Integration of Damage Stability into a Risk Management Framework

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ABSTRACT

The multi-dimensional character of ship safety requires a framework where holistic risk management can be performed efficiently and cost-effectively. In this respect, the links between safety performance indicators and ship life-cycle attributes (ship parameters, operational characteristics, etc.) should be established probabilistically in order to capture the inherent variations of this process and account for the evident diversity. In light of this situation, a data mining framework for ship safety management is presented in this paper. The approach builds on Bayesian Networks, as a risk modelling technique, and on the systematic extraction of information stored in available data. Particular emphasis is placed on the integration of aspects of damage stability into such a framework for an overall management of ship life-cycle safety.

KEYWORDS

Damage stability; risk management; accident database; data mining; Bayesian network; decision support

INTRODUCTION

To address ship damage stability properly is an important issue of ship life-cycle safety. This is due to the fact that it links explicitly to the instance of ship capsizing, which can ultimately lead to catastrophic losses of life and property. In this sense, having enough residual stability following flooding is one of the few last safe guards to protect life at sea. Moreover, with the dramatically increased public expectation for higher safety and public regard for human life and the environment, damage stability inevitably remains one of the focal issues concerning ship safety. The subsequent concerted effort has led to the radical move from deterministic codes of conduct to a probabilistic approach, which represents a philosophical change of the way that ship safety is treated.

It is indeed a significant achievement for those who have devoted themselves to the development of a probabilistic regulatory framework in the field. Nevertheless, it is also important to bear in mind that a fully developed risk-based framework towards ship life-cycle safety is far from maturation. As it has been pointed out in [Vassalos, 2004], the current probabilistic concept of ship subdivision focuses not on absolute collision damage safety of a ship or “total” ship safety but on conditional safety. In the context of risk-based approaches, the mathematical model for collision risk can be written as Equation (1) and major effort for the development of a probabilistic approach towards ship damage stability has been spent on a single component, $P_{f|w|c}$ This implies that the current formulations overlook the contributions of different operational profiles (e.g. density of shipping, ship type) and the ensuing consequences, all of which might suggest considerably different levels of actual risk level

$$R_c = P_c \times P_{w|c} \times P_{f|w|c} \times C_c \qquad (1)$$

Where P_c probability of a collision incident, dependent on the loading condition, area of operation, geography / topology / bathymetry, route, traffic density, ship type, human factors, etc. $P_{w|c}$ Probability of water ingress, conditional on collision (accounting for all the above); $P_{f|w|c}$ is probability of failure (capsize/sinkage/collapse), conditional on collision and water ingress; expressed as a function of (sea state, structural strength and time); C_c stands for consequences deriving from the collision incident, accounting for loss of (or injury to) life and property and for impact to the environment. The former will be time – dependent and will be the result of evacuation analysis and the latter of e.g.; probabilistic oil outflow using relevant models of oil spill damages and results from known accidents or through analysis from first-principles tools

On the other hand, it is important to realize that the estimated Attained Index of Subdivision (A) for a specific design solution can be best described as a measure of global (ship-level) averaged ship survivability, which aims to place absolute trust on the effort to be made at design stage. However, such a measure has significant difficulty to reflect local survivability of a ship for a specific situation (e.g. damage openings, status of vicinal watertight subdivisions, environment conditions). In this respect, a system allowing fast and accurate survivability assessment at operational stage, particularly in emergency situations for crisis management, can be a useful means for the protection of life at sea. For this specific issue, the decision support system as described in (Jasionowski, 2010) is one of the very few pioneering research focusing on real-time ship subdivision management for crisis management.

With this in mind, this paper will attempt to describe an overall risk management framework, in which ship damage stability can be integrated effectively. It will enable a system allowing holistic treatment of ship safety both at design and operational stages under one overarching framework.

A RISK MANAGEMENT FRAMEWORK

The multi-dimensional character of ship safety requires a framework where holistic risk management can be performed efficiently and cost-effectively. In this respect, the links between safety performance indicators and ship life-cycle attributes (ship parameters, operational characteristics, etc.) should be established probabilistically in order to capture the inherent variations of this process and account for their evident diversity. In light of this situation, a data mining framework for ship safety management is described next.

With the detailed work presented in (Cai, et al, 2010, 2011), this section elaborates on the high level structure of the approach, where particular emphasis is placed on the integration of damage stability into the whole framework. It comprises three key modules: a database, a data process module, and a model presentation/inference module. A high level flow chart is provided in Figure 1 to depict the interrelationships.

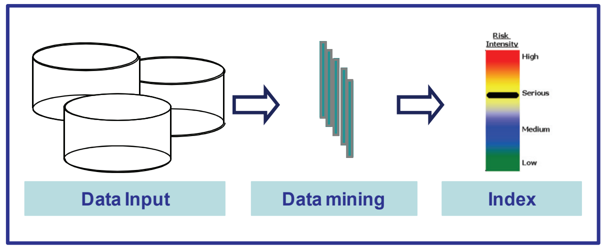

Fig. 1: A high-level flow chart of the risk management system

Database Development

Safety-related data is collected and stored in a relational database. Considering what constitutes ship safety, it is governed by a handful of factors (undesirable events) which, when considered individually or in combination, define a limited set of scenarios. These factors represent major accident categories with calculable frequencies and consequences, which inherently control the life-cycle of a ship at sea. In the case of passenger ships, it has been found that flooding- and fire-related scenarios comprise over 90% of the risk (regarding loss of life) and almost 100% of all the events leading to decisions to abandon the ship. As a result, the total risk should be sought through analyzing the principal hazards: collision, grounding and fire. According to the definition of risk, its quantification of the interested hazard can be estimated through the product of a number of probabilities defining critical scenarios and the ensuing societal consequences, as illustrated below.

$$R_{collision} = P_{collision} \times P_{water\_ingress|collision}$$
$$\times P_{failure|water\_ingress|collision} \times C_{collision}$$

$$R_{ground} = P_{ground} \times P_{water\_ingress|ground} \times P_{failure|water\_ingress|ground} \times C_{ground}$$

$$R_{fire} = P_{fire} \times P_{growth|ignition} \times P_{escalation|growth|ignition} \times C_{fire}$$

The subsequent task is to identify a list of dominant variables playing important roles in estimating the aforementioned risk components. Certainly, it would be practically infeasible to record hundreds of thousands of elemental parameters that determine the exact safety level of a ship. Therefore, a promising way is to rely on the latest understanding and up-to-date risk models, which take advantage of the continuous effort and accumulation in understanding the underlying physical phenomena.

Concerning the issue of ship damage stability, its influence on the overall risk level is reflected through $P_{failure|water\_ingress|collision}$. Regarding this, significant effort has been devoted to addressing it from a probabilistic perspective, particularly through projects HARDER and SAFEDOR as reported in (Mains, 2001, HARDER, 2001, Jasionowski, 2006]. On this basis, three groups of important variables can be identified, which are not exhaustive.

- Ship design parameters: length, beam, depth, subdivision arrangement, long lower hold, side casing, centre casing, etc.
- Operational parameters: ship loading, trim, draught, status of vicinal watertight subdivisions, etc.
- Situation-specific parameters: damage characteristics (e.g. location, length, and penetration), sea state, etc.

The influence of the aforementioned parameters is reflected currently through a number of stability measures: *KG*, GZ_{max}, *Range*. Given the list of parameters, both historical accidents and first-principles tools should be utilized for supplying pertinent data.

Data Mining

The need for more sophisticated data analysis techniques is derived from the fact that classical regression analysis becomes inefficient to cope with a mathematical model containing more than a handful of variables at a time. This has given rise to the subject of data mining, which aims to transform a data set containing many variables into a meaningful and interpretable model through multivariate data analysis techniques.

Due to the diversity of data mining techniques, the identification of the most adequate platform and the associated "mining" techniques are of great importance. In this respect, Bayesian networks (BNs), offer a unique platform for fulfilling the intended goals. This is attributed to (i) their inherent capability for probability inference, (ii) the transparency and flexibility of presenting complex relationships, and (iii) to the foundation that has been laid in the maritime industry.

Deriving from the above, data mining techniques focus on identifying complex interrelationships rationally in the case of more than a few variables (i.e. the skeleton of a Bayesian network model) and on quantifying conditional probability tables objectively for all variables (i.e. the probabilistic information of a Bayesian network model).

Risk Management

On the basis of the foregoing, it becomes straightforward to transform the collected maritime casualty data into probabilistic models which are materialized in the form of a Bayesian network. Nevertheless, it is important to ensure that the obtained models are intelligent enough for the purposes of the decision making process of risk management.

As the parameters recorded in the database focus mainly on the dominant influential design and operational factors and the timeline development of the hazards under consideration, it is important to realize that the subsequently obtained Bayesian network models can easily accommodate the sequential events that lead to the manifestation of a specific hazard. For instance, they contain the occurrence of an event, its escalation, and ultimately, the possible consequences. As the information is stored probabilistically, such a model can be regarded as a generic risk model for risk level estimation. From this point of view, a Bayesian network model is equivalent to a conventional risk contribution tree (i.e. fault tree, event tree) for risk analysis.

On the other hand, with ship design, operational and situation-specific parameters recorded in the database and utilized for data processing, their influences on the scenario-defining variables in the aforementioned risk models can be established without much difficulty. In this case, the Bayesian network model can be regarded as a risk-knowledge model, where the knowledge of the interrelationships between manageable (physical) entities and the key risk components are stored and expressed probabilistically. In this way, the risk level of the interested hazard is ultimately conditional on the statuses of these three groups of parameters: ship design, operational, and situation-specific parameters. Figure 2 exhibits conceptually such unique characteristics of Bayesian network models.

In this way, it becomes apparent that through the methodology of employing the new database and pertinent data mining techniques, the obtained Bayesian network model can be used as a tool for risk level estimation. In the meantime, it also facilitates a fast evaluation of various risk control options for effective decision making. A unique advantage of such an approach is that decisions can be made on a transparent and objective basis.

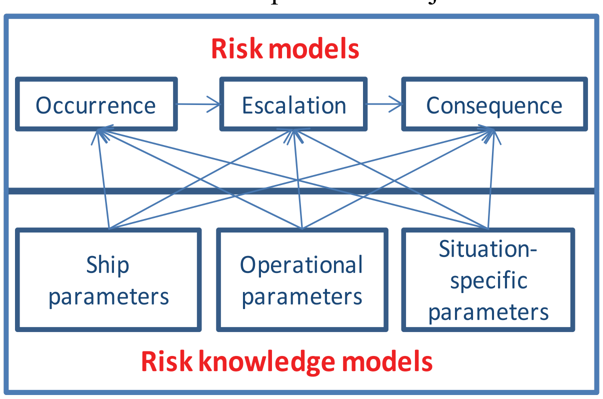

Figure 2: A conceptual Bayesian network model

A CASE STUDY

The proposed methodology will be demonstrated through a case study of the impact of various important parameters on the performance of ship damage stability (i.e. $P_{failure|water\_ingress|collision}$). The parameters are those identified for investigation in the HARDER project. The experiment data of a RoRo Passenger design (PRR01) with a predefined opening is used for Bayesian network model training (Tuzcu and Tagg, 2001). The parameters considered are:

- Loading condition (draught)
- Permeability
- Trim
- KG
- GZmax
- GZrange
- Sea State
- Ship Capsize (within 2400 seconds)

The collected 424 data records were imported into the Bayesian network learning program developed in statistical computing software R (http://www.r-project.org/). The resulting network model is shown in Figure 3.

According to Figure 3, the parameters included in the model can be further classified as tabulated in Table 1. As a result, by altering the statuses of various parameters as needed at different stages (i.e. design, operation, and crisis management), their influence on ship damage stability performance can be assessed instantly.

Table 1: Classification of the Variables

Generic Risk model	Variables
	Ship capsize
Risk knowledge model	Variables
Ship parameters	Permeability KG
Operational parameter	Loading condition (draught) Trim KG
Situation-specific parameter	GZ_{max} Range Sea state

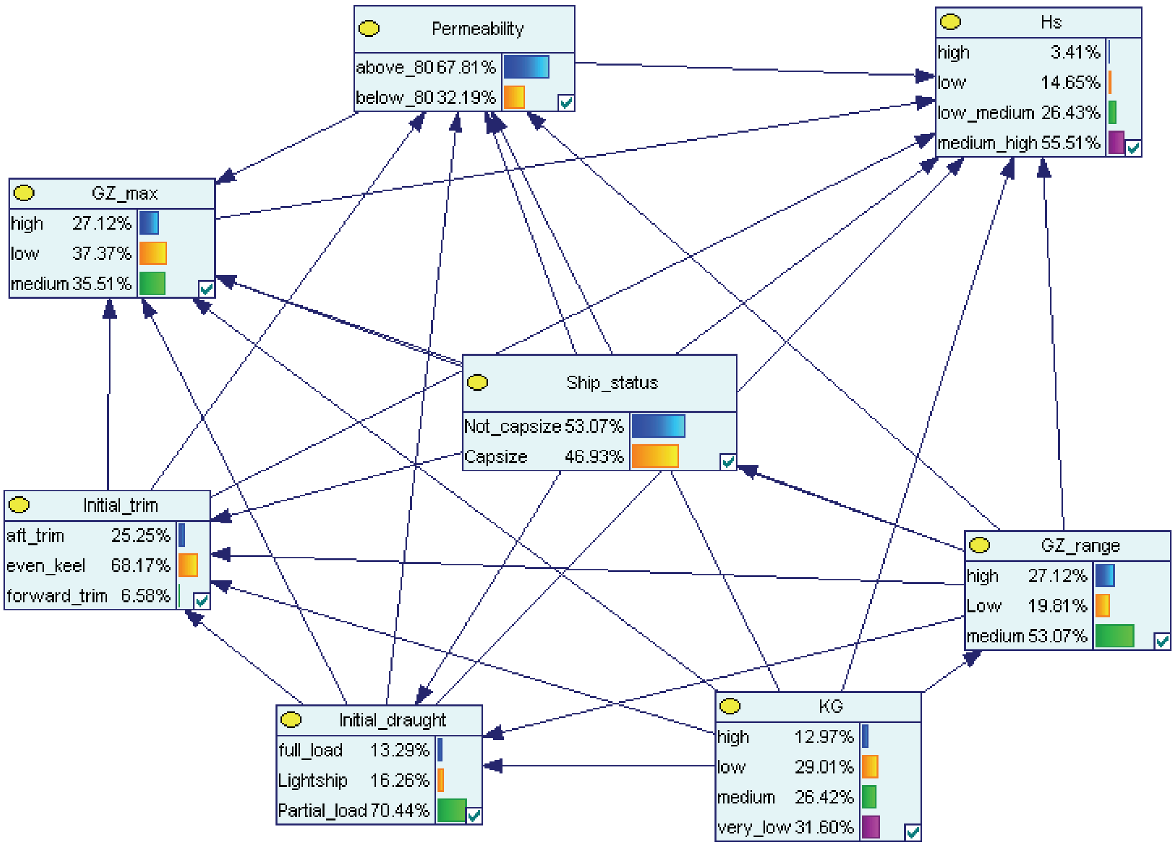

Figure 3: Constructed Bayesian network model indicating the expected conditional probability for the model to capsize within 2400 seconds with the predefined damage opening is 0.4693.

In the case of design stage, ship parameters can be investigated. For instance, through altering the permeability of a selected space, its influence on the ship stability with a predefined damage opening can be estimated easily.

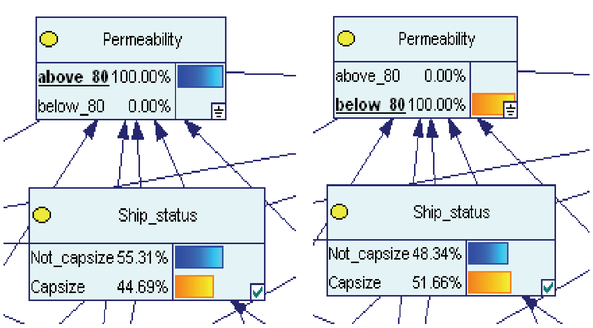

Figure 4: The probabilities for the design to capsize, within 2400 seconds under a predefined damage opening given the permeabilities are above 0.80 and below 0.80, are 0.4469 and 0.5166, respectively.

Similar manipulation can be performed for operational parameters at operational stage. For instance, through ballasting operation, KG can be adjusted to a lower position. The change from a medium KG (between 12.89 and 13.46) to a lower KG (between 12.20 and 12.89) also leads to the decrease of the probability for the ship to capsize (from 0.4923 to 0.4617) for a given damage opening.

It is understood that more parameters should be included in the model for the sake of design, operation, and crisis management. Unfortunately, this is most likely restricted by the amount of resources that is available for data collection. Regarding this, properly validated first-principles tools can be regarded as a promising way to generate pertinent data objectively and cost-effectively.

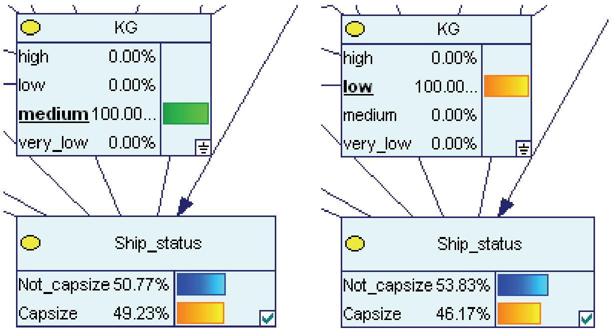

Figure 5: The probabilities for the ship to capsize, within 2400 seconds under a predefined damage opening given KG is between 12.89 and 13.46 and KG is between 12.20 and 13.89, are 0.4923 and 0.4617, respectively.

CONCLUSION

A unique approach towards risk management has been presented in this paper. Emphasis is placed on the integration of ship damage stability into the system at a framework level. HARDER - Updated damage sta Future development will focus on the development of an integrated risk management environment, in which the user interface for data input, relevant databases, data mining techniques, and graphic presentations of risk index would be accommodated.

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