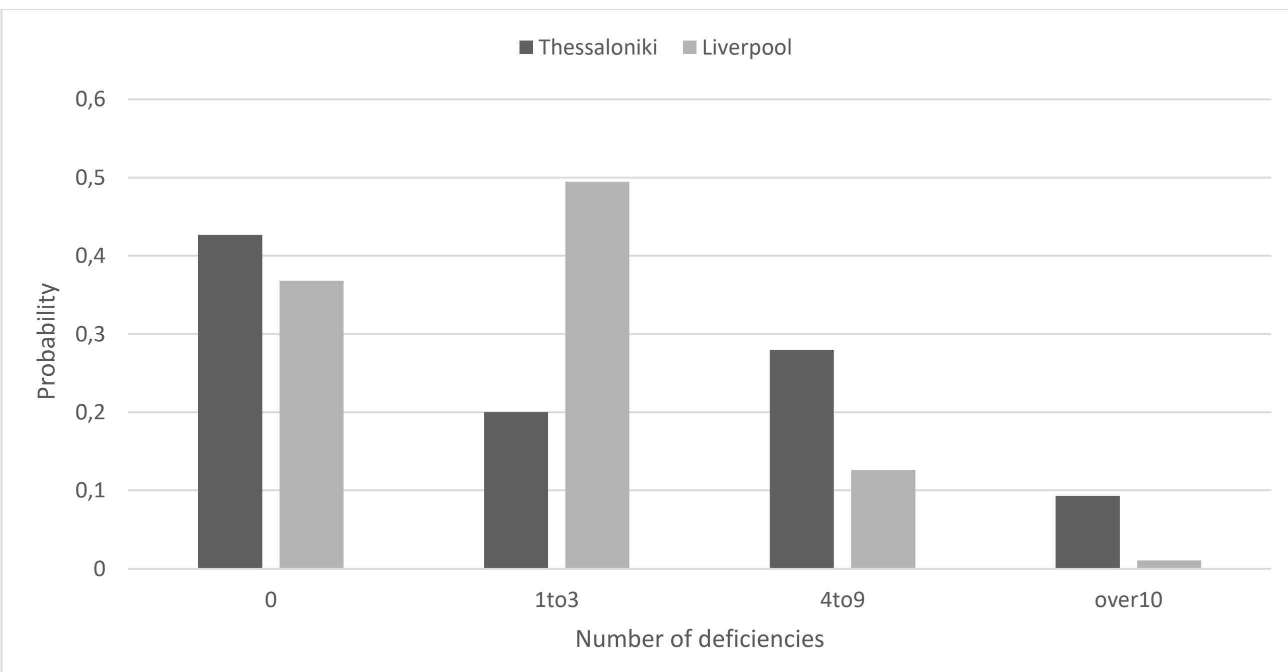


Figure 4.5 Number of deficiencies at the Thessaloniki and Liverpool port in 2018

Ship Risk Profile

After the implementation of the NIR, Ship Risk Profile is used to target ships for Port State Control inspections at the ports of the members of Paris MOU. Using the methodology described in Chapter 3 the Ship Risk Profile was calculated for all vessels inspected at the Thessaloniki and Liverpool ports during 2018. Figure 4.6 presents the percentages of Low Risk Ships (LRS), Standard Risk Ships (SRS) and High Risk Ships (HRS) inspected at the two ports.

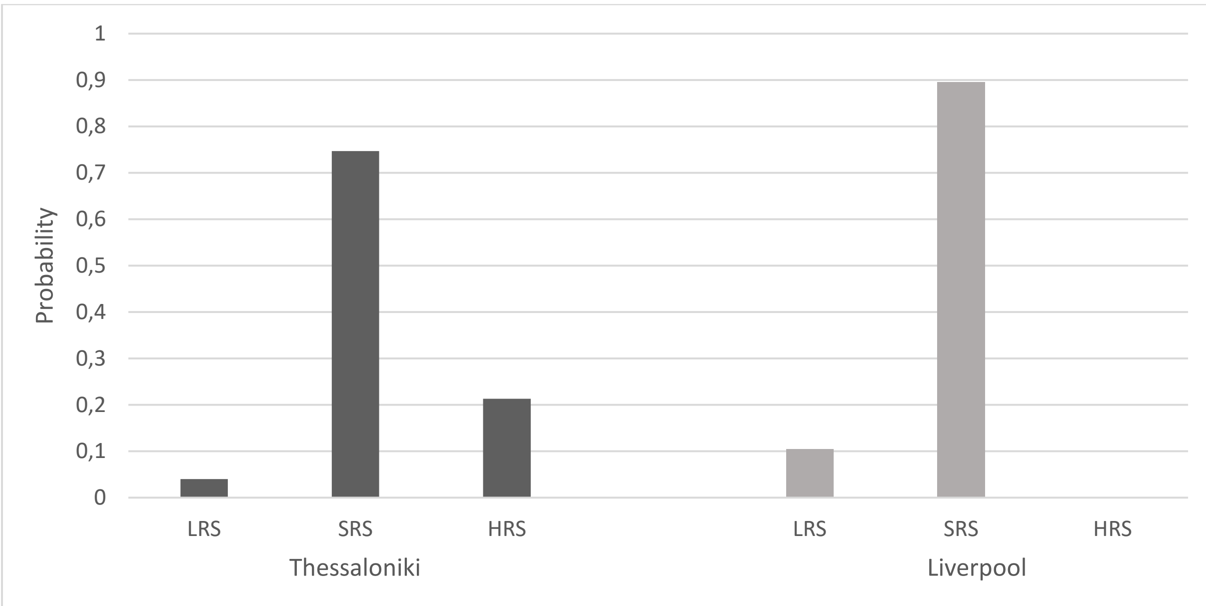


Figure 4.6 Ship Risk Profile of vessels inspected at the two ports during 2018

Most of the ships inspected at both ports are characterized as Standard Risk Ships. However, at Thessaloniki port 2 out of 10 ships inspected are characterized as High Risk Ship, while at Liverpool port no such vessels were inspected.

Age of the ship

Figures 4.7 and 4.8 represent the age of the vessels inspected at the two ports. Vessels inspected at Liverpool port are mainly under 15 years old with a mean value 10.25 years. On the other hand, those inspected at Thessaloniki port are older and their age have a mean value of 19.70 years.

The higher age of ships inspected at Thessaloniki port is connected with the higher detention rate and the higher number of deficiencies found in the inspections compared to vessels inspected at the Liverpool port.

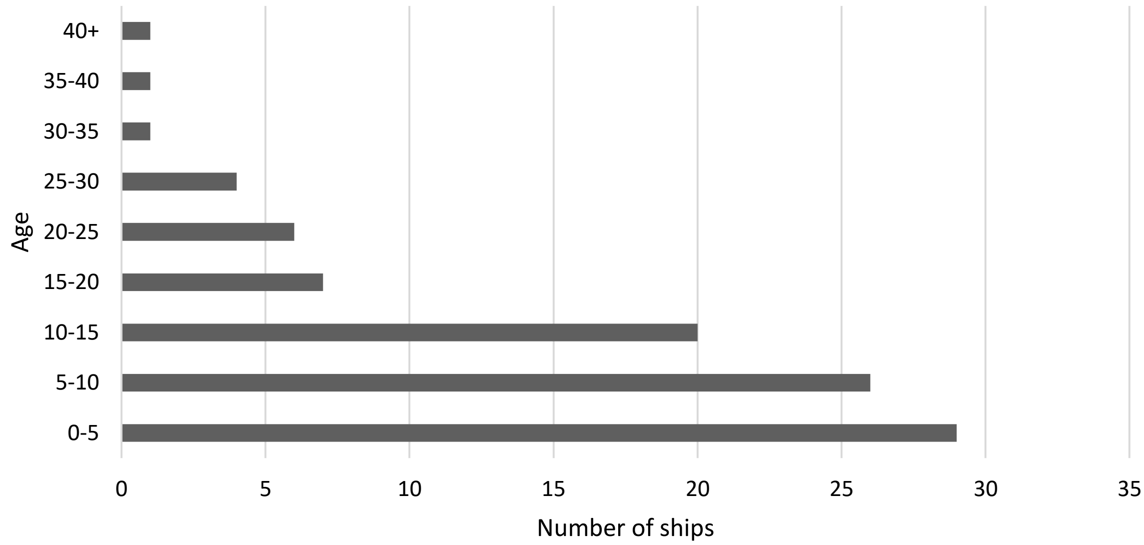


Figure 4.7 Age of vessels inspected at Liverpool port during 2018

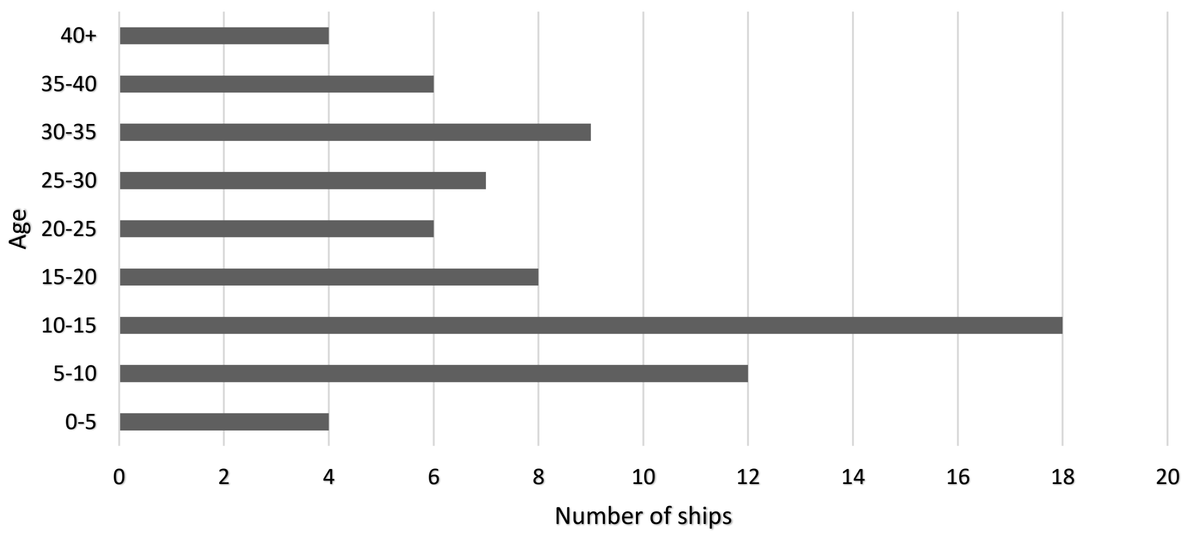


Figure 4.8 Age of vessels inspected at Thessaloniki port during 2018

Type of ship

Figure 4.9 and Figure 4.10 show the type of vessels inspected at Liverpool and Thessaloniki ports during 2018.

Significant differences between the types of vessels inspected at the two ports can be observed. Most of vessels inspected at Liverpool port was bulk carriers followed by general cargo, containers and chemical tankers. On the other hand, general cargo vessels were by far the most common type of ships inspected at Thessaloniki followed by containers and bulk carriers.

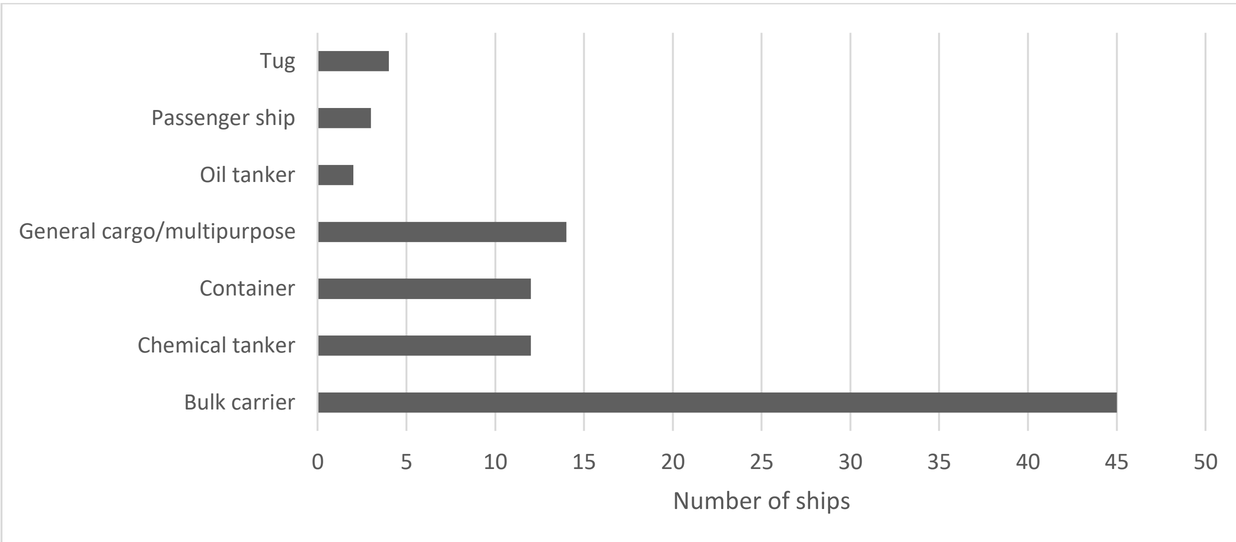


Figure 4.9 Type of vessels inspected at Liverpool port during 2018

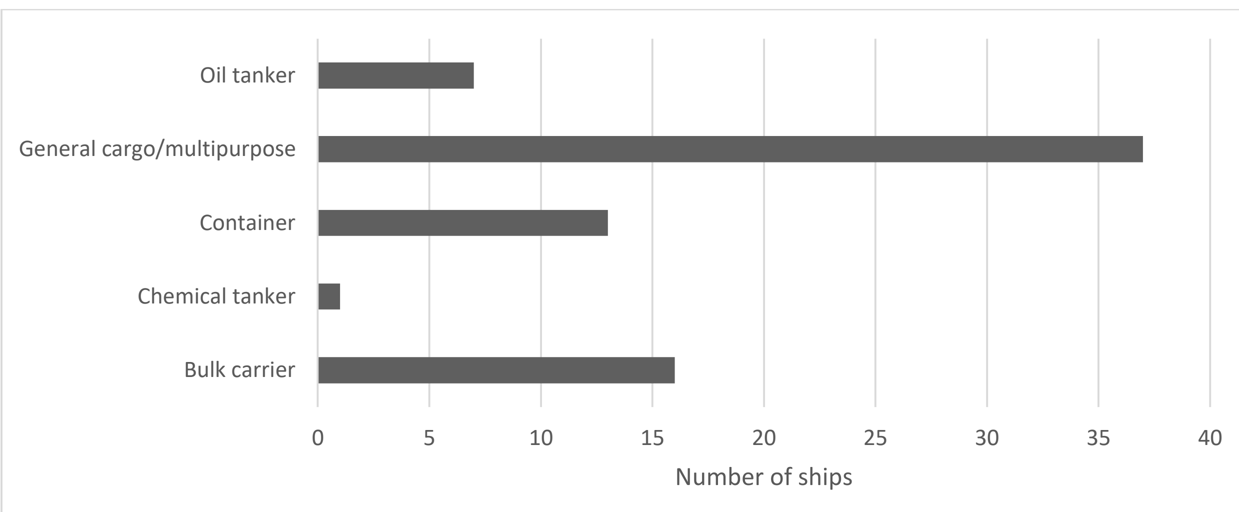


Figure 4.10 Type of vessels inspected at Thessaloniki port during 2018

Gross Tonnage

According to Annex 7 of Paris MOU text there is no connection between ship's risk and gross tonnage. However, it is observed that vessels inspected at Thessaloniki port have a mean value of 15.401, while those inspected at Liverpool port have a mean value of 22.363. Later, the Bayesian Network model will also use gross tonnage data in an attempt to analyze how it affects the detentions and deficiencies.

Categories of deficiencies

As analyzed in Chapter 3, Paris MOU organization has published a list with all categories of deficiencies that can be found in a Port State Control inspection along with their unique codes. Each category has many sub-categories about every single defective item. However, the current research will focus only on categories in order to get more accurate results.

At Thessaloniki port, 75 vessels were inspected during 2018 and 242 deficiencies were found from 14 different categories. Figure 4.11 presents the number of deficiencies found during the inspections for each category.

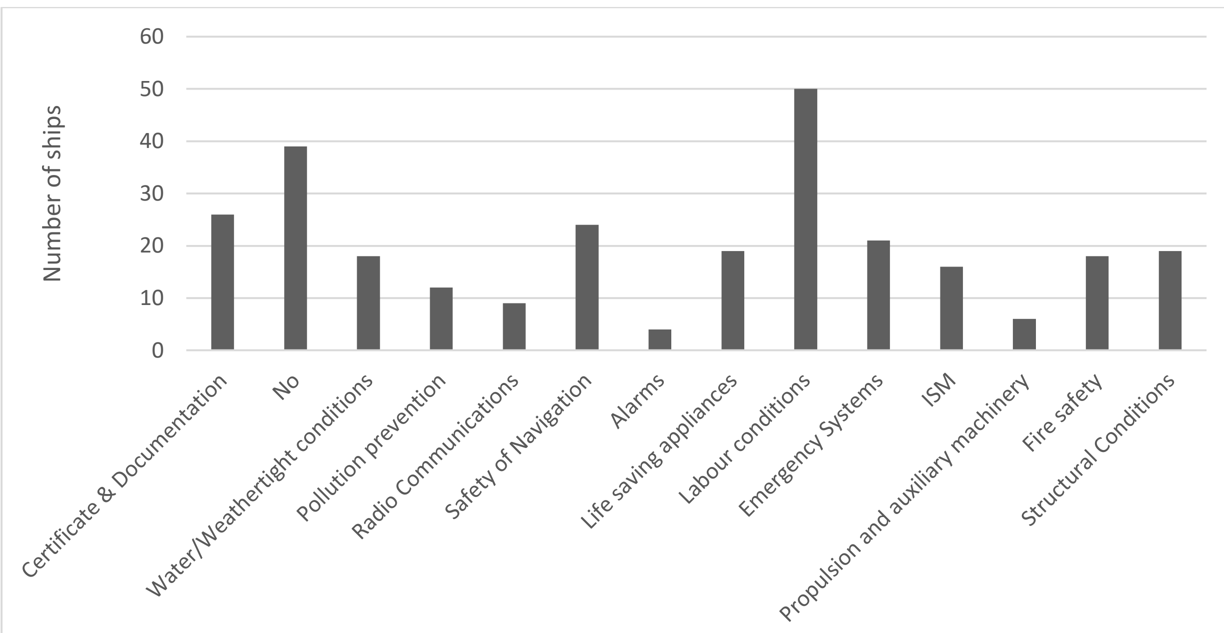


Figure 4.11 Number of deficiencies found at Thessaloniki port for the different categories

Most of the deficiencies found are associated with labour Conditions followed by deficiencies associated with the certificates and documentation. On the other hand, only a few deficiencies were about alarms or propulsion and auxiliary machinery.

At the port of Liverpool, 95 vessels were inspected and 178 deficiencies were found from 17 categories. Figure 4.12 shows the number of deficiencies recorded for the different categories.

As it can be observed, most of the deficiencies found are associated with labour conditions, as in the port of Thessaloniki. However, deficiencies about the safety of navigation or fire safety are more than those about certificates and documentation. Moreover, only one or two deficiencies found associated with categories like structural conditions, alarms, radio communications and living and working conditions.

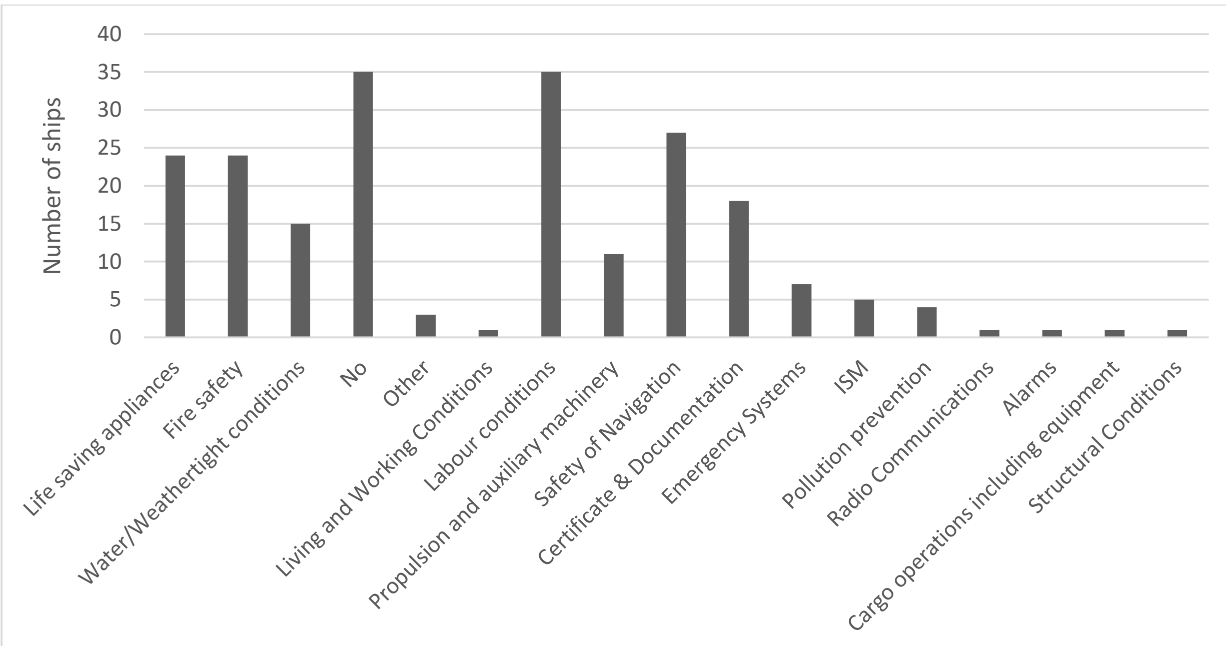


Figure 4.12 Number of deficiencies found at Liverpool port for the different categories

4.4 Bayesian Network models

4.4.1 Introduction

In this chapter, four Bayesian network models are developed using the data collected as described above. Two models are used to analyze the Thessaloniki port and two models the Liverpool port.

The first two Bayesian network models, one for each port, will be used to analyze how risk factors such as the flag, the age, the Recognized Organization etc, influence the number of deficiencies and the detention.

The other two models focus on categories of deficiencies and how the risk factors influencing specific deficiencies.

The Bayesian Network software “Genie” (Druzdzel, 1999) is used to construct the Bayesian network models. Genie is an easy-to-use but also powerful tool for modeling and learning with Bayesian networks, dynamic Bayesian networks, and influence diagrams.

As mentioned above, the construction of a Bayesian Network model runs in two phases. Firstly, the identification of the risk variables and the set of dependence and independence assumptions between them. This leads to an acyclic directed graph (DAG) called topology consisting of nodes that represent risk variables and links between them representing dependence.

Finally, in order to fully construct a Bayesian Network, a conditional probability table (CPT) including all risk variables is yet to be defined.

4.4.2 Risk Variables

All models use the same variables except from those that focus on categories of deficiencies that have one extra variable. The risk variables along with their states are explained below.

1. Flag

This variable has three states: white, grey and black. Using the data collected as described above and the “White, Grey and Black (WGB) list” which is published by Paris MOU organization all flags was characterized as white, grey or black.

2. Recognized Organization (RO)

The four states (High, Medium, Low and Very Low) of this variable was created by classifying the ROs using the performance list that Paris MOU organization publishes.

3. Age

Vessel age is an important factor influencing ship risk. This variable has nine states as vessel age was categorized in groups of five years each in order to be manageable for the model. So state “0to5” refers to vessels being under 5 years old while state “5to10” refers to vessels which age is $5 < x \leq 10$.

4. Type

This variable describes the different types of ships inspected and has different states for each type (Container, bulk carrier, chemical tanker, etc.). The name for every state is the same as Paris MOU organization uses to describe ship types.

5. Type of inspection

There are three types of inspections that can be carried out by a Port State Control officer: initial inspection, more detailed inspection, expanded inspection. Therefore, this variable has the three states mentioned above depending on how much in depth the vessel was examined.

6. Gross Tonnage

Gross tonnage is a nonlinear measure of a ship's overall internal volume. The gross tonnage measurement has a number of legal and administrative uses. It is used to determine regulations, safety rules, registration fees, and port charges for the vessel. This variable has three states: small, medium and big. Vessels with gross tonnage under 5.000 are characterized as small while vessels with tonnage over 30000 as big. The remaining are classified as medium.

7. Company Performance

After the implementation of the NIR, company performance is one of the parameters used to determine Ship Risk Profile. This variable has three states: high, medium and low. Company performance was calculated using data collected as described above and the methodology as described in Chapter 3.

8. Deficiencies

This variable represents the number of deficiencies found in the particular inspection. A vessel with many deficiencies is more likely to be detained. However, a vessel with a small number of major deficiencies can also get detained.

The number of deficiencies was also categorized in groups in order to be manageable by the network. Therefore, this variable has four states. "Zero" state for vessels with no deficiencies, "1to3" for vessels found with 1, 2 or 3 deficiencies, "4to9" and "over10".

9. Detention

The Port State Control officers exercise professional judgment alongside with the detailed guide of Paris MOU (Paris MoU on Port State Control, 2019) in order to decide whether to detain a ship or not considering the number and nature of deficiencies found.

This variable has two states, "Detention" or "No_Detention" depending on the result of this particular inspection.

10. Risk Profile

This variable represents the ship risk calculated according to Annex 7 of Paris MOU and following the procedure described in details above. Therefore, it has 3 states: "Low_Risk_Ship" for vessels meeting low risks criteria, "High_Risk_Ship" for vessels considered dangerous and "Standard_Risk_Ship" for the others.

4.4.3 Topology

Genie software can automatically define the topology of a Bayesian Network model using a data file through a learning algorithm.

A data file consisting of 10 columns, one for each risk variable, was created using "Microsoft Excel" software and given as an input to Genie in order to apply structural learning. The PC algorithm was chosen as the most suitable among the available algorithms due to its advantages as described in Chapter 3.

The result was a complex graph with many links between variables. Therefore, some of those links considered meaningless or even incorrect were deleted in order to simplify the model.

Figure 4.13 presents the Bayesian Network model topology. Risk variables described above are represented as nodes. The following topology is the same for both ports models.

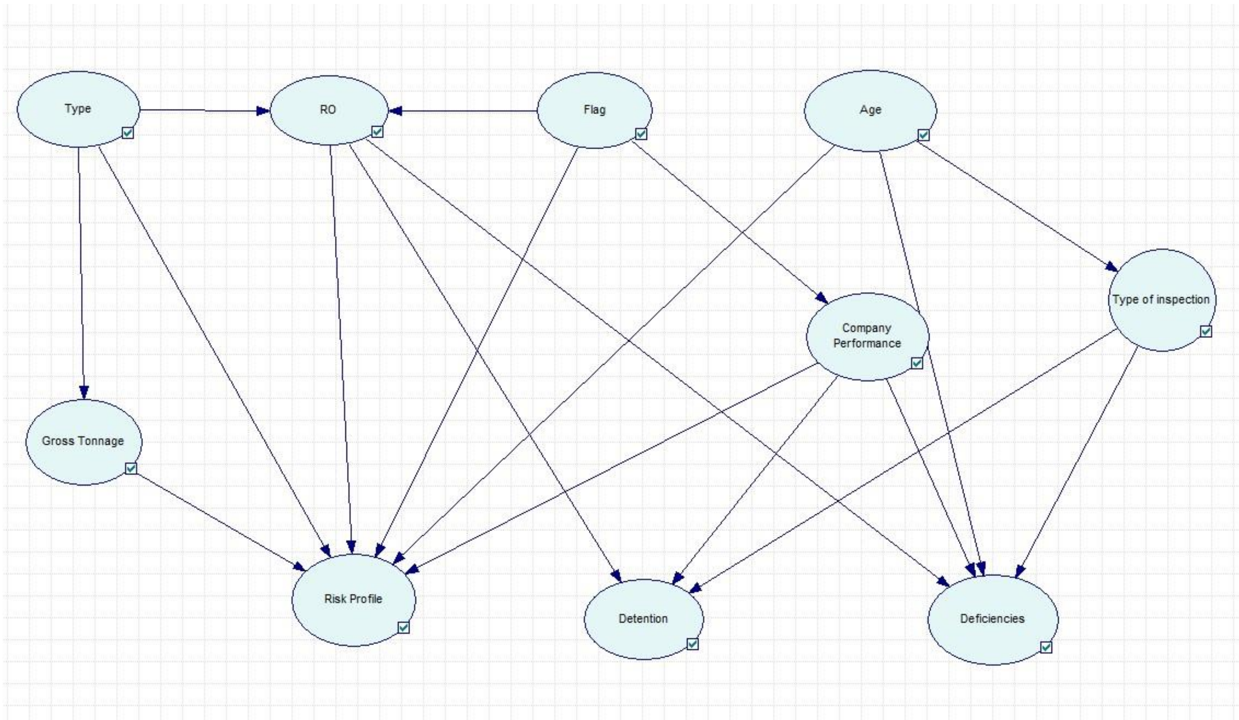


Figure 4.13 Topology of the Bayesian Network model

- Nodes representing the risk variables "Type", "Flag" and "Age" have no parents. All these variables are describing vessel characteristics and are not influenced by other variables. They are on the top of the Bayesian Network model.
- The variable that represents the Recognized Organization (RO) is influenced by the type and the flag due to the trend for specific types and flags to choose specific ROs.
- Gross Tonnage is influenced by the type of the vessel as long as different types lead to different tonnage categories.
- "Risk Profile" is influenced by all factors contributing to its definition according to Paris MOU text as explained above
- Nodes representing the risk variables "Deficiencies", "Risk Profile" and "Detention" are not influencing other variables. All these variables represent the results of the inspection and have no influence on the risk factors. They are on the bottom of the Bayesian Network model.

As mentioned above, two models are also developed in order to analyze the influence of the risk factors on the deficiency categories at the two ports. A different Microsoft Excel file was created in which every column describes a variable. However, many vessels have more than one deficiency, the record of each ship is repeated as many times as the number of deficiencies found. For this reason, those models will be used only to analyze categories of deficiencies.

Figure 4.14 presents the Bayesian Network model topology of the model developed to analyze the influence of risk factors on the deficiency categories.

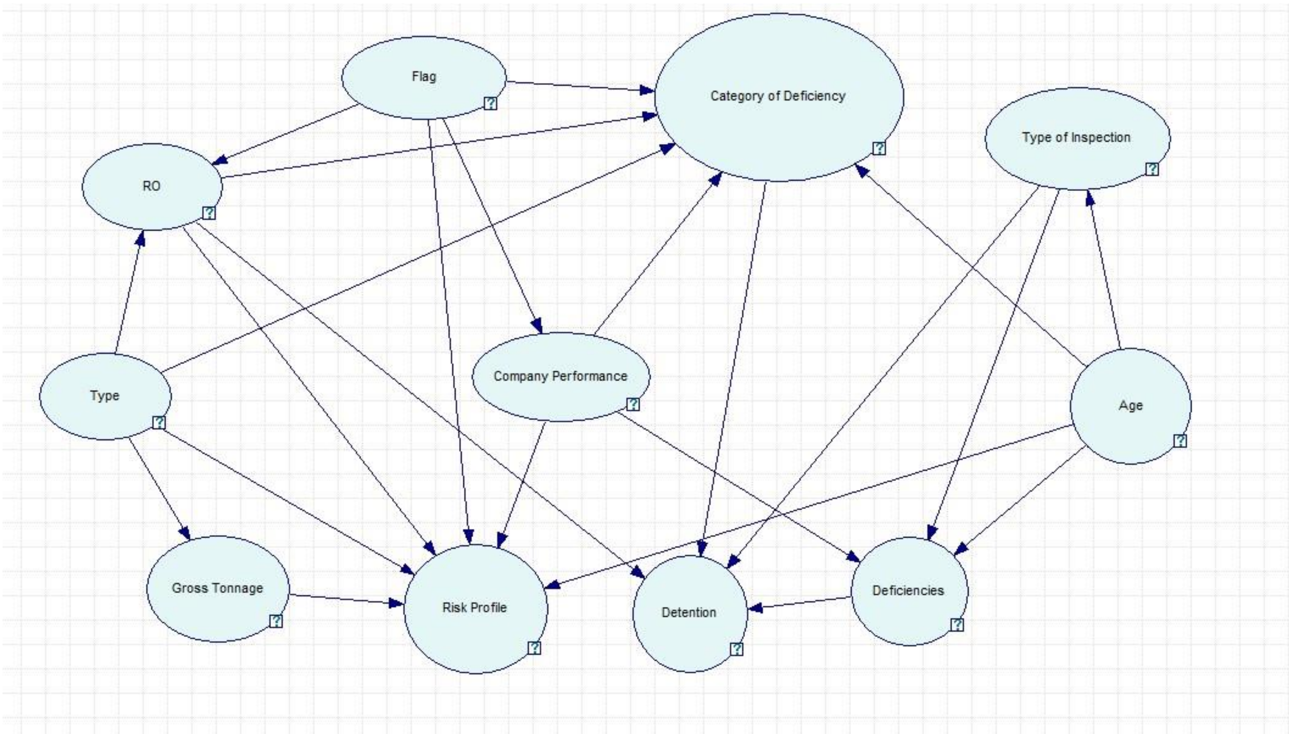


Figure 4.14 Topology of the Bayesian Network model developed to analyze categories of deficiencies

- As explained above, nodes representing the variables about vessel characteristics such as "Age", "Type" and "Flag" are not influenced by other nodes.
- Nodes representing inspection's results such as "Detention" and "Category of Deficiency" are not influencing risk factors. "Risk Profile" also does not influence any node.
- "Category of Deficiency" is on the bottom of the Bayesian Network model as it does not influence other nodes. It is influenced by vessel characteristics such as "Age", "Type" and "Flag". Moreover, nodes such as "Company Performance" and "RO" influence the "Category of Deficiency" due to the fact that the performance of the company and the RO can lead to specific types of deficiencies.

- The node “Deficiencies”, representing the number of deficiencies, is not connected with “Category of Deficiency” as the number of deficiencies found in a Port State Control inspection is not directly associated with the category they belong to.

4.4.4 Parameters

The network parameters of all models are learned using Genie software and the EM learning algorithm Dempster et al. (1977).

Using as input the same data files used for topology definition, Genie software generates the probability tables of all model nodes.

Variables that do not have parents, such as the “Age”, have marginal probability tables. Table 4.1 shows the probability table of the variable “Age” from Thessaloniki’s model as learned by Genie software using EM algorithm.

Age	Probability
0to5	0.0694
5to10	0.2549
10to15	0.1483
15to20	0.1224
20to25	0.0541
25to30	0.1119
30to35	0.1161
35to40	0.0683
Over40	0.0541

Table 4.1 Probability table of the variable “Age”

However, the probability tables of the variables that are influenced by others, i.e. have parents, are not simple marginal probability distributions but Conditional Probability Tables (CPTs), for each state of the parent variable.

Table 4.2 presents the Conditional Probability Table (CPT) of the variable “Company Performance”, obtained from Thessaloniki’s model, which is influenced by the variable Flag.

Flag	White	Grey	Black
Low	0.1836	0.1666	0.85
Medium	0.7551	0.8333	0.15
High	0.0612	0	0

Table 4.2 Probability table of the variable “Company Performance”

For variables that have more than one parent, CPTs are very complex and are not illustrated in this dissertation. However, the CPTs of the variables have been considered below in Results chapter.

4.5 Model Results

The Bayesian Network models presented above are used to analyze how risk factors influencing Port State control inspection's results in terms of number of deficiencies and detention.

The first group of results is about presenting the prior probability distributions of each risk variable as calculated by the Bayesian Network models. Moreover, results obtained from model are compared with those calculated before using Port State Control inspection records.

The posterior probability distributions of the models' nodes are calculated by including evidence in specific variables to have a better picture of the influence that risk factors have in inspection's results in the two ports. Figures comparing posterior probability distributions with the prior ones are presented in order to understand how the information included in the model changes the probability of the states of each variable.

4.5.1 Prior probability distributions of model variables

Prior probability distributions – Thessaloniki port

Based on the topology of the Bayesian Network model and on the inspection data the Genie software calculates the prior probability distribution of each node. Figure 4.15 shows the results of the model of the Thessaloniki port.

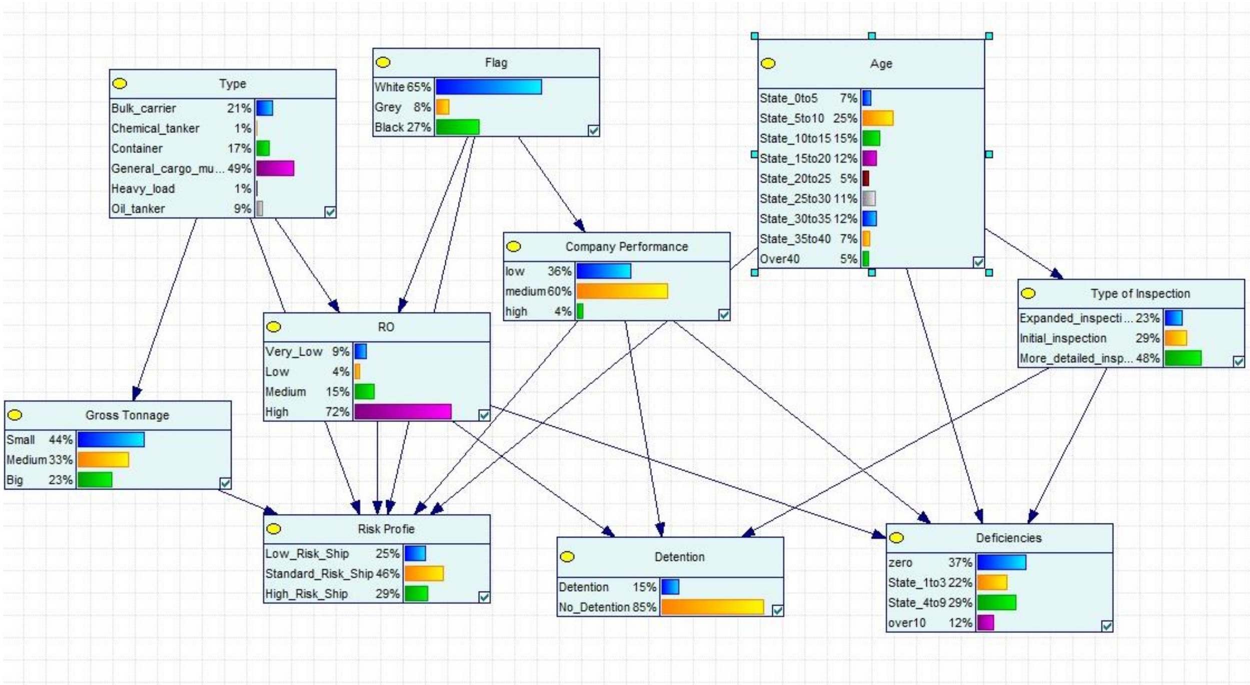


Figure 4.15 Bayesian Network model results of the Thessaloniki port

- The detention rate, according to the model, for vessels inspected at Thessaloniki port is 15%. This number is higher than the actual detention rate calculated from inspection data (9.33%).
- Concerning Ship Risk Profile, the probability of a vessel to be characterized as High Risk Ship (HRS) is very close to the actual one (29% to 26%). However, according to model results, 25% of the vessels are characterized as Low Risk Ships (LRS) while the number calculated from data is much lower, 4%.
- The probability of finding zero deficiencies after a Port State Control inspection at Thessaloniki port is 37% according to the model while calculated from data as 43%. On the other hand, the Bayesian Network model calculates the probability of finding 10 or more deficiencies during the inspection as 12% while the actual probability obtained from data is 9%.

The difference between the values calculated from data and the model results are due to the limited sample size that contains data of Port State Control inspections of one year only. Moreover, after learning the topology, some links were deleted to reduce the complexity of the model, which also affects the parameter learning and the model results.

Prior probability distributions – Liverpool

Based on the dependent and independent relations between the model variables along with the one year inspection data at the port of Liverpool, the Bayesian Network model calculates the prior probability distributions for each node. Figure 4.16 presents the final results of the model developed using Port State Control inspection data at Liverpool port during 2018.

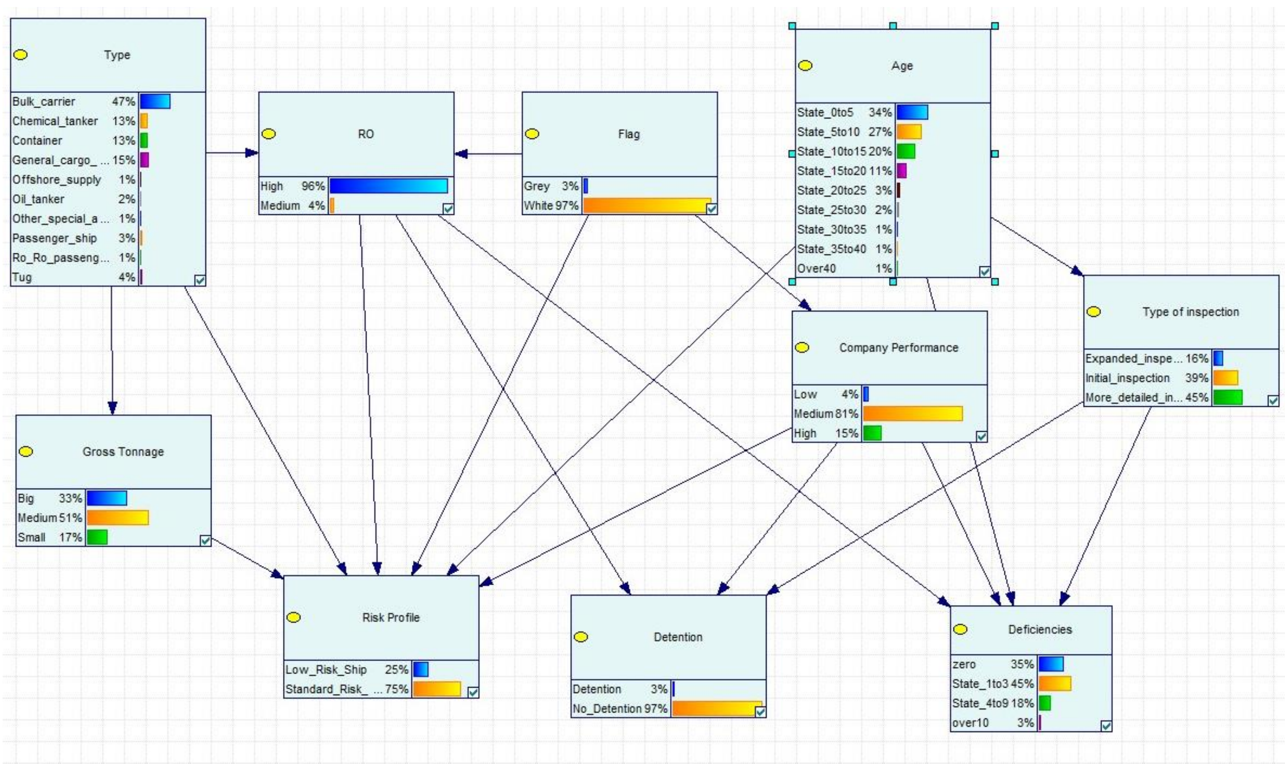


Figure 4.16 Bayesian Network model results of the Liverpool port

- The detention rate is 3% as calculated from the model while the actual detention rate calculated from the inspections records is 1.05%. The two values are close, a good evidence about the reliability of the model developed.
- Concerning Ship Risk Profile, the model calculates the probability of ship classified as "Low Risk Ship" as 25% while the actual probability is 11%. Moreover, according to the results obtained from the model, the probability of a vessel categorized as "Standard Risk Ship" is 75% which is much lower than the value calculated using Port State Control inspection data (89%). Finally, both model and data eliminate the probability of having a vessel classified as "High Risk Ship" inspected at Liverpool's port.

- Bayesian Network model calculates the probability of finding zero deficiencies as 35%, value that is very close to the actual probability calculated using the data (36%). Moreover, according to model result, the probability of finding 1 to 3 deficiencies is 45% while calculated as 49%. Finally, the model calculates the probabilities of finding 4 to 9 and over 10 as 18% and 3% respectively. The actual values calculated above are 13% and 1% respectively.

4.5.2 Posterior probability distributions of model variables

Given the results presented above, a further analysis for the Port State Control inspections can be done through the Bayesian Network model. Genie software allows calculating posterior probability distributions of each variable given evidences on some particular states of model nodes, adjusting the model to a new situation in which one or more information is available.

In fact, all probability distributions are calculated in a form of conditional probability given the event established as evidence.

Such analysis helps having a better picture about how each risk factor influences Port State Control inspection results in terms of number of deficiencies and detentions. Conclusions can help vessel owners take better decisions and avoid many deficiencies and detentions.

Thessaloniki port

Figure 4.17 presents the prior probability distribution of the variable representing the number of deficiencies found in the Port State Control inspections carried out at the Thessaloniki port during 2018 as calculated by the Bayesian Network model.

Some scenarios including evidences are presented below in order to analyze how risk factors, such as the age, RO, company performance and flag are influencing the probability distribution of the deficiencies found in a Port State Control inspection and the detention rate.

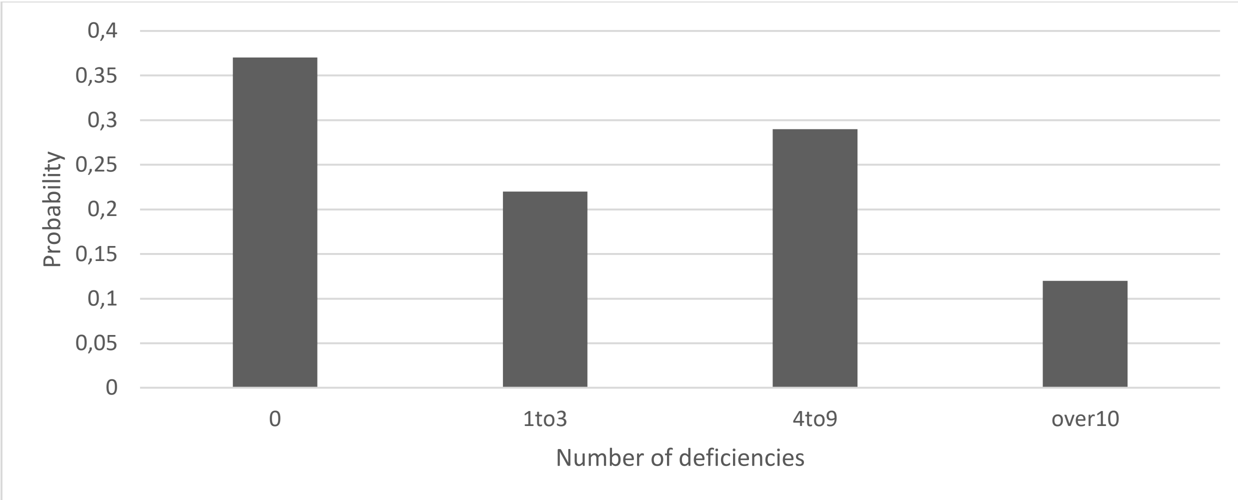


Figure 4.17 Prior probability distribution of number of deficiencies of the Thessaloniki port

A mean value for the prior probability distribution of the variable representing the number of deficiencies can be calculated as shown below:

$$E[X] = 0 * 0.37 + 2 * 0.22 + 6.5 * 0.29 + 11^{5} * 0.12 = 3.645 \qquad (4.1)$$

The detention rate according to the prior results of the model is calculated as 15%.

- Evidence : Age="0 to 5"

Setting an evidence that the ship inspected is relatively new, under 5 years old, a different probability distribution of the number of deficiencies is obtained.

Figure 4.18 presents the posterior probability distribution, given the age of the ship is under 5 years old, compared to the prior distribution (with no evidences).

[5] Almost all observations for state "over10" are between 10 and 12 so we choose 11 as the mean value of the state

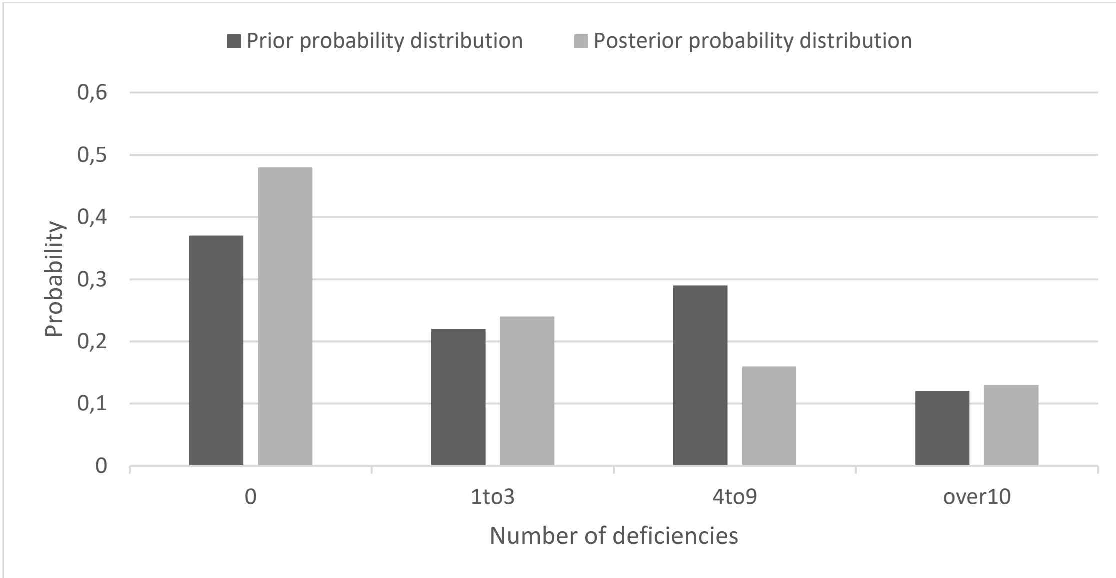


Figure 4.18 Prior and posterior probability distributions given the age is under 5 years (Thessaloniki port).

The new mean value of the posterior probability distribution of the number of deficiencies can be calculated as $E[X|age < 5] = 2.95$.

As it is clear, the information that the ship inspected is under 5 years old leads to significant increase of the possibility of not finding deficiencies during the inspection. The probability of the state "zero" is increasing from 37% to 48%. The age of the ship is an important factor leading to deficiencies during the inspection process. However, it is also observed that state "over 10" has not decreased as expected. Age is not the only factor influencing the number of deficiencies as even the information that the vessel inspected is under 5 years also maintain the probability of having more than 10 deficiencies at the same levels.

Moreover, the information that the age of the ship inspected is under 5 years old have almost no impact on the detention rate. The new detention rate is calculated as 13% which is similar to the detention rate before including the evidence that was 15%.

- Evidence : RO ="Very Low"

Including an evidence that the Recognized Organization of the ship inspected is classified as "Very Low" according to Paris MOU performance list also changes the probability distribution of the variable representing the number of deficiencies found in the inspection.

Figure 4.19 shows the posterior probability distribution, given the RO is “Very Low”, in comparison with the prior distribution.

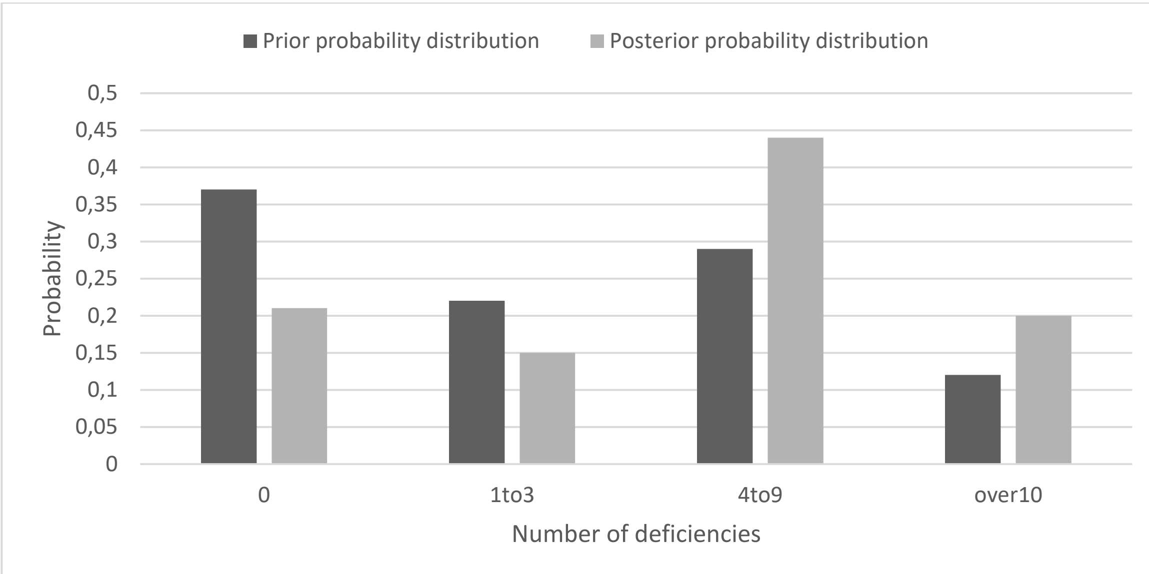


Figure 4.19 Prior and posterior probability distributions given the RO is classified as “Very Low”

The new mean value of the variable representing the number of deficiencies is calculates as $E[X|RO = Very\ Low] = 5.36$

As can be observed, the information that the vessel inspected has a Recognized Organization categorized as “Very Low” leads to equal decrease of the probabilities having zero or 1 to 3 deficiencies and increases the probabilities of having 4 to 9 or over 10 deficiencies found during a Port State Control inspection.

The fact that the Recognized Organization of the vessel inspected is classified as “Very Low” changes significantly the detention rate. The Bayesian Network model calculates the detention rate as 26% while without including the evidence was 15%.

- Evidence : Company Performance= “Low”

Company Performance is a risk factor introduced with the implementation of the NIR and is calculated as described in Chapter 3.

Given the fact that the company performance of vessel inspected is classified as “Low”, the posterior probability distribution of the number of deficiencies can be calculated.

Figure 4.20 presents the posterior probability distribution of the risk variable "Number of deficiencies", given the fact that the company performance is "Low", in comparison with the prior probability distribution.

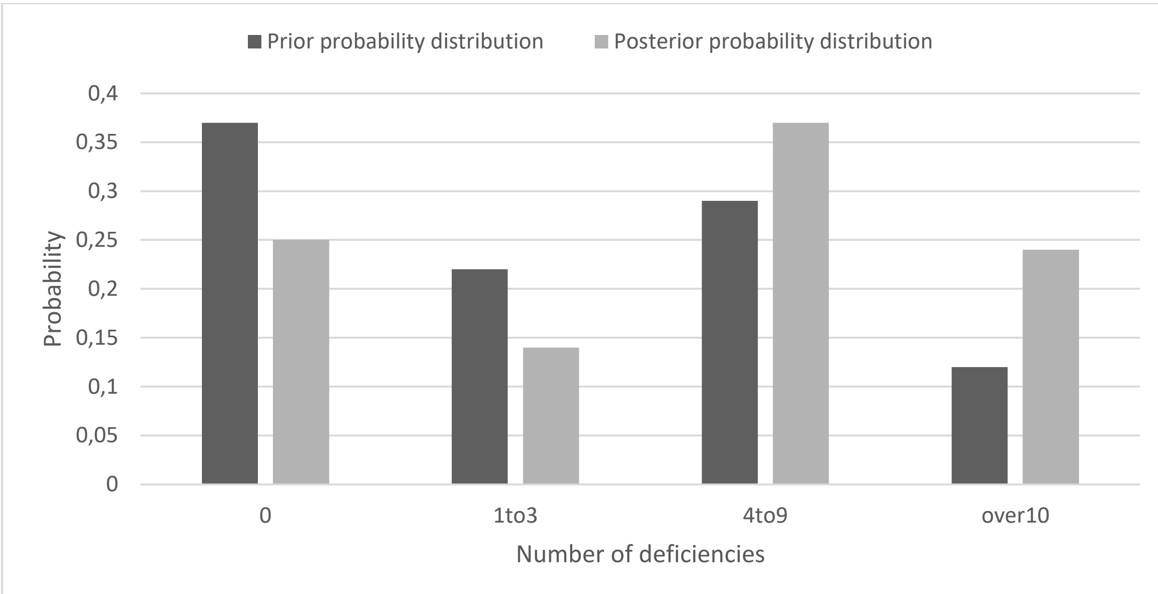


Figure 4.20 Prior and posterior probability distributions given the Company performance is "Low"

The mean value of the posterior probability distribution of the variable "Deficiencies" given the fact that company performance is "low" is calculated as $E[X|CP = \text{Low}] = 5.325$.

The information that the company performance of the vessel inspected is classified as "Low", according to Paris MOU criteria, decreases the probability of finding zero or 1 to 3 deficiencies during a Port State Control inspection. On the other hand, a significant increase in the probability of the vessel being found with more than 10 deficiencies is observed. Moreover, the probability of finding 4 to 9 deficiencies is increased too.

Including to the model the evidence that the Company Performance is low changes the detention rate as well. Before adding the information, the detention rate as 15% while the new information updates the detention rate calculation to 29%.

- Evidence : Deficiencies "zero" and no detention

Including evidences in a node being on the bottom of the model provides useful information on the factors influencing it. For example, including evidences on the result of the inspection, in terms of number of deficiencies found and detention, can also help analyzing how risk factors influence those two variables.

Given the information that no deficiencies were found so the ship did not get a detention in a Port State Control inspection, the Bayesian Network model recalculates the probability distributions of all variables such as "Company Performance", "RO", "Age" and "Flag".

Figures 4.21, 4.22, 4.23 and 4.24 present the prior probability distributions of variables " Age", "Company Performance", "RO" and "Flag" in comparison with the posterior probability distributions given that zero deficiencies found and the vessel did not get a detention.

The posterior probability distribution gives much higher probability in the event of the vessel inspected be under 10 years old. On the other hand, the probabilities of finding no deficiencies and get no detention are much lower for the old vessels.

The information that no deficiencies are found and no detention increase the probability of having a company with performance classified as "Medium". On the other hand, the probability of having a low company performance is decreased while the probability of a high company performance remains the same.

In the posterior probability distribution the probability of having a Recognized Organization classified as "High" is much higher than in the prior distribution while the probabilities of having "Very Low", "Low" and "Medium' are lower.

The information included in the model increases the probability that the flag is classified as "White" while decreases the probability of a "Black" flag. Finally, the probability of the flag classified as "Grey" remains the same as it was already low.

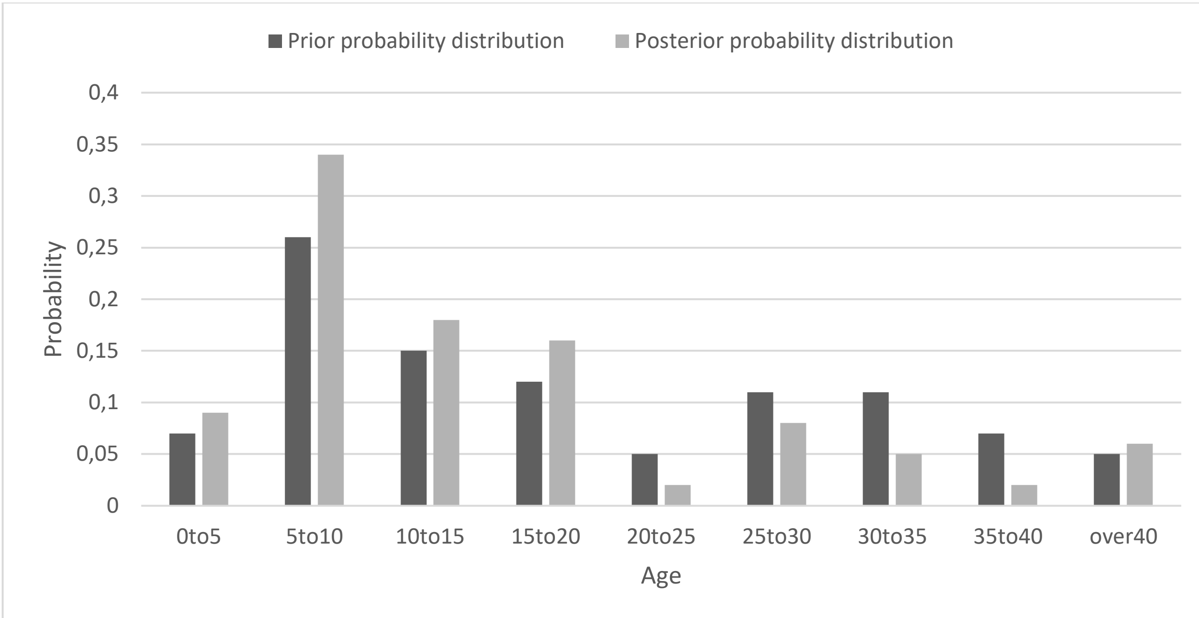


Figure 4.21 Prior and posterior probability distributions of "Age" given no deficiencies and no detention

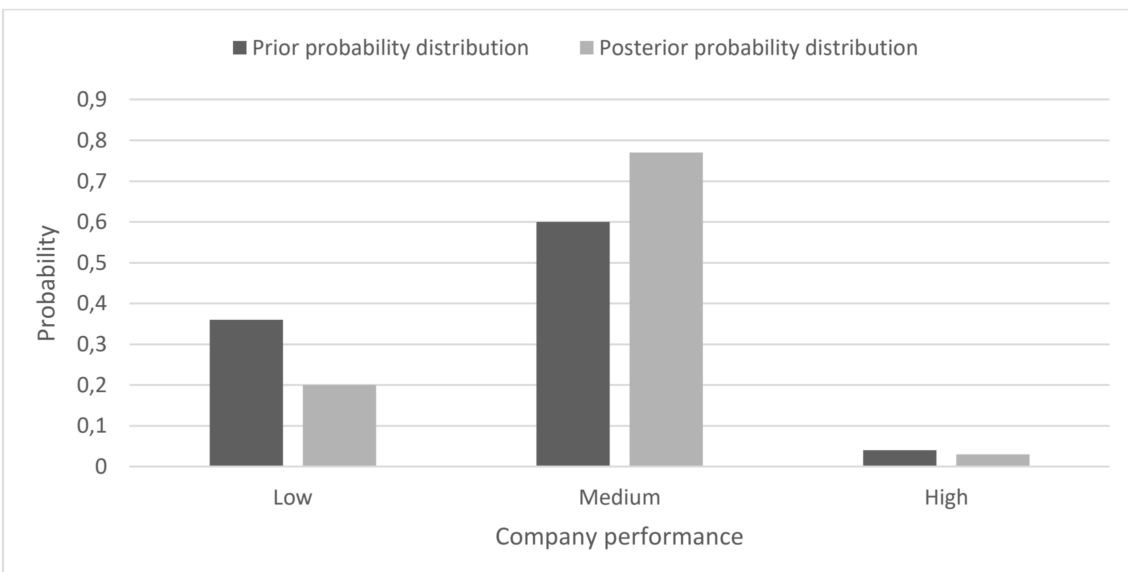


Figure 4.22 Prior and posterior probability distributions of "Company Performance" given no deficiencies and no detention

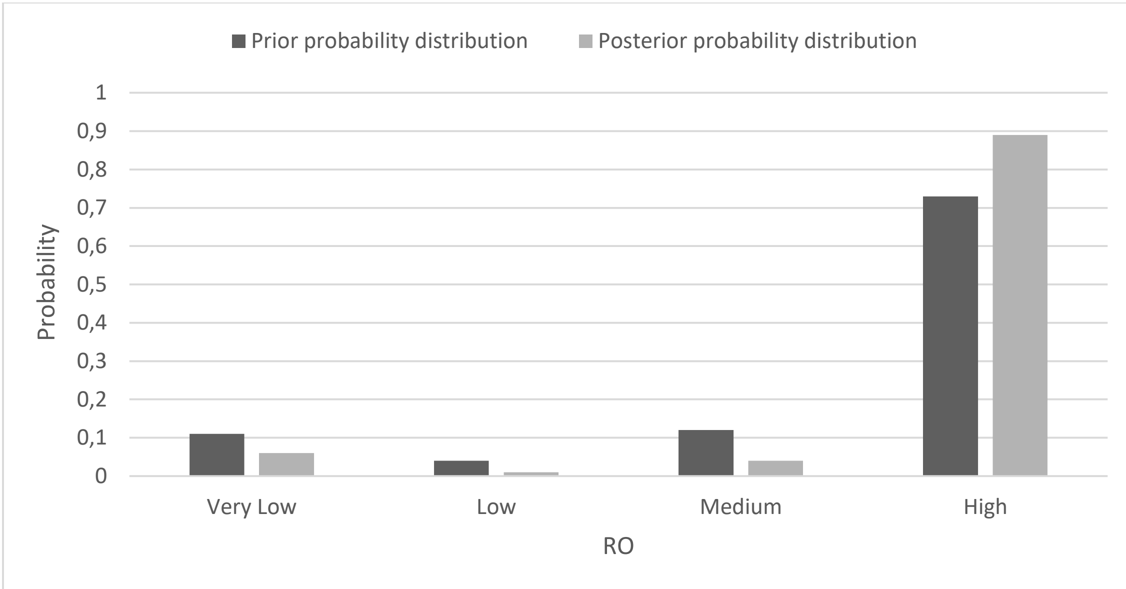


Figure 4.23 Prior and posterior probability distributions of "RO" given no deficiencies and no detention

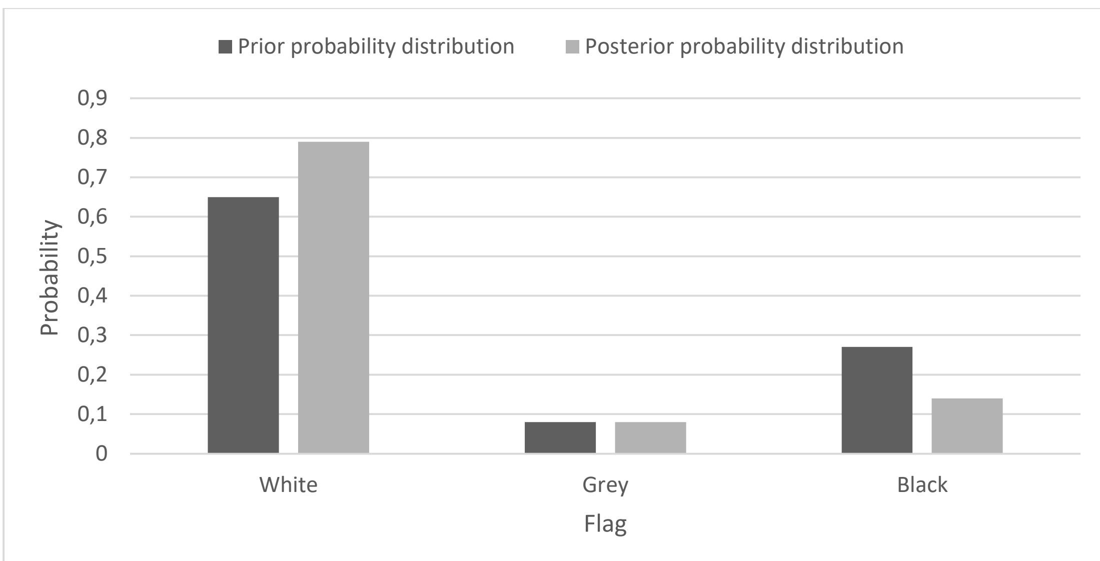


Figure 4.24 Prior and posterior probability distributions of "Flag" given no deficiencies and no detention

Liverpool port

Figure 4.25 presents the probability distribution of the variable representing the number of deficiencies found in a Port State Control inspection carried out at Liverpool during 2018 as calculated by the Bayesian Network model.

This prior probability distribution changes by including evidences to the model. Some evidences about risk factors such as the age, RO, company performance and flag are included in the model and presented below in an attempt to analyze how they affect the probability distribution of the deficiencies found in a Port State Control inspection and the detention rate.

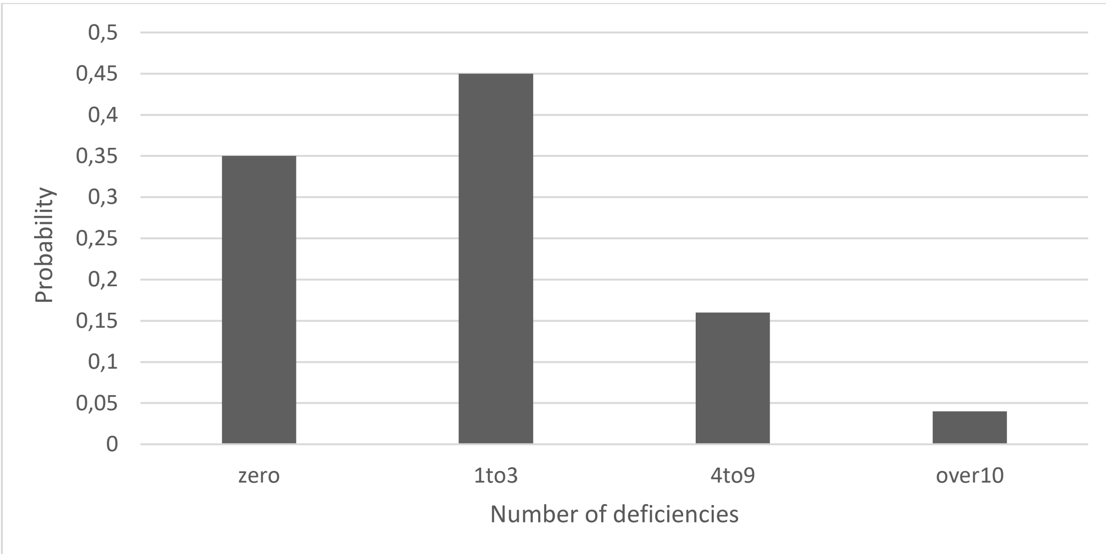


Figure 4.25 Prior probability distribution of the variable "Deficiencies" Liverpool port

A mean value of the prior probability distribution of the variable representing the number of deficiencies can be calculated as shown below:

$$E[X] = 0 * 0.35 + 2 * 0.45 + 6.5 * 0.18 + 11 * 0.03 = 2.4 \quad (4.2)$$

The detention rate according to the results of the model is calculated as 3%.

- Evidence : Age "0 to 5"

Including the evidence that the ship inspected is under 5 years old changes the probability distribution of the variable representing the number of deficiencies.

Figure 4.26 shows the posterior probability distribution, given the age of the ship is under 5 years old, in comparison with the prior distribution (before including evidences).

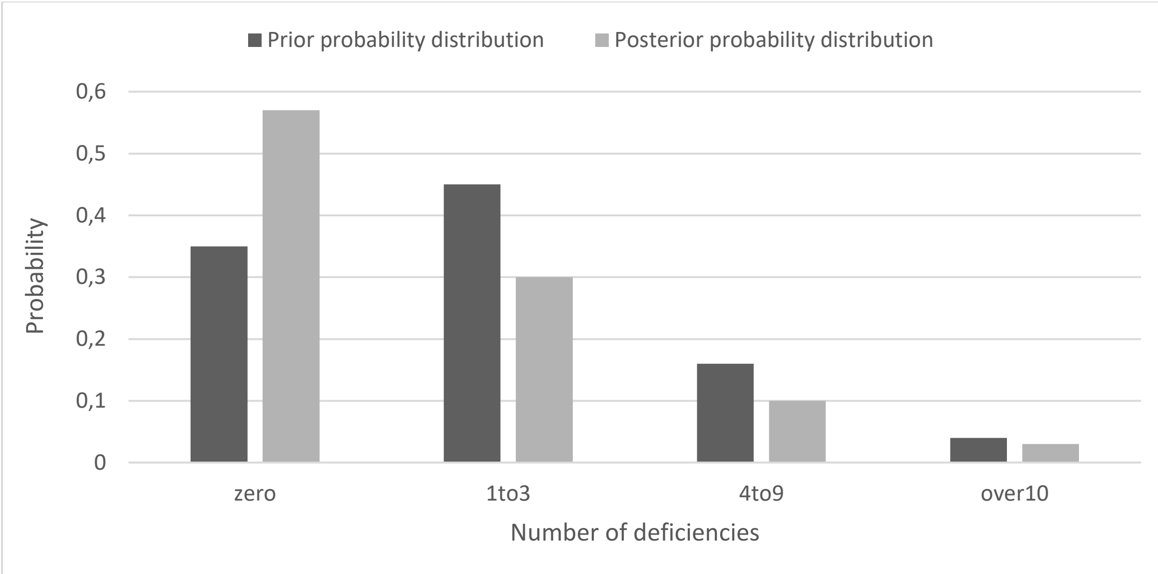


Figure 4.26 Prior and posterior probability distributions given the age is under 5 years (Liverpool port).

The mean value of the posterior probability distribution can be calculated as $E[X|age \leq 5] = 1.55$

As it can be observed, the information added to the model increased the probability of finding zero deficiencies during a Port State Control inspection. On the other hand, the probabilities of finding 1 to 3 or 4 to 9 deficiencies seem to decrease. For a recently constructed vessel inspected at Liverpool port the probability of having no deficiencies is 56%.

Moreover, including the evidence about the age has no impact on the detention rate, which remains at 3%, an already low value.

- Evidence : RO “Medium”

Figure 4.27 presents the posterior probability distribution, given the information that the Recognized Organization (RO) of the vessel inspected is classified as “Medium” performance.

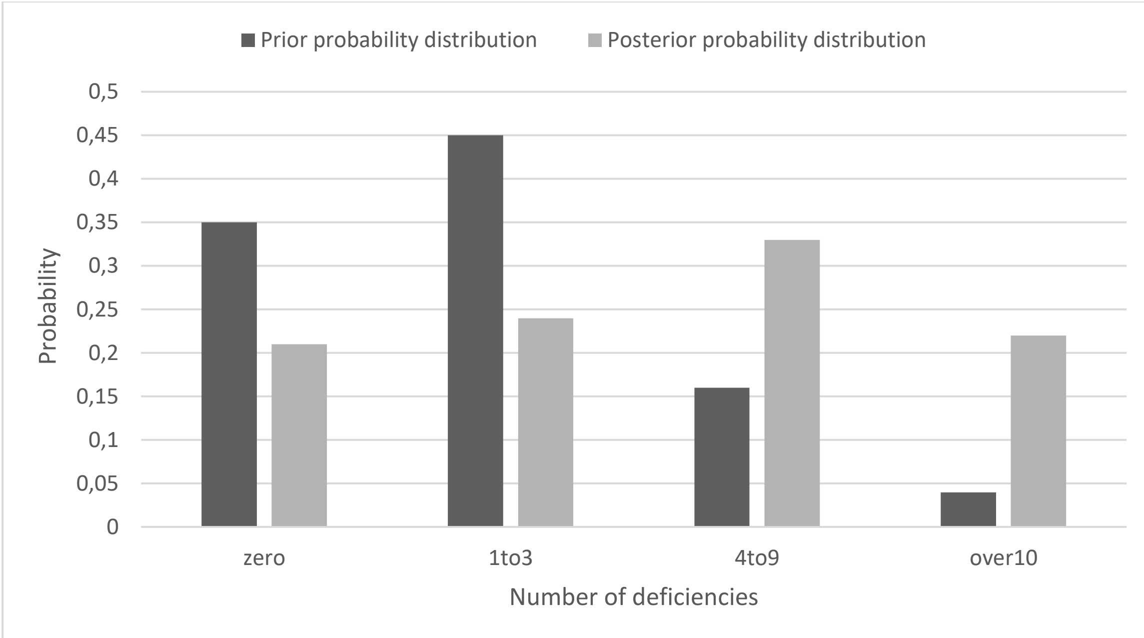


Figure 4.27 Prior and posterior probability distributions given the RO is "Medium" (Liverpool port).

The mean value of the posterior probability distribution can be calculated as $E[X|RO = "medium"] = 5.05$

The information that the RO performance of the ship inspected is categorized as "Medium" decreases the probability of finding zero or 1 to 3 deficiencies. On the other hand, the probability of having 4 to 9 deficiencies is significantly increased as well as the probability of finding more than 10 deficiencies.

The detention rate, after including the evidence, is calculated as 10% while without the evidence was calculated as 3%.

- Evidence : Company Performance "Low"

Figure 4.23 presents the posterior probability distribution of the variable representing the number of deficiencies given the fact that the company performance of the vessel inspected is classified as "Low".

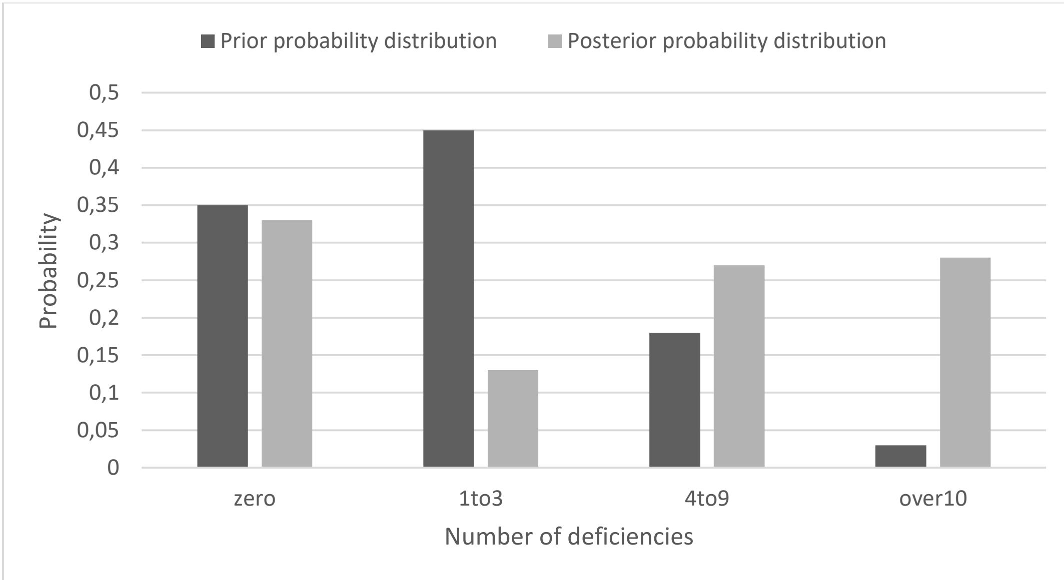


Figure 4.28 Prior and posterior probability distributions given the company performance is "Low" (Liverpool port).

The mean value of the posterior probability distribution can be calculated as $E[X|CP = "Low"] = 5.1$

As it can be observed, given the information that the company performance is low, the probability of having 1 to 3 deficiencies decreases significantly. Moreover, the probabilities of having 4 to 9 or over 10 deficiencies increase. However, the probability of finding no deficiencies remains at the same levels despite the fact that the company performance is classified as low.

The detention rate, given the information about the low company performance, is calculated as 61%. A value that is much higher than the previous one, without including the evidence.

- Evidence : Deficiencies "zero" and no detention

Including an evidence to the nodes representing the number of deficiencies and the detention, changes the probability distribution of the "Age", even though the age is not directly influencing these two variables.

Figure 4.29 presents the posterior probability distributions of the variable "Age" no deficiencies found and no detention.

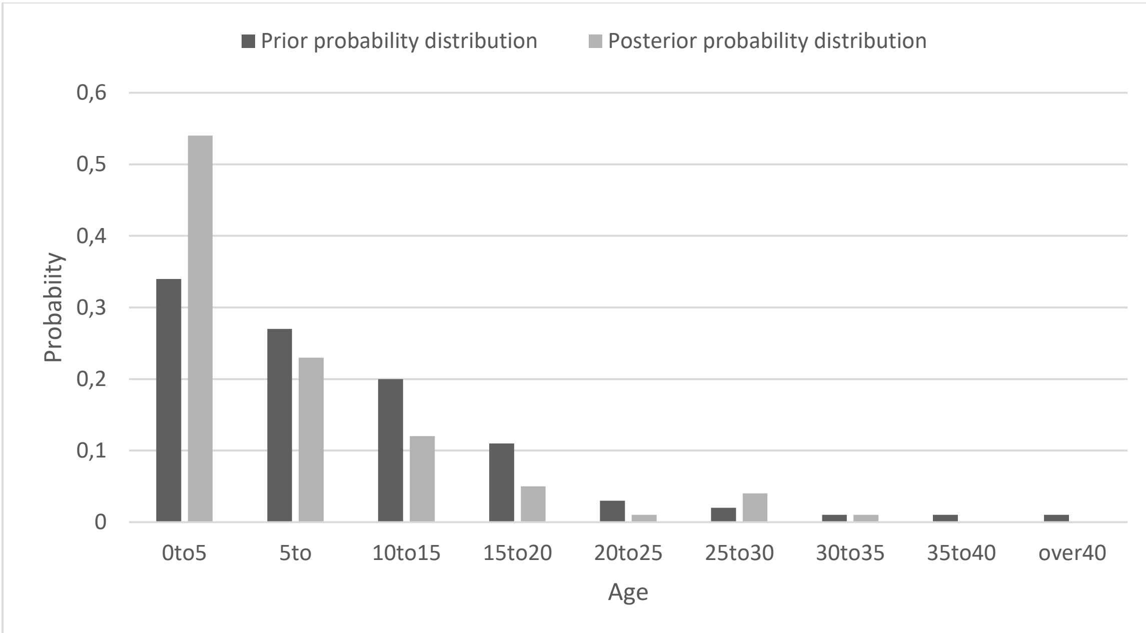


Figure 4.29 Prior and posterior probability distributions of "Age" given no deficiencies and no detention (Liverpool port).

Including the evidence that no deficiencies were found so no detention of the vessel, the probability the ship is under 5 years old increases (54%). On the other hand, the probabilities of the other states decrease, especially for the states 35 to 40 and over 40 years the probability is 0%.

4.5.3 Probabilistic analysis of deficiencies categories

As mentioned above, two separate models are developed to analyze how risk factors influence the different categories of deficiencies found in a Port State Control Inspection.

The Bayesian Network models developed before calculated the probability of finding deficiencies of any category during a Port State Control Inspection at Thessaloniki and Liverpool ports.

In an attempt to analyze how risk factors such as age, flag and RO influence the categories of deficiencies found in a Port State Control some evidences are included in the second set of models developed with detailed information on the type of deficiencies found in the two ports. As mentioned above, including evidence is the process of providing some information to the model and calculating the changes in the probability distribution of the variables.

Such analysis leads to conclusions on the way risk factors influence specific categories of deficiencies and could help ship owners take better decisions in order to avoid specific deficiencies leading to detention or Port State Control inspectors to give more attention to some areas during the inspection.

Below are presented some scenarios in which evidences are included in the models leading to changes in the probability distribution of the variable "Category of Deficiency".

- Evidence: Old vessel with black flag and poor company performance at Thessaloniki port

Including evidences to the model in order to simulate a scenario in which an old vessel (age 30 to 35) with a flag classified as "Black" and a company performance categorized as "Low", a new probability distribution of the variable "Category of deficiency" is obtained.

Figure 4.30 presents the posterior probability distribution of the categories of deficiencies, given the information described above, in comparison with the prior probability distribution (with no evidences).

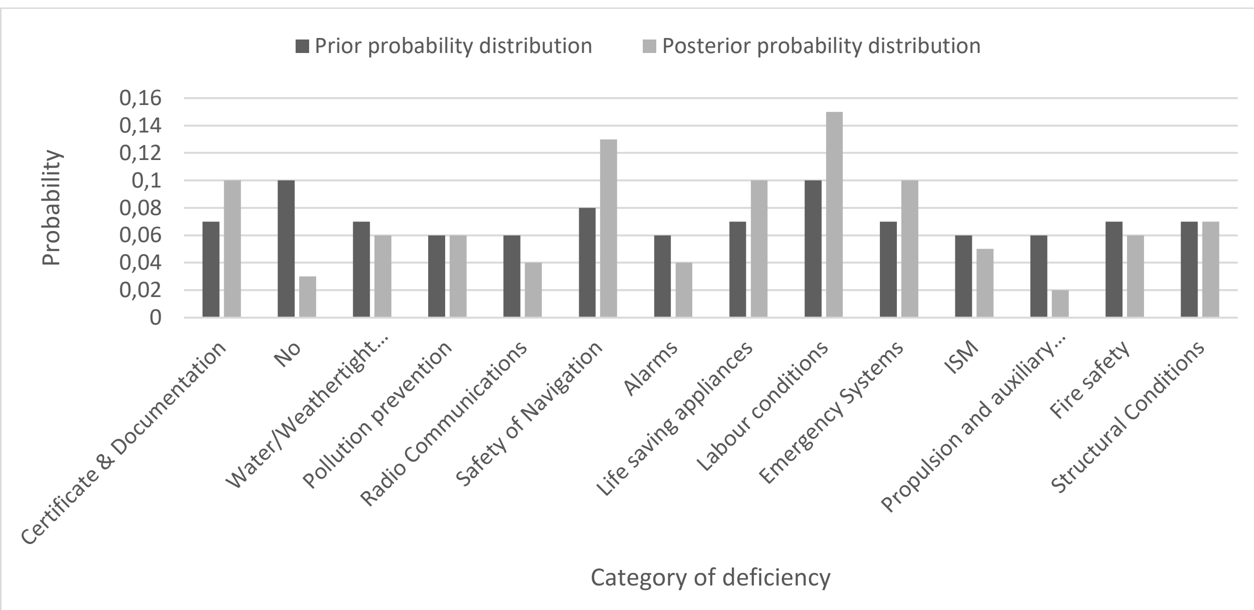


Figure 4.30 Prior and posterior probability distributions of categories of deficiencies

It is easily observed that the information about the age, the flag and the company performance of the inspected vessel leads to a significant decrease in the probability of having no deficiencies.

The categories of deficiencies with the most important increase are "Labour Conditions" and "Safety of navigation" followed by "Certificate and Documentation", "Lifesaving appliances" and "Emergency Systems"

- Evidence : Bulk carrier with "white" flag, "high" RO and "high" company performance at Liverpool port

In the following scenario a bulk carrier with a flag classified as "white", a RO categorized as "high" and a company performance classified as "high" is arriving for inspection at Liverpool port. Including the evidences mentioned above to the model, a new probability distribution of the categories of deficiencies is calculated.

The ship, due to its low risk level, is not expected to have many deficiencies. However, using the BN model, the inspector can notice the categories that are more likely to be defective items.

Figure 4.31 presents the posterior probability distribution, given the evidences mentioned above, of the variable "Category of Deficiency" in comparison with the prior probability distribution.

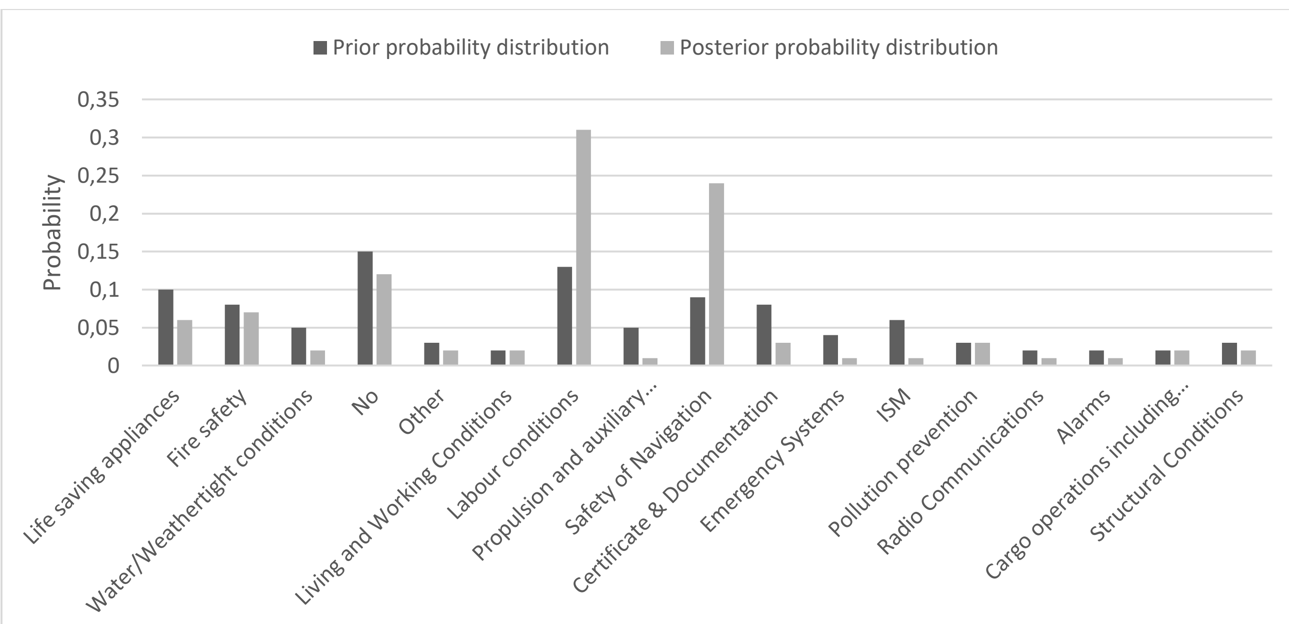


Figure 4.31 Prior and posterior probability distributions of "Category of deficiency", bulk carrier scenario (Liverpool port).

Even though the classification of vessel's flag, RO and company performance is good, there are specific categories of deficiencies with high probability. "Labour Conditions" is the most likely deficiency category followed by "Safety of Navigation". Port State Control officers can use such models in order to predict which categories are more likely to be defective and give special attention to them during the inspection.

- Evidence : General Cargo with "Very Low" RO, "Low" company performance and "Black " flag at Thessaloniki port

In the following scenario, a General cargo/multipurpose vessel with a RO classified as "Very Low", a company performance categorized as "Low" and a flag classified as "Black" is arriving for inspection at Thessaloniki port. Including the above information as evidence to the model, a new probability distribution of the "Category of Deficiency" is initialized.

Figure 4.32 presents the posterior probability distribution, given the evidences mentioned above, of the variable "Category of Deficiency" in comparison with the prior probability distribution.

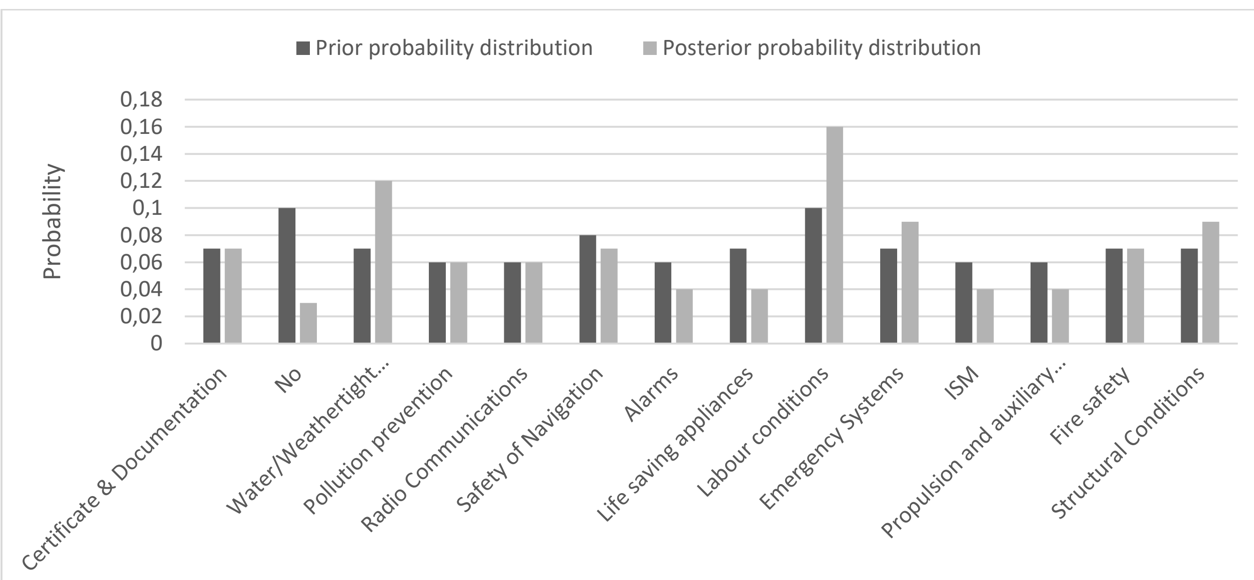


Figure 4.32 Prior and posterior probability distributions of "Category of deficiency", general cargo scenario.

As mentioned above, such analysis can help Port State Control inspectors to give special attention to specific categories of deficiencies during the inspection. As it can be observed, the vessel described above is likely to have deficiencies associated with labour conditions and Water/Waterlight conditions.

4.5.4 Probabilistic analysis of the inspection practices at Liverpool and Thessaloniki ports

A probabilistic analysis of the Port State Control inspection practices at the Thessaloniki and Liverpool ports, is conducted using the Bayesian Network models developed before. The main objective is to see if there are significant differences on the focus given to a particular group of deficiencies during a Port State Control inspection at the two ports.

Some evidences are included to the Bayesian Network models to analyze the categories of deficiencies. A scenario in which a low risk ship is inspected at both ports is simulated. The evidences included to the model are that the age of the ship is between 5 and 10 years old, the vessel is under a flag classified as "White" and the Recognized Organization performance is "High". The evidences included change the probability distribution of the variable "Category of deficiency". Figure 4.33 and 4.34 present the prior and posterior probability distributions of the variable "Category of deficiency" for Liverpool and Thessaloniki ports, respectively.

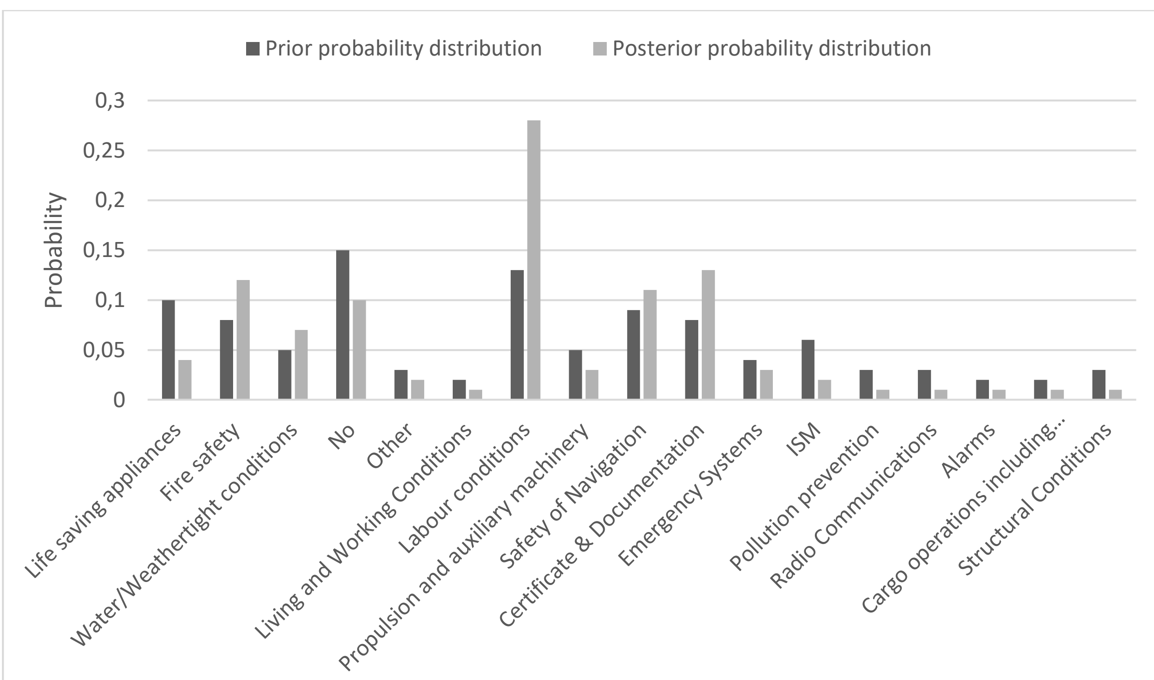


Figure 4.33 Prior and posterior probability distributions of "Category of deficiency", low risk ship, Liverpool port.

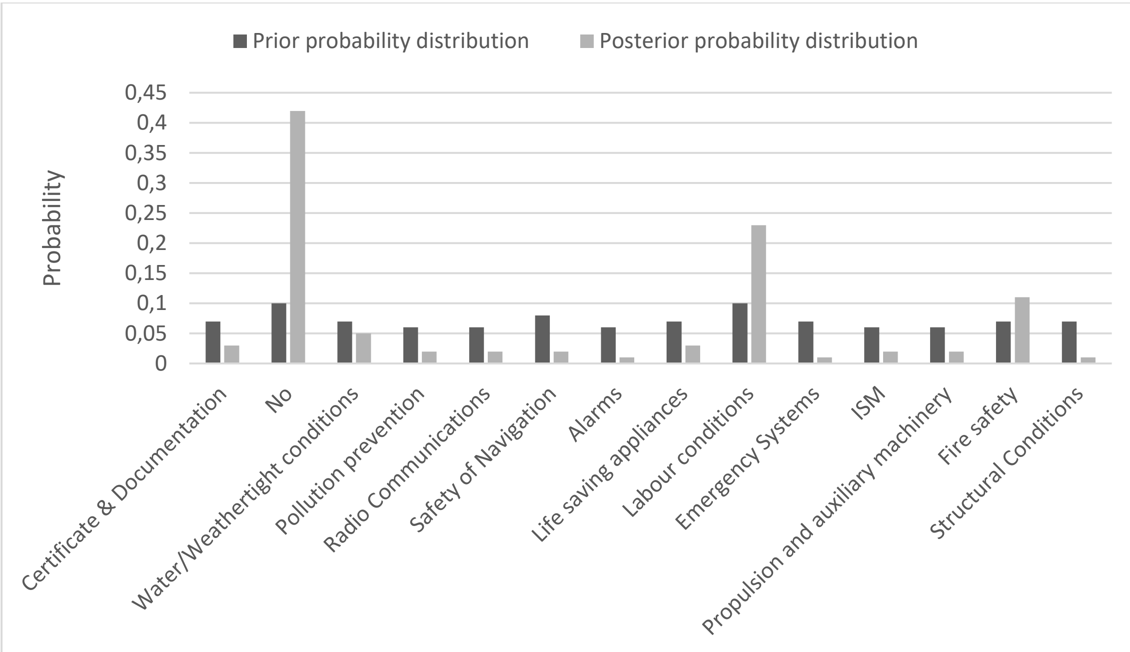


Figure 4.34 Prior and posterior probability distributions of "Category of deficiency", low risk ship, Thessaloniki port.

- The probability of the category "Labour Conditions" increases from 13% to 28% for Liverpool port and from 10% to 23% for Thessaloniki port. "Labour Conditions" is the category with the higher increase for both ports.
- The probability of the category "Certificate and Documentation" increases from 8% to 13% for Liverpool port. Concerning Thessaloniki port, the posterior probability of the state "Certificate and Documentation" is 7% while the prior probability is 3%.
- The probability of the category "Fire Safety" increases from 7% to 11% for Thessaloniki port and from 8% to 12% for Liverpool port.
- Despite the fact that the ship is considered as Low Risk, the posterior probability of finding no deficiencies, at Liverpool port, is 10% while the prior one is 15%. On the other hand, the posterior probability of the state "No" increases from 10% to 42% for Thessaloniki port.

5. Conclusions and future work

5.1 Conclusions

The Port State Control regimes have been developed to eliminate substandard ships that threatened the safety of life, property and the environment. Paris Memorandum of Understanding on Port State Control (Paris MoU) was established in 1982 by fourteen European countries. Nowadays, the organization 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.

On the 1 January 2011 the Paris MoU introduced a New Inspection Regime (NIR). Under this New Inspection Regime the old Target Factor system is replaced by a risk-based one, the Ship Risk Profile.

The risk influencing factors that are used to define Ship Risk Profile along with the way it is calculated is first analyzed in Chapter 3. Moreover, an analysis of Port State Control inspections covering the period from 2008 to 2017 is conducted, from which some useful conclusions can be drawn:

- After the implementation of the NIR (2011), the number of inspections every year dropped significantly while the number of individual vessels inspected increased. This is a result of using a risk based system for targeting ships. Such a system rewards quality shipping with a reduced inspection burden while more ships can be inspected.
- Detention rate has dropped after the implementation of the NIR. Concerning the ship type, "General Cargo / multipurpose" ships have the highest detention rate by far. However, this ship type is not considered to be high risk and does not contribute to the definition of the Ship Risk Profile.
- Most of the vessels inspected were characterized as Standard Risk Ships (SRS) (83%) while only 6% were classified as High Risk Ships (HRS) and 5% Low Risk Ships(LRS). More factors should be used to define Ship Risk Profile so more ships will be classified as LRS or HRS and the selection scheme be more efficient.

It has been shown that there is a growing interest in using Bayesian networks for probabilistic modelling of Port State Control inspections. The capability of representing rather complex, not necessarily causal but uncertain relationships makes Bayesian Networks a powerful tool for risk modelling. Especially, the data-driven approach on developing Bayesian Network models reduces the dependence on human experts and in some cases increases the accuracy of the model.

In the present dissertation, four Bayesian Network models are developed using Port State Control inspection data from inspections carried out at Thessaloniki and Liverpool port during 2018. The main objective is to characterize probabilistically the influence of the risk influencing factors on the Ship Risk Profile and on the deficiencies identified in the inspection at the two ports. The process of including evidences helps to have a better picture of how individual risk factors influence number of deficiencies found and detentions on a Port State Control inspection. In addition to the results presented in Chapter 4, some useful conclusions can be drawn:

- Respectively young ships, under 10 years old, seem to have less deficiencies and not get detained. However, the age of the ship is not a major factor that can lead to significant change on the number of deficiencies found.
- Factors such as the "Company Performance" and the "RO performance" seems to have a major impact on the number of deficiencies found and detention rate among the other factors. Poor company or RO performance lead to more deficiencies found on a Port State Control inspection.

Two separate models are developed to analyze how risk factors influence the different categories of deficiencies found in a Port State Control Inspection. Such Bayesian Network models can be served as the prediction tool for port authorities under different conditions. When a vessel arrives at a port, the port authority can use the proposed prediction tool to predict which categories are more likely to be defective. This can lead to a more focused and effective inspection process.

Such scenarios are simulated by including evidences in the Bayesian Network models and some useful conclusion can be drawn:

- For a vessel considered to be low risk, a bulk carrier with a flag classified as "white", a RO categorized as "high" and a company performance classified as "high", inspected at Liverpool port, "Labour Conditions" and "Safety of navigation" are the two deficiency categories that are more possible to be defective.

- For a vessel considered to be high risk, a General cargo/multipurpose vessel with a RO classified as "Very Low", a company performance categorized as "Low" and a flag classified as "Black", inspected at Thessaloniki port, "Labour Conditions" and "Water/Waterlight conditions" are the two deficiency categories that are more possible to be defective.

The present dissertation has shown the merits of Bayesian Network models for analyzing the influence of risk factors on the inspection results in terms of number and type of deficiencies. Moreover, Bayesian Network models can be used by port authority as prediction tools to predict which categories are more likely to be defective. However, the Port State Control inspection data used for the development of the Bayesian Network models in this dissertation refer to one year and to two ports only, which limits the potential of the models.

5.2 Recommendations for future work

Based on the present dissertation, some improvements can be done. Further work should focus on the following aspects:

- Data used for the Bayesian Network model development should be referred to more than one year and to more than two ports of the Paris MOU region. A larger sample of Port State Control inspection records can lead to a better model and to more accurate inferences.
- To develop a ship risk index that extends the concept of the Ship Risk Profile, which is heavily dependent on generic static parameters and on the inspection history of the flag State of the ships, by incorporation additional risk influencing factors.

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