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A Bayesian Belief Network modelling of organisational factors in risk analysis: A case study in maritime transportation

P. Trucco[a,*], E. Cagno[a], F. Ruggeri[b], O. Grande[a]

[a]*Department of Management, Economics and Industrial Engineering—Politecnico di Milano, Piazza Leonardo da Vinci, 32, I-20133 Milano, Italy*
[b]*CNR IMATI, via E.Bassini, 15, I-20133 Milano, Italy*

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Abstract

The paper presents an innovative approach to integrate Human and Organisational Factors (HOF) into risk analysis. The approach has been developed and applied to a case study in the maritime industry, but it can also be utilised in other sectors. A Bayesian Belief Network (BBN) has been developed to model the Maritime Transport System (MTS), by taking into account its different actors (i.e., ship-owner, shipyard, port and regulator) and their mutual influences. The latter have been modelled by means of a set of dependent variables whose combinations express the relevant functions performed by each actor. The BBN model of the MTS has been used in a case study for the quantification of HOF in the risk analysis carried out at the preliminary design stage of High Speed Craft (HSC). The study has focused on a collision in open sea hazard carried out by means of an original method of integration of a Fault Tree Analysis (FTA) of technical elements with a BBN model of the influences of organisational functions and regulations, as suggested by the International Maritime Organisation's (IMO) Guidelines for Formal Safety Assessment (FSA). The approach has allowed the identification of probabilistic correlations between the basic events of a collision accident and the BBN model of the operational and organisational conditions. The linkage can be exploited in different ways, especially to support identification and evaluation of risk control options also at the organisational level. Conditional probabilities for the BBN have been estimated by means of experts' judgments, collected from an international panel of different European countries. Finally, a sensitivity analysis has been carried out over the model to identify configurations of the MTS leading to a significant reduction of accident probability during the operation of the HSC.

Keywords: Bayesian Belief Network; Risk analysis; Human and organisational factors; Maritime industry

1. Introduction

Despite the remarkable effort performed at different levels to achieve a safe Maritime Transport System (MTS), the occurrence of accidents and incidents at sea is still increasing. Statistics published by the European Transport Safety Council [1] reveal that in Europe maritime accidents are responsible yearly for 140 deaths and 1.5 billion € of goods loss and damages. Globally, the MTS is responsible for 0.33 deaths per 100 million person-km, 4 times riskier than the air transport system, that accounts for 0.08 deaths per 100 million person-km. Grounding (32%), striking (24%) and collision (16%) are the most frequent occurrences and they have the highest rate of casualties.

It is widely recognised that the human element plays the major role in most accidents involving modern ships. Thus, the Lord Carver report of the UK House of Lords summed it up succinctly when stating that it "is the received wisdom that four out of five ship casualties […] are due to human error […]". Also national statistics shown in Fig. 1 (Transportation Safety Board of Canada [2]), attribute 74% of the accidents at sea to human errors and only 20% to technical failures. As shown in Fig. 2, 45% of the accident reports assess the misjudgement (mistake) of ship masters and pilots as predominant causes; in another 42% of cases human errors refer to lack of comprehension between the pilot and the master, inattention of the pilot and of the officer of the watch (OOW) or lack of communication among crew members.

*Corresponding author. Tel.: +39 02 23 99 4053; fax: +39 02 23 99 4067.
E-mail address: paolo.trucco@polimi.it (P. Trucco).

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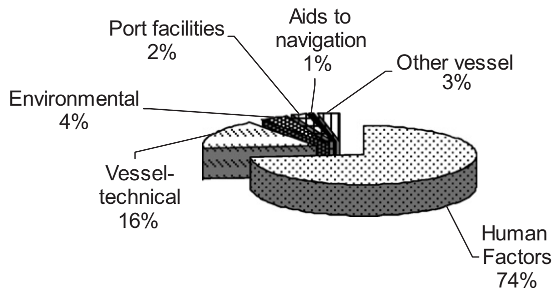

Fig. 1. Main causes of accidents at sea.

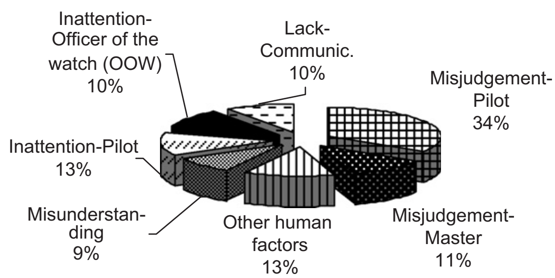

Fig. 2. Types of human errors in accidents at sea.

Similar results are pointed out by a statistical analysis based on data of the Lloyds Informative Maritime Service [3] concerning more than 15,000 accidents in a time span of 10 years. Lloyds' statistics show that an uncorrected course and an excessive speed with respect to the traffic in the sea zone are responsible for about 50% of all the maritime accidents, particularly groundings. Moreover, 70–80% of the accidents are due to human mistakes or other events attributed to the human behaviour.

While technical solutions will continue to play an important role, there is widespread agreement that the key means of tackling the human element contribution to accidents will be via safety management, including inspection and training.

Starting with a deeper understanding of the role of the human element in the safety performance of maritime transport, a new issue is emerging; indeed, the official report concerning the Zeebrugge incident (capsizing of a passenger ship) [4] already pointed out that it was not due to a coincidence of independent technical failures and human errors, but a systematic change in the organisational behaviour of operators under the influence of economic pressure in a strongly competitive environment. Thus, a systematic safety analysis of the MTS needs to be enlarged to include interactions and effects of decisions taken by various actors of the MTS, and workplace and context conditions, including the economic pressure affecting the maritime sector.

Various parties (operators, shipyards, regulators and government) in their respective working contexts are very often involved in a sequence of events leading to an accident; this is the most critical issue in developing an effective risk or accident analysis. The error of the operator onboard a ship is only the final act of a long and complex chain of organisational and systemic errors (i.e. the so-called latent failures). Rasmussen highlighted the conflicting interactions between parties in MTS, evidenced by his accident analysis of oil tankers and ferryboats [5–7].

The need for a systemic approach to analyse the MTS safety is therefore clear, not only focused on mistakes and violations of the operators, but also aimed at finding, if they exist, the causes at the various levels of the socio-technical system, which competes for determining the accidents. The International Maritime Organisation (IMO) provides a rational and systematic approach for assessing risk in shipping activity: a comprehensive model is suggested to take into consideration different influences with an impact on the technical and engineering system of a ship. In fact the Formal Safety Assessment (FSA) describes a generic model (shown in Fig. 3) that considers the ship's technical and engineering system, in the centre of the model, as related to the functions representing the passengers and crew behaviour that subsequently is influenced by management and the organisational structure; finally, the model shows the outer influence of the environmental context that represents the influences of all parties interested in shipping. Each subsystem is dynamically affected by the others both directly and indirectly; a complex model is requested to represent these relationships between variables of each subsystem.

This approach and the necessity of incorporating human reliability analysis into the FSA process [8], suggests the use of a Risk Contribution Diagram (RCD) for modelling the network of influences on an event in a complex system [9] as development of Risk Contribution Tree (RCT) described by FSA: this method allows the linkage between failures at the operational level with their direct causes, and the underlying organisational and regulatory influences.

Also Bayesian Belief Network (BBN) [10] has been used for the purpose of integrating the analysis of human and hardware failures and reflecting the hierarchical nature of influence domains. Thus the BBN model can be regarded as a RCD in which the effects of such factors are represented in terms of conditional probabilities. Moreover, from a risk reduction standpoint, the European Commission (EC) funded a project, called S@S—Safety at Speed [11]—to develop a Functional Model (FM) of the MTS. The FM helps in identifying the critical interactions among actors that

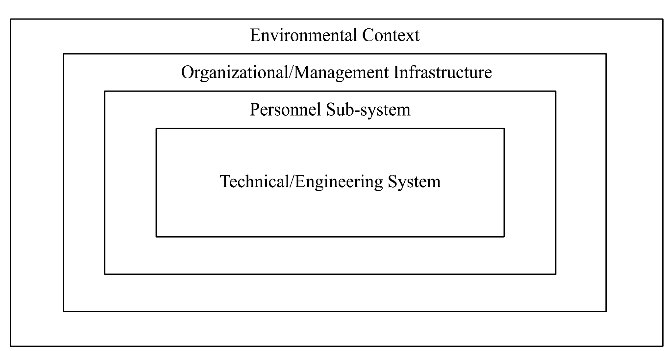

Fig. 3. Components of the integrated system for application of the Formal Safety Assessment (FSA) [8].

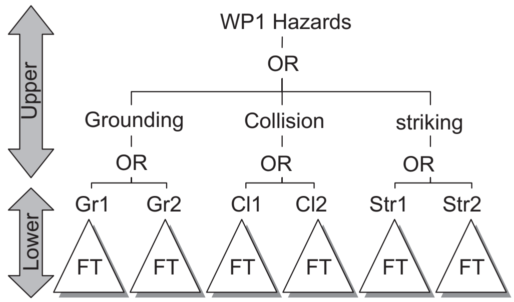

Fig. 4. Framework of the Hazard Analysis developed within the S@S project.

can trigger unwanted events and the parameters that can be used to improve the situation. The objective of the project was to develop a formal methodology for the safety design of High Speed Craft (HSC) using state-of-the-art techniques and tools [12]. At the same time, S@S wanted to promote a safety-culture approach for integrating safety effectively in the process of ship design. Specifically, the research project developed a set of Fault Trees (FTs) representing different hazards (collision, grounding, fire, flooding, …) and aiming to support the selection of the best risk control option within the design process of a HSC, as shown in Fig. 4.

The basis of a FM of the MTS was the identification of the main parties involved in the MTS and a set of their critical activities; each activity is modelled as a function. The FM is then represented as a network of mutual influences and interdependencies that allows an understanding of how changes within the MTS can propagate and ultimately affect safety. In particular, the FM aims to explain how Human and Organisational Factors (HOF) can undermine safety and lead to unwanted events. The FM of the MTS has been developed in three phases, showing the increasing maturity of the model.

The paper proposes a model and a comprehensive approach, based on Fault Tree Analysis (FTA) and BBN, to integrate HOF within a risk analysis study. Previous versions of the model have been presented [10,13]. With respect to the latter, the present paper reports a complete evolution of the model and a comprehensive approach. Specifically, a method to study the impact of single organisational factors on the overall safety performance of the system (namely an HSC), on a quantitative basis, will be presented. Referring to the "Collision in Open Sea" FTA developed by the S@S project [11], the results of a sensitivity analysis of HOF over the probability of occurrence of both the basic events (BEs) and the top event (TE) will be presented.

2. Bayesian Belief Network

A BBN is a Directed Acyclic Graph (DAG) consisting of a set of nodes, representing variables with a finite set of states, and edges, representing the probabilistic causal dependence among the variables. The nodes with edges directed into them are called "child" nodes and the nodes from which the edges depart are called "parent" nodes (if there is an edge from node X_1 to another node X_2, X_1 is called parent of X_2; refer Fig. 5) and nodes without arches directed into them are called "root" nodes (X_3 in Fig. 5). The DAG represents the structure of causal dependence between nodes and gives the qualitative part of causal reasoning in a BBN, thus the relations between variables and the corresponding states give the quantitative part, consisting of a Conditional Probabilistic Table (CPT) attached to each node with parents, as shown in Table 1.

The chain rule says that a Bayesian Network is a representation of the joint distribution over all the variables represented in the DAG and the marginal and the conditional probabilities can be computed for each node of the network.

If U is an universe of variables:

$$U = \{X_1, X_2, \ldots, X_n\}, \tag{1}$$

the joint probability of U is then:

$$P(U) = \prod_{i=1}^{n-1} P(X_i|X_{i+1}, \ldots, X_n). \tag{2}$$

From the joint probability distribution $P(U)$, various marginal and conditional probabilities can be computed, e.g. $P(X_i)$, $P(X_i|X_j)$ or $P(X_i|e)$ where, in general, e is an evidence:

$$e = \{e_1, e_2, \ldots, e_m\}, \tag{3}$$

that is an information received from external sources about the possible states/values of a subset of the variables of the network (1).

For a set of discrete variables, X_i, the evidence appears in the form of a likelihood distribution over the states of X_i: if an observation is given over some variables of the network, the probability of occurrence of some events can be

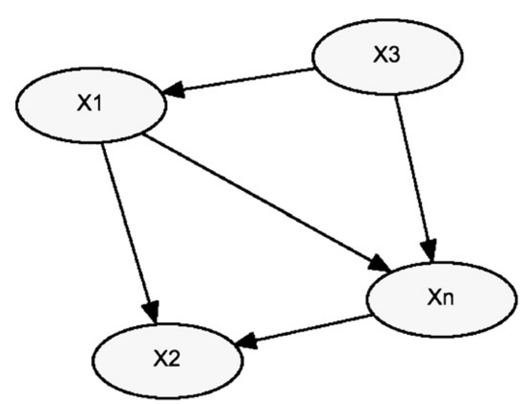

Fig. 5. Sample of Bayesian Belief Network (BBN).

Table 1
Example of conditional probability table (CPT) for X_n

	X_1	State 1		State 2	
	X_3	State 1	State 2	State 1	State 2
X_n	State 1	0.9	0.2	0.5	0.3
	State 2	0.1	0.8	0.5	0.7

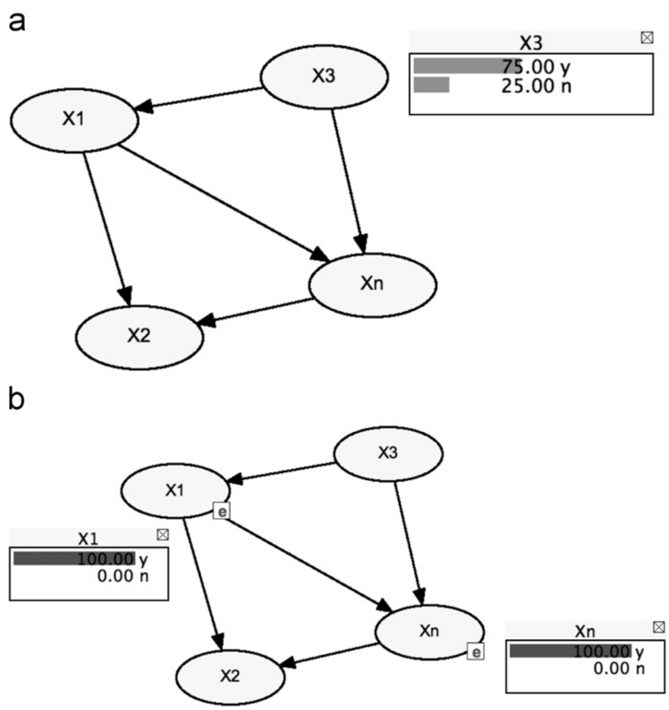

Fig. 6. Sample Directed Acyclic Graph (DAG) with "soft" (a) and "hard" (b) evidences.

calculated given the evidence:

$$P(U|e) = \frac{P(U,e)}{P(e)}. \tag{4}$$

An evidence is called "hard" when it is an exact observation of the state of the variables, whilst it is "soft" when a non-definite information is given, expressed in terms of likelihood for the states of the variable [14], as shown in Fig. 6.

In other terms, a probabilistic inference is given that is capable to updating our belief about events given observations, then it is possible to perform a sensitivity analysis of probabilities given different subsets of evidences.

3. Applications of BBN in risk analysis

Scientific literature on risk analysis shows a recent diffusion of the use of BBN [15]. BBN is mainly seen as a tool allowing the analyst to exploit different information, deterministic or probabilistic, emerging from the real world, under the condition of complex relations between a large number of variables. Reported applications comprise a large range of risk analysis studies, such as: the classification of components and subsystems of a nuclear plant based on safety performance assessment [16], the estimate of the unknown prevalence of a chronic disease affecting a specified population [17], the assessment of integrated fire prevention and protection systems [18], the integration of different eutrophication models for synthesis, prediction, and uncertainty analysis [19]. The Bayesian approach provides also an aid for decision-making as a tool for improving the qualitative analysis throughout numerical procedures [20] and to find a suitable reliability framework for dynamic systems [21].

In particular, the literature provides several frameworks for analysing the organisational context of accidents in order to improve the operational safety: the BBN model allows obtaining the occurrences of operational accidents that includes organisational factors, as the study of organisational causes in commercial aviation [22], where the high complexity of technical, HOF requires a quantitative model to reduce the fatal accident rate. A strategy for integration of the organisational risk in the FTA is also proposed for aircraft maintenance planning [23] in order to assess the impact on accident probability; purpose of this model is to develop an explicit path from organisational and management factors to the accidents. The same problem is analysed in a framework on reduction of Signal Passed At Danger (SPAD) incidents in rail crashes on UK rail network [24]; in this case BBN is used to obtain possible configurations of events leading to an accident and to understand the interactions of actors in the organisation that contribute to the incident. An application of BBN into a FSA of Large Passenger Ships Navigation is reported in recent deliverables of IMO Maritime Safety Committee [25,26]; the BBN is used to develop simple models of selected hazards (e.g. grounding or collision) incorporating few influencing factors at the organisational level (e.g. safety culture).

Finally an example of BBN model is shown that helps the decision making process at design level [27], where BBN is used to estimate the distribution of the harm to people produced by fire in a building.

4. Use of BBN for modelling HOF in risk analysis

Bayesian Networks are often used for causal representation of the phenomena involved in a complex system or process, where information is based on expert knowledge. This approach allows a better analysis of a dependable system [28] as a result of additional capabilities of the BBN respect to the FTA (e.g. common cause failure dependencies, diagnostic reasoning). In this case a BBN is an extension of FT, suitable for a great number of applications in risk analysis where the combined use of conventional and non-conventional methods is needed.

The proposed approach uses BBN as a modelling tool to quantify the organisational structure of a complex socio-technical system in order to obtain a better estimate of the probability of occurrence of an hazard, given a specific configuration of critical HOF [10]. Indeed, the scope of the BBN is to implement the organisational model so as to analyse the propagation of influences amongst the functions of different actors within the system (expressed as conditional probabilities). Given a set of FTs representing relevant hazards of the system under analysis, the BBN is then used to modify the probability of occurrence of those BEs affected by the capabilities and the level of performance of critical organisational functions, as shown in Fig. 7.

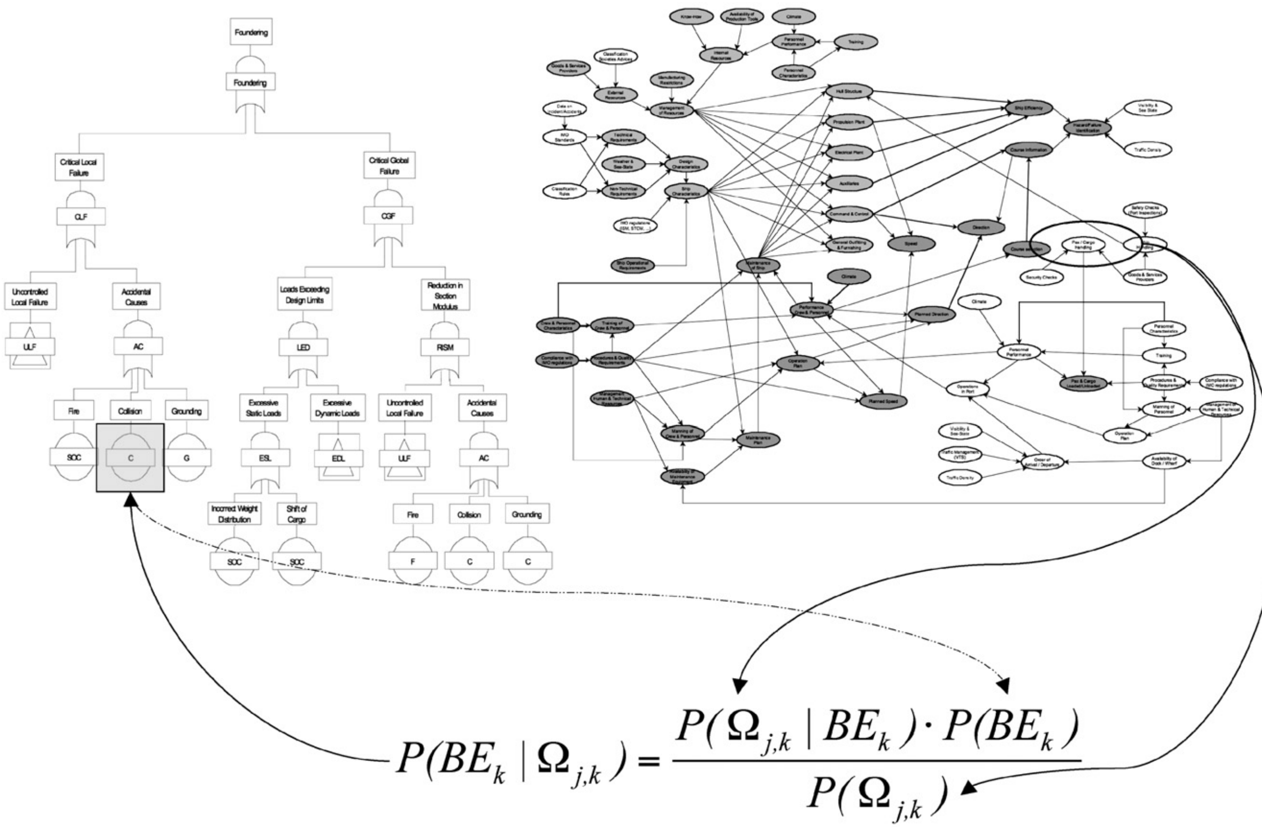

Fig. 7. Linkage between Bayesian Belief Network (BBN) and Fault Tree (FT) through the Bayes' theorem.

Table 2
Conditional probability table (CPT) of the dummy organisational configuration variable (Ω_k) of the BE_k "Helmsman error"

Crew knowledge		High				Low			
Position		Correct		Incorrect		Correct		Incorrect	
GPS[a]		W	O	W	O	W	O	W	O
Ω_i	H-C-W	1							
	H-C-O		1						
	H-I-W			1					
	H-I-O				1				
	L-C-W					1			
	L-C-O						1		
	L-I-W							1	
	L-I-O								1

[a]W, working; O, out of order.

The influence of organisational factors on the probability of occurrence of a single BE has been estimated by means of the basic Bayes theorem. To this end the concept of "organisational configuration variable" (Ω) has been introduced, a fictitious variable acting as the conjunction between the BBN model and the FT. The states of Ω_k are the j mutually exclusive combinations of states of those variables of the BBN model that influence BE_k (Table 2). Thus, taking into account the experts' belief on the contribution of organisational factors, it is possible to update the probability of occurrence of the basic event (BE_k), either technical or human, given a certain knowledge over its correspondent organisational configuration variable (Ω_k) as follows:

$$P(\text{BE}_k|\Omega_{j,k}) = \frac{P(\Omega_{j,k}|\text{BE}_k)P(\text{BE}_k)}{P(\Omega_{j,k})}, \tag{5}$$

where

- $\Omega_{j,k}$ is the jth state of the "organisational configuration variable" representing the influence of the organisational factors on BE_k; $P(\text{BE}_k|\Omega_{j,k})$ is the posterior probability of occurrence of BE_k given $\Omega_{j,k}$;
- $P(\text{BE}_k)$ is the prior probability of occurrence of BE_k provided by statistical analysis of historical data or a predictive model based on past data;
- $P(\Omega_{j,k})$ is the probability of state j of the k "organisational configuration variable" estimated through the BBN given a marginal distribution for the root nodes, as the one described in Table 2;
- $P(\Omega_{j,k}|\text{BE}_k)$ is the degree of belief in the occurrence of $\Omega_{j,k}$ given the occurrence of BE_k; the value of $P(\Omega_{j,k}|\text{BE}_k)$ was expressed through tables as the one shown in Table 3, reporting the experts' answer to questions such as: "Given a Helmsman error, what is the likelihood that it has occurred under the following organisational context: High Crew Knowledge, Correct Position and Working GPS?".

Table 3
Estimates of the $P(\Omega_{j,k}|\mathrm{BE}_k)$ for BE_k "Helmsman error"

Crew knowledge		High				Low			
Position		Correct		Incorrect		Correct		Incorrect	
GPS[a]		W	O	W	O	W	O	W	O
Ω_i	5%	5%	10%	10%	15%	15%	15%	25%	100%

[a]W, working; O, out of order.

Table 4
Ranking of the organisational configuration variables (Ω_j) according to the number of Basic Events (BEs) they affects (minimal cutsets of the fault tree identified 25 critical BEs)

Organisational configuration variables (Ω_k)	Number of critical BEs affected
Performance of crew and personnel (PCP)	25/25
Training of crew and personnel (TCP)	9/25
Course information (CI)	6/25
Direction (D)	6/25

The proposed method of assigning probabilities is, probably, one of the simplest ones and works well when the number of factors is relatively small, as in the case of Table 2. All possible combinations of the levels of the factors are considered to form a partition of the measurable space and probabilities are assigned to each one of them. When the number of factors exceeds 3, then a possible simplification is given by identifying only the most influential factors. Finally, (marginal) probability densities could be specified for each factor and the joint density on all factors could be obtained by using copulas. The choice of proper correlations and kernels are difficult problems to be solved. A thorough discussion of these approaches is well beyond the scope of the current paper and the interested reader is referred to the paper by Palomo et al. [29], which deals with a different, but similar, problem.

The FTA of "Collision in open sea", developed by the S@S project [11], has been used for the case study, providing a quantification of the influences that some of the variables of the BBN have on some BEs, specifically 38 human errors and 26 technical failures. Indeed, the proposed approach allowed identifying probabilistic correlations between 64 BEs of the FT and the BBN model of the organisational functions within the MTS, represented by 64 organisational configuration variables. Appendix A shows the graphical representation of the BBN organisational model of the MTS, while Appendix B reports the actors and their s comprised in the model. This linkage can be exploited in different ways, the most important one being to support the identification and evaluation of risk control options for HSC collision also at the organisational level.

4.1. On the hypothesis of independent BEs when connecting FT with BBN

Integration of BBN and FTA leads to consider the potential analytical problem of continuing to use Minimal Cut Sets (MCSs) to resolve the FT. Indeed, the simplified method of MCSs can be used only under the hypothesis of independent BEs, while the BBN clearly establish a set of common causal factors at an organisational level.

Moreover, the "beta factor" method [30], which is generally used to compute the joint probability of dependent BEs, only covers situations with different BEs affected by a single common cause failure, and this is no longer the situation faced. Table 4 shows the number of BEs affected by the most important organisational configuration variables (Ω_k). Nevertheless, it is possible to consider that the BBN model gives back the joint probability of the organisational configuration variables, noted as $P(\Omega_k)$, thus taking into consideration all the contributions of the network of dependent factors, by means of the known conditional probability tables and the correct use of the Chain Rule [13]. Indeed the computation of $P(\Omega_k)$ is a straightforward consequence of the structure of the BBN. Once the BBN is laid down and all the conditional probabilities from one level to the next one are provided, along with the probability of the top level, then straightforward applications of the Chain Rule brings to compute all $P(\Omega_k)$, at the bottom level of the BBN. Given a set of evidences, the proposed integration of FTA and BBN is thus able to directly provide the analyst with the joint probability values of all the BEs affected by common organisational factors and no further calculations are needed.

4.2. Setting of the operational and organisational conditions within the BBN model

The capability of the BBN to increase the belief about events is useful to analyse the effects of some subsets of observations given when the ship operations are influenced by certain design solutions, crew characteristics or other Organisational Conditions (shipyard resources, regulations, etc.) or by likely Operational Conditions (sea state, traffic density, etc.).

In order to consider these observations into a risk analysis of an hazard (e.g. collision in open sea) the Bayes' theorem is used, where a set of (soft) evidences is postulated as a non-definite information about Organisational or Operational Conditions [14]. If e is a set of evidences:

$$e = \{e_1, e_2, \ldots, e_m\}, \tag{6}$$

the Bayes' rule says that:

$$P(\mathrm{BE}_k|\Omega_{j,k}, e) = \frac{P(\Omega_{j,k}, e|\mathrm{BE}_k)P(\mathrm{BE}_k)}{P(\Omega_{j,k}, e)}. \tag{7}$$

Since conditional independence, given BE_k, between $\Omega_{j,k}$ and e implies that:

$$P(\Omega_{j,k}, e|\mathrm{BE}_k) = P(\Omega_{j,k}|\mathrm{BE}_k)P(e|\mathrm{BE}_k), \tag{8}$$

$$P(\Omega_{j,k}, e) = P(\Omega_{j,k})P(e), \tag{9}$$

then Bayes' Theorem implies:

$$P(\mathrm{BE}_k|\Omega_{j,k}, e) = \frac{P(\Omega_{j,k}|\mathrm{BE}_k)P(e|\mathrm{BE}_k)P(\mathrm{BE}_k)}{P(\Omega_{j,k})P(e)}. \tag{10}$$

Therefore results a new factor, as shown in:

$$\frac{P(e|\mathrm{BE}_k)}{P(e)}, \tag{11}$$

that represents the influence that the evidence e has on the probability of occurrence of BE_k variable state:

$$\text{posterior} \propto \text{likelihood}\frac{P(e|\mathrm{BE}_k)}{P(e)}\text{prior}. \tag{12}$$

Thus multiplying the likelihood function and the prior of a BE by this factor, it is possible to measure how much an evidence influences the occurrence of a BE. By this rule the BBN Organisational Model results in an inference engine for the calculation of beliefs on BEs given observations representing the influence of HOF on BEs.

For example in the case study two different categories of independent variables (evidences) within the MTS have been defined:

- Ship Design and Management Parameters—D&MP (e.g., shipyard resources, crew characteristics, ship operational requirements, …).
- Operational Conditions—OC (e.g., weather and sea state, traffic density, …).

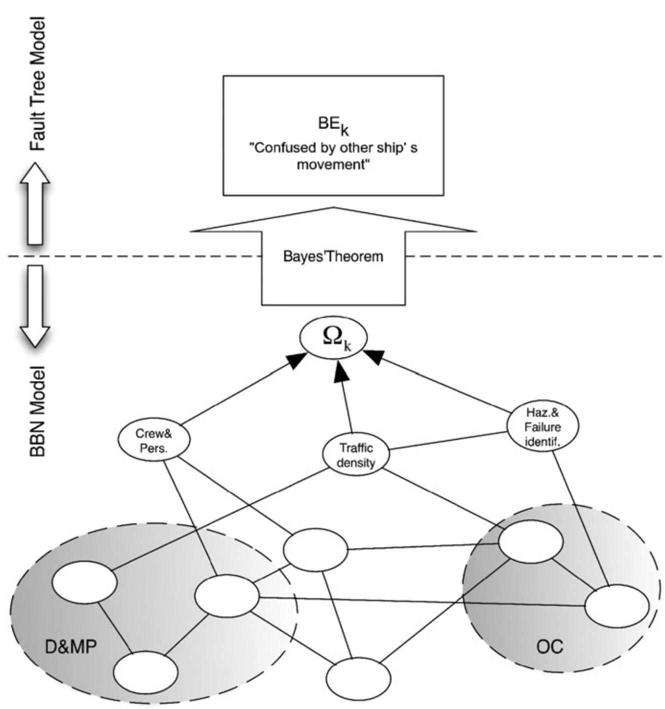

Fig. 8. Example of the use of the organisational configuration variable (Ω_k) in linking appropriate variables of the Bayesian Belief Network (BBN) with a specific BE_k of the Fault Tree (FT).

Referring, for example, to the BE "Confused by other ship movements" (human error) its organisational configuration variable is defined by the combinations of states of three variables of the MTS model: "Crew and Personnel performance", "Traffic density" and "Hazard/failure identification". The network of dependencies within the BBN directly or indirectly connects D&MP and OC variables with the organisational configuration variable of the considered BE, thus enabling a sensitivity analysis over the probabilities of occurrence of the BE, i.e. P(Confused by other ship movements$|\Omega_j$), or TE, i.e. P(Collision$|\Omega_j$), when the probability of Ω_j is modified by different configurations of D&MP or OC variables, as shown in Fig. 8.

5. Case study: a collision hazard for HSC

The proposed approach is applied to a case of interest: the influence of critical organisational functions on the probability of collision in open sea of an HSC, given a set of Operational Conditions. The connection between primary variables (evidences) of the BBN and the BEs of the FT allowed to estimate the impact of changes in the former to the probability of occurrence of the TE (ship collision). The original model [13] has been developed along three major steps: MTS analysis, Qualitative Model Formulation, Quantitative Model Formulation. In the first step, a wide-spectrum analysis of the MTS was led to identify the main actors and their critical functions, referring to an 'ideal' situation in which 'everyone follows the rules'. This phase was carried out through interviews to maritime operators, shipyards and classification societies. Five main actors have been identified, namely: the Operator (that represents the maritime company), the Shipyard, the Port, the Regulator (that represents all the certification and regulatory bodies) and, finally, the Environment, considered also from a socio-technical point of view. Secondly, functions performed by each actor were identified, under the hypothesis that the behaviours of the actors are perfectly pertaining to the provisions and the safety procedures. The description of the functions allowed to clarify and better understand the roles and the duties of each actor within the MTS, considered as a socio-technical system. Thus the Structured Analysis Design Technique (SADT) representation of the MTS was turned into a Bayesian network representation, as it is reported as an example in Fig. 9. The main difference between these two representations is that the SADT representation is function driven, whilst the BBN one is variable driven. Indeed, as shown in Fig. 9, the function 'To Follow Planned Course' is explicitly represented as a box, whilst the same function is implicitly represented by the dependence of the *Course Information* variable on the three variables *Crew Knowledge*, *Position* and *GPS* as explicitly represented by the three arrows. As a final result, the MTS was transformed in a complex network of influences, where experts quantified the model by filling out CPTs for each node of the network. A panel of six experts, with relevant experience in managing risk in the maritime sector, was involved in the process of quantification. They

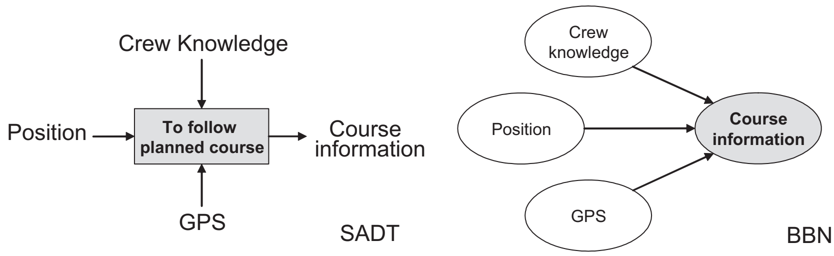

Fig. 9. From Structured Analysis Design Technique (SADT) to Bayesian Belief Network (BBN) modelling.

gave an estimate of the minimum and maximum likelihood in every conditional influence involving two or more variables of the network The elicitation process has be carried out with recursive technique (e.g. Delphi method) in order to guarantee the convergence of the results and the final results were commented and adjusted again during further interviews.

5.1. FTA of the "collision in open sea" and selection of critical BEs

The BEs of the Collision in Open Sea are referred to three different categories:

- Human Errors.
- Automation and Mechanical Failures.
- Manoeuvring Errors.

The identification of the MCSs allowed to operate, before the quantitative analysis, the selection of critical BEs: it has been chosen to take into consideration only the MCSs for which the sum of the probabilities generates at least the 80% of the total probability of the TE:

$$\sum_{i=1}^{n} P(\mathrm{MCS}_i) \geqslant 0.8 P(\mathrm{TE}_{\mathrm{Collision}}). \tag{13}$$

By means of the Fussel–Vesely Importance function [30], it has been also possible to order the BEs on the basis of their influence on the TE:

$$I_{\mathrm{FV}}(\mathrm{BE}) = \frac{\sum_{C_i:\mathrm{BE}\in C_i} P(\mathrm{MCS}_i)}{\sum_{C_i} P(\mathrm{MCS}_i)}, \tag{14}$$

where C_i is the set of MCS_i comprising BE.

The most relevant BEs for the hazard under analysis are reported in Table 5. Such events contribute to determine the probability of occurrence of the collision in accordance with the FT theory [30] given the influence of the organisational configuration variables (Ω_k):

$$P(\mathrm{TE}|\Omega_{j,k}) = \sum_{C_i:\mathrm{BE}\in C_i} P(\mathrm{MCS}_i|\Omega_{j,k}). \tag{15}$$

5.2. Definition of operational conditions and design and management parameters

The sensitivity analysis of the collision hazard has been carried out choosing appropriate settings for the operational and organisational conditions (evidences in Table 6). To this end, two different operational conditions have been set as reference navigation conditions for the analysis. The first one, named "Mediterranean Sea", refers to a situation of high traffic density with good weather-marine and traffic conditions, whereas the second, named "North Sea", refers to a navigation route with low traffic but heavy weather-marine and traffic conditions (Table 7). Since the variable can vary within the interval [0, 1], a value $Y = 0.1$ indicates a "weak" influence of the corresponding factor, whereas a value of $Y = 0.9$ denotes a "strong" influence.

Table 5
List of critical basic events (BEs) ordered with the F–V Importance function

No.	Code	Description	F–V Importance
1	BE46	Other ship fails to avoid close quarters	1
2	BE19	Confused by other ship's movement	6.19e-1
3	BE63	Internal communication failure	5.07e-1
4	BE16	Assuming other ship will change courses	3.15e-1
5	BE18	Bad evaluation of speed and course of other ship	1.03e-1
6	BE13	Watch-keeping failure	2.73e-3
7	BE2	Fail to make use of radar	1.48e-3

5.3. Analysis of experiments and discussion of results

For each one of the navigation conditions ("Mediterranean Sea" and "North Sea") the D&MP have been used as parameters of an experiment's analysis in order to evaluate the influence of HOF in different navigation conditions:

$$\frac{\Delta P(\mathrm{TE}|\Omega_{j,k})}{\Delta(\Omega_{j,k})} \to \begin{cases} \dfrac{\Delta P(\mathrm{TE}|\Omega_{j,k(\text{North Sea})})}{\Delta(\mathrm{D\&MP})}, \\ \dfrac{\Delta P(\mathrm{TE}|\Omega_{j,k(\text{Mediterranean Sea})})}{\Delta(\mathrm{D\&MP})}. \end{cases} \tag{16}$$

The objective was to evaluate, using a Design of Experiment (DOE) project, the sensibility of the conditional probabilities of the BE—$P(\mathrm{BE}_k|\Omega_{j,k})$—and, therefore, of the TE—$P(\mathrm{TE}|\Omega_{j,k})$—to a variation of the organisational factors given a navigation conditions. The analysis on the

Table 6
Classification of operational conditions (OC) and Design & Management Parameters (D&MP)

Evidence	Importance[a]	Correlated Bes
Crew & Personnel Characteristics	3.83	12/12
Compliance with IMO regulations	1.83	9/12
Climate	1.75	11/12
Traffic density	0.66	2/12
Visibility & sea state	0.66	3/12

[a]Mean value of the F–V Importance index of the influenced basic events (BEs).

Table 7
States of Operational Conditions (OC) evidences

Evidence	Mediterranean Sea		North Sea	
	Y	N	Y	N
Bad climate	0.1	0.9	0.9	0.1
Traffic Density	0.9	0.1	0.1	0.9
Bad visibility & Sea State	0.1	0.9	0.9	0.1

combined effects of the D&MP of the MTS has taken into account two classes of evidences:

- CREW—this class comprises only the variable "Crew & Personnel Characteristics", evaluating an organisational characteristic of the Operator of the ship.
- IMO—this class comprises two variables of the organisational model of the MTS: "Compliance with IMO regulations" and "IMO regulations". The former evaluates the degree of compliance to the IMO regulations of the Operator's activities, whereas the latter refers to the quality and transparency of the IMO regulations as such.

This framework provides a 2^2 experiment with two factors (CREW and IMO) of two states (+ and −). It is possible to plot the results of the analysis in a graph highlighting the quantitative variation of the probability of occurrence of a single BE (e.g. BE 19—"Confused by other ship' s movement" shown in Fig. 10) when the combination of factors changes. The representation makes evident that crew and personnel are the factors with the greatest influence on the BE.

The same kind of analysis can also be carried out for the TE, as shown in Fig. 11. Moreover, it is possible to verify the existence of interactions between factors. The greater importance of the variable "Crew" with respect to "IMO" is evident again. The difference in P(TE) values in case of "Mediterranean Sea" or "North Sea" navigation conditions (i.e., for different Operational Conditions), can be highlighted also with the same state of the two factors. The results (ref. Fig. 11) allow to say that the importance of the factor Crew is even greater in case of bad sea conditions (i.e., HSC operation in North Sea) and, since there is no evidence of inter-crossed effects (i.e. improving the characteristics of the crew, always a smaller reduction in probability of occurrence is obtained due to a wider application of the norms suggested by the IMO); evidently trained and

Fig. 10. Sensitivity analysis of the Design & Management Parameters (D&MP) over the probability of occurrence of BE19—"Confused by other ship's movement".

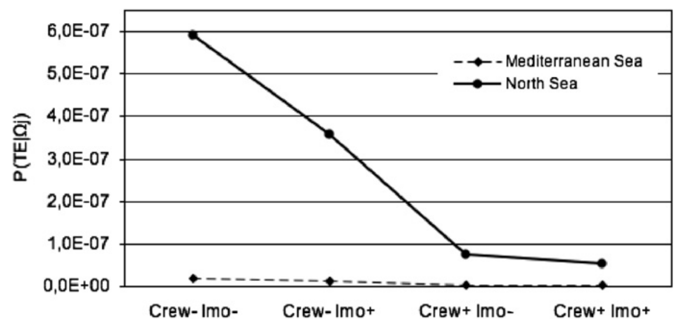

Fig. 11. Sensitivity analysis of the Design & Management Parameters (D&MP) over the probability of collision—$P(\mathrm{TE}|\Omega_{j,k})$—under different Operational Conditions (OC).

educated crews tend to reduce the safety improvement supported by of the compliance to standard procedures.

The analysis carried out highlighted the great effect of risk reduction, in case of collision, imputable to the human factors and, in particular, to the factor "Crew" (an order greater than "IMO"). Nevertheless, a positive (+) state of the evidence "Crew & Personnel Characteristics" and "Personnel Characteristics" presupposes a strategy of selection and training of the crews aimed at risk reduction.

6. Conclusions

The use of Bayesian Belief Network (BBN) modelling in Formal Safety Assessment (FSA) has been suggested in a recent document (7 February 2006) submitted by the Japan body of maritime safety to the IMO Maritime Safety Committee (MSC\81\18-1) [9]. In the conclusions the document suggests the use of BBN as a risk analysis tool, since the complexity of the system cannot be correctly modelled only by a Risk Contribution Tree (i.e. the joint use of FTs and Event Trees).

This paper has proposed a coherent approach to exploit BBN in developing better risk models of complex socio-technical systems, particularly when the need of taking into account Human and Organisational Factors (HOF) is crucial. Under this point of view the proposed approach is consistent and should be carefully used as human error analysis technique when the expert's elicitation process is critical for performing quantitative analyses in case of lack of data and statistics [8].

Unlike other methods of integration between Fault Tree (FT) and BBN documented in literature (e.g. the method proposed by Mohaghegh and Mosleh [23]) the proposed approach does not require any further calculation to correctly take into account the dependencies among the basic events (BEs) of the FT established by the BBN model. Moreover, as the proposed method of calculation uses the BBN model only to modify a prior probability of the BEs and does not generate them directly, it results in a simpler quantification process of the BBN when the elicitation of experts' judgements is used. Indeed an expert is more comfortable (and reliable) in estimating the probability that a set of organisational factors are able to increase/reduce a known generic probability of occurrence of a certain basic event, instead of directly estimate the probability of occurrence of the basic event given a postulated set of organisational factors.

The case study of a collision hazard for an HSC has demonstrated that the BBN modelling of HOFs can be used in risk analysis to identify further opportunities of risk mitigation acting at the organisational and regulatory level of the MTS.

The proposed model could also be used as a tool for supporting retrospective analyses based on incident reporting or accident investigation, such as the identification of latent failures at the organisational level. Moreover, since the probabilities of a generic BBN are updateable given a set of evidences collected from the field, the BBN model of organisational risk factors is updateable over time exploiting data provided by accident/incident databases (e.g. IMO, MAIB) and/or gathered from voluntary reporting systems (e.g. CHIRP).

Finally, further areas of application should be explored considering the proposed model as a support tool for safety management and decision-making at different levels (policy, design or operating procedures, etc.) and for different stakeholders of the maritime industry. As a matter of fact, while for the policy makers and regulators the objective is safety with affordability as a requirement, for the industry (e.g., ship operators, shipyards, port) the objective is affordability with safety as a requirement. The proposed approach is suitable for further extensions on the side of economic analysis in order to help the regulators to evaluate the economic impact over the entire MTS of postulated safety standards, and the business actors in identifying the most efficient way to achieve safety improvements.

Appendix A

Overall Bayesian Belief Network (BBN) model of the Maritime Transport System (MTS) (Fig. A.1).

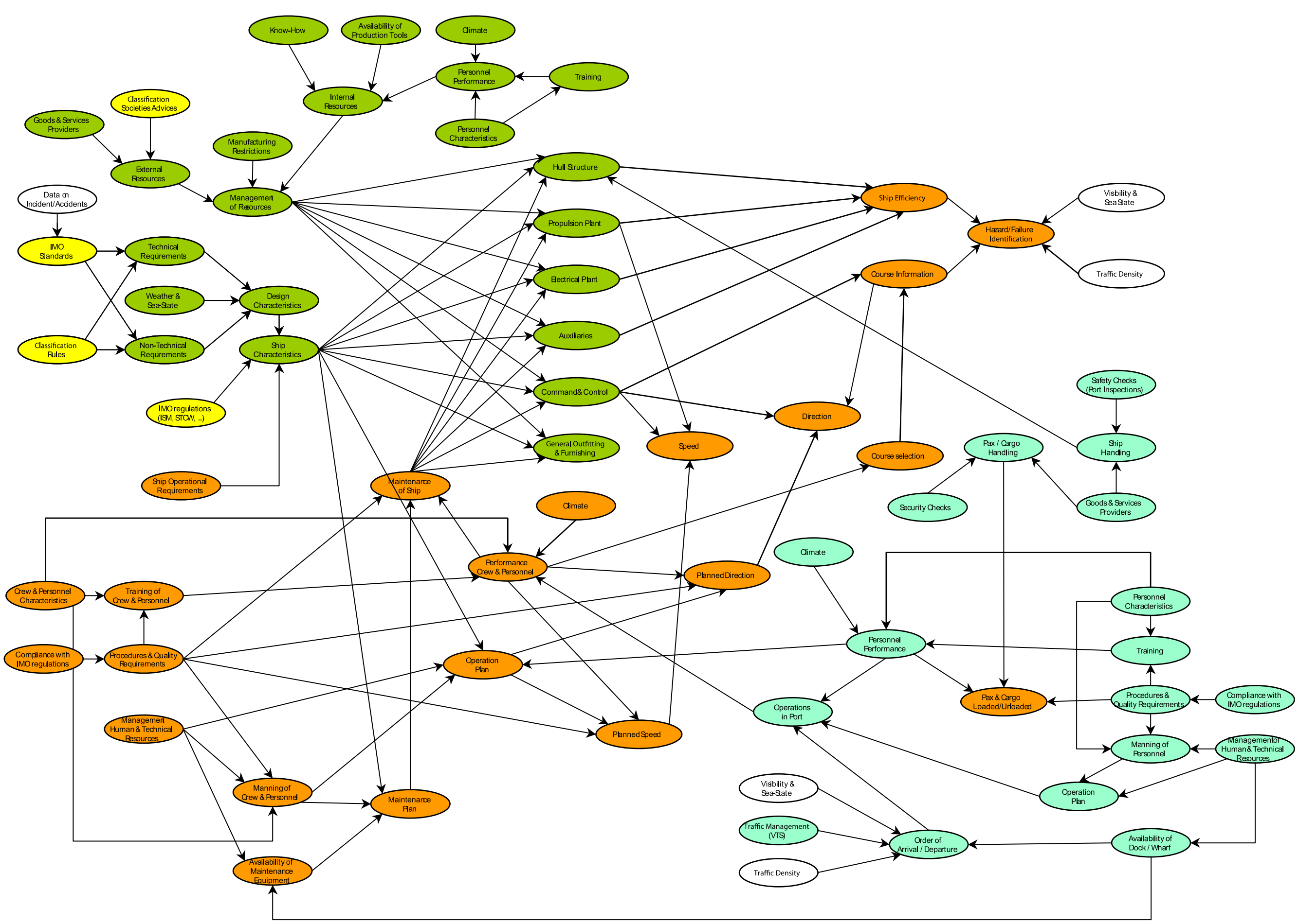

Fig. A.1. Overall Bayesian Belief Network (BBN) model of the Maritime Transport System (MTS).

Appendix B

List of functions of Bayesian Belief Network (BBN) divided into actors (Table B.1).

Table B.1
List of functions of Bayesian Belief Network (BBN) divided into actors

Actors	Operator	Port	Environment	Shipyard	Regulatory bodies
Functions	Procedures & quality requirements	Procedures & quality requirements	Data on incident/accident	Training	IMO standards
	Training of crew & personnel	Availability of Dock/Wharf	Visibility and sea state	External resources	Classification rules
	Availability of maintenance equipment	Training	Traffic density	Technical requirements	IMO regulations
	Manning of crew & personnel	Operation plan		Non technical requirements	Classification societies advices
	Operation plan	Cargo (& Pax) handling		Internal resources	
	Maintenance plan	Ship handling		Management of resources	
	Maintenance of ship	Personnel performance		Personnel performance	
	Performance personnel & crew	Manning of personnel		Design characteristics	
	Course selection	Personnel characteristics		Ship characteristics	
	Course information	Traffic management (VTS)		Propulsion plant	
	Speed	Order of arrival/departure		Electrical plant	
	Planned Speed	Climate		Auxiliaries	
	Direction	Security checks		Command & control	
	Planned direction	Safety checks (Port inspections)		General outfitting & furnishing	
	Cargo (& Pax) loaded/unloaded	Good & services providers		Hull structure	
	Ship efficiency	Operations in port		Good & services providers	
	Hazard/failure identification	Compliance with IMO regulations		Manufacturing restrictions	
	Climate	Management of Human & technical resources		Know-how	
	Ship operational requirements			Availability of productions tools	
	Crew & personnel characteristics			Climate	
	Compliance with IMO regulations			Personnel characteristics	
	Management of human & technical resources			Wheater & sea state	

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