THE USE OF BAYESIAN NETWORKS FOR RISK ASSESSMENT OF SHIP CAPSIZING AS AN ALTERNATIVE WAY OF EVALUATING THE OPERATIONAL SAFETY OF A SHIP AT SEA

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In this article, the application of the risk assessment of a stability failure of an intact ship in operation is presented. The assessment is performed for a specific Ro-ro/passenger ship for a number of anticipated operational conditions with the use of the state-of-the-art numerical model of ship dynamics. Subsequently the results which are obtained are organized in a probabilistic meta-model with the use of Bayesian Belief Network and Bayesian learning algorithm. Finally, the probabilistic meta-model is used as a tool for operational risk assessment of a ship with respect to capsizing in dead-ship conditions, where a ship is exposed to unfavorable action of wave and wind. To inform the end-users about the quality of the meta-model and its validity, the appropriate analyses are performed.

The results are presented in a form of F-N curve and are compared with the existing prescriptive stability criteria issued by the International Maritime Organization. Good agreement is found for those cases, where ship fulfills the IMO stability criteria by large amount. However, for the cases where the prescriptive IMO criteria are barely met, the results of risk assessment clearly indicate that the risk level is not acceptable for a ship.

I. INTRODUCTION

The main commonly discussed features of maritime transport are usually its safety and effectiveness. Among them the ships safety issues are crucial from the operational point of view. One of the most critical features of seagoing ships related to their safety is stability influencing ship's overall sea-keeping performance. The loading condition of a ship causing the insufficient stability may lead to her capsizing or generally the stability accident which is commonly defined as exceeding the amplitude of rolling or an angle of heel at which operating or handling of a ship is not possible anymore.[1] Generally, such an approach focusing on the excessive heel avoidance is valid both in a port during cargo operations and in rough sea when underway.[2,3]

Contemporary approach towards stability incidents avoidance is mainly based on an assessment procedure with the use of a set of rules and criteria known as the Code on Intact Ship Stability (IS Code) issued by the International Maritime Organization (IMO).[4,5] The criteria qualify the shape of the righting arm curve. In addition, the weather criterion is to ensure the sufficient stability of a ship to withstand the severe wind guests during rolling.[1] The weather criterion is the only, which is partly based on the model of heeling phenomenon not only on the statistical data, while the rest of criteria are based on the statistics of historical disasters only.[6] Despite being widely used, the rules are of prescriptive and retrospective nature, thus are hardly applicable for novel designs of ships. Moreover, even if they are applied to classical designs, the rules do not account for certain stability accident scenarios, which can pose severe risk to a ship.[7] These are: parametric resonance, issues with ship maneuverability on wave, aka wave broaching and surf-riding, issues with excessive accelerations or ship behavior on waves after the loss of propulsion and maneuvering characteristics, aka Dead Ship Conditions (DSC). Therefore a continuous debate exists at the IMO's forum on how to improve the IS Code so it can reflect all the relevant accident scenarios taking into account the physics of the phenomena and the operational characteristics of a vessel.[8–10]

To address numerous challenges unattainable for current prescriptive criteria listed in IS Code, the second generation ship stability criteria are being developed. The idea behind these criteria is based on three steps approach. First and second is the evaluation of ship vulnerability to a typical stability accident scenario. The third level is a direct stability assessment.

In case of first- and the second-generation ship stability criteria an incommodious drawback arises since the final result of the performed stability evaluation is of binary nature. The stability may be sufficient found as safe or insufficient meant as unsafe. In reality, the range of assessment outcome is wider therefore the risk-based approach could be introduced. If so, the continuous variable called risk of stability-related accident becomes the factor describing the safety of ship in operation.

In the maritime transportation domain, the concept of risk is mainly applied to: the process of rulemaking at the IMO level[11], the process of ship design[12–15], the accident response planning[16–21], identify high risk area and to evaluate the importance of risk contributing factors as well as to evaluate effect of modifications to traffic schemes.[22–26] However to our best knowledge it has not been used for the evaluation of safety of a single ship in operations. The main idea of the concept of risk is to facilitate the decision-making on a specific process, which in the case presented here would be the safe operations of a merchant ship in a specific sea area. It could be done by introducing a model that collects in a systematic manner all available, relevant evidences on the process in questions, allows quick inference for a set of conditions and represents the quality of the model and the influence of the associated uncertainties.[27] The model delivers additional piece of information beyond the standard stability criteria that can be used for reasoning about the safety of the analyzed process, accounting for the inherent uncertainties, which are in most cases hidden from the user in the present IS Code.

Therefore, in this paper we present a meta-model that can be used for the risk assessment of ship capsizing when in DSC. To develop the model we used a 6 DOF ship motion model and simulate several thousands of operational conditions. Subsequently the obtained data were organized in a probabilistic meta-model with the use of Bayesian Network, which is a recognized tool for reasoning under uncertainty. Finally, the obtained meta-model can act as an alternative way of evaluating the operational safety of a ship at sea by delivering an information about risk level associated with a given operations in a given set of weather and loading conditions for a specific ship.

The remainder of the paper is organized as follows: section II elaborates on the methods and materials used to develop the meta-model. The meta-model and obtained results are presented in Section III, and discussed further in Section IV. The concluding remarks are provided in Section V.

II. METHODS

The method for risk assessment presented here combines deterministic and probabilistic approach. First, the number or simulations are run for a specific Ro-ro/passenger ship (RoPax) for a number of anticipated operational conditions with the use of the state-of-the-art numerical model of ship dynamics. This allows us to overcome the shortcomings of the existing static methods that are used for safety assessment of a ship. The simulations method allow the analysis of numerous scenarios, where a ship is exposed to varying environmental loads, delivering a wide set of ship responses in terms of roll angle and time to reach the maximum roll angle, given hydro-meteorological conditions. Second, the obtained results are systematically organized in a probabilistic meta-model with the use of machine learning techniques. For that purpose Bayesian Networks (BNs) and the associated learning algorithms are applied. Probabilistic meta-model overcomes some of the issues of static, deterministic methods adopted nowadays for safety evaluation of a ship in operation. The probabilistic meta-model accounts for the dynamics of a ship thus it describes the risk associated with a given operation on a probability scale, recognizing the inherent uncertainties in the explanatory variables. Third, the probabilistic meta-model is used as a tool for operational risk assessment of a ship with respect to capsizing in dead-ship conditions, where a ship is exposed to unfavourable action of wave and wind.

Moreover, the application of the Bayesian network, allows the end user not only to predict the level of risk given set of inputs (predictive reasoning) but also the backward reasoning from the effect to the causes can be made. The latter helps to determine the required value for input parameters in order to obtain the desired value of the output. These issues are briefly elaborated upon in this section.

II.A. The concept of meta-model

The probabilistic meta-model presented here, turns the deterministic model of ship motions into probabilistic, by executing it in a loop for a large number of repetitions (17300) for varying set of conditions characterizing a ship (stability conditions, repair time, evacuation time, number of people on board) and environment (wave parameters, time of a day). The main aim of the metamodeling undertaken here is to study the output and input relationships and then fitting right metamodels to represent that behavior. Due to inherent uncertainty in the explanatory variables and taking into account the main objective of the meta-model we decided to reflect the input-output relationships in the probabilistic fashion. The objective of the meta-model is to inform the potential end-users about the most probable level of risk of capsizing associated with ship operations in given set of conditions relevant to that type of risk.

A graphical representation of the concept of meta-model adopted here is shown in Figure 1. Therein a flow of information along with its sources is presented. The nodes filled with grey represent the data obtained from the numerical simulation program Laidyn (described in section II.C.1), which simulates the motion of a ship in six degree of freedom for regular and irregular waves. The nodes outlined with the dashed lines represent the parameters, which are based on literature, whereas a node with solid line is based on certain assumptions. The outcome node is outlined with bold solid line and is called f-N curve, representing the probability (f) of experiencing a number of fatalities falling in a certain interval (N) when a ship experiences DSC. The risk measure adopted here is however the cumulative probability of the consequences and the F-N curve is a graphical representation of it.[28] The risk model parameters are described in greater details in section II.C.2

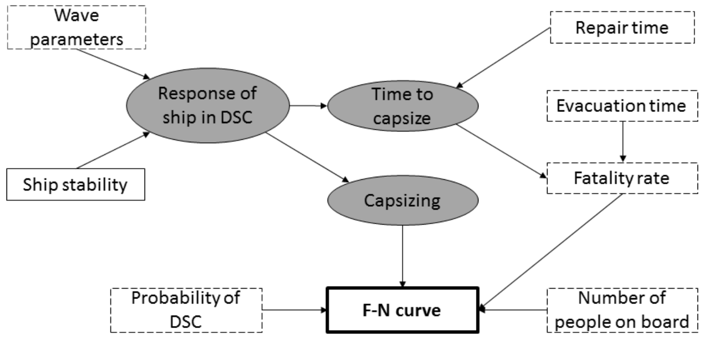

Fig. 1. A concept of meta-models estimating risk of ship capsizing as a result of DSC.

II.B. Meta-model development

II.B.1.Bayesian Networks

As a risk-modelling tool we selected BNs, since these have a number of favorable characteristics. BNs can contextualize the occurrence of specific consequences through situational factors, which represent observable aspects of the studied system. They furthermore allow integration of different types of evidence through various types of probabilities and provide a means for performing sensitivity analysis and the value-of-information analysis. It is also rather straightforward to incorporate alternative hypotheses in the model. For those and other reasons the BNs are relatively widely used tools for risk modeling.[16,17,21,29–35]

BNs represent a class of probabilistic graphical models, defined as a pair $\Delta=\{\mathbf{G}(V,A),\mathbf{P}\}$[36], where $G(\mathbf{V},\mathbf{A})$ is the graphical component and $\mathbf{P}$ the probabilistic component of the model. $G(\mathbf{V},\mathbf{A})$ is in the form of a directed acyclic graph (DAG), where the nodes represent the variables $\boldsymbol{V}=\{V_1,\ldots,V_n\}$ and the arcs ($\mathbf{A}$) represent the conditional (in)dependence relationships between these. $\mathbf{P}$ consists of a set of conditional probability tables (CPTs), containing the conditional probabilities of a variable given its parents: $P(V_i|\boldsymbol{Pa}(V_i))$, for each variable V_i, $i=1,\ldots,n$ in the network. $\boldsymbol{Pa}(V_i)$ signifies the set of parents of V_i in G, and node V_j is a parent of node V_i if there is a directed edge from V_j to V_i. A BN encodes a factorization of the joint probability distribution (JDP) over all variables in $\mathbf{V}$:

$$P(V)=\prod_{i=1}^{n}P\left(V_i\mid \boldsymbol{Pa}\left(V_i\right)\right) \qquad (1)$$

By adopting BNs as modeling tools one can perform two types of reasoning: forward and backward. In forward reasoning mode, called also predictive reasoning, one propagates new information about potential causes (explanatory variables) through a model, following the directions of the network arcs, in order to updated beliefs about the effects (response variables). In backward reasoning mode, called diagnostic, one fixes the desired value of the response variable, and the model propagates it backward along the network arcs, to determine the most likely values for the causes. The latter feature is relevant for risk management, since it can give some hints on what parameters to manipulate first and how much to obtain the desired risk level.

II.B.1. Methods of developing BBN meta-model

There are four main methods of constructing BNs to model a particular situation: 1) by eliciting the experts' knowledge and organizing it into BNs; 2) by synthetizing knowledge from other sources into BNs; 3) by learning BNs from data; 4) mixture of the above. To develop the meta-model presented in this paper we adopt the fourth technique, meaning that we utilize the available data supported by experts' knowledge. Learning of BNs, usually, involves two stages. First is to learn the graphical structure (**G**) and second is to learn parameters for the structure (**P**), expressed in a form of CPTs. In this paper the structure of the model is learned from the wide set containing the results from simulation supported by the background knowledge provided by the experts. The latter considers the relations between variables, which experts thought are proven to exist and must be present in the model as well as the relations, which are not proved to exist, therefore their presence in the model is not justified. Once the structure is defined, the model parameters are learned from data.

To develop the meta-model we use GeNie software package, which offers a wide range of learning algorithms, depending on available data and model requirements.[37] To develop the structure we apply PC algorithm that offers the user to ability to incorporate the background knowledge to the model that could constrain the search.[38,39] The parameters corresponding to a structure determined by the PC algorithm are estimated with the use of the EM method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models.[40]

II.C. What is behind the meta-model

In order to determine ship behavior on waves a computer program called LaiDyn is applied.[41] The program simulates ship motions in six degrees of freedom in regular and irregular seas, for a wide range of speed of a ship. The parameters of interest here are roll angle and time to develop such roll angle at which ship is considered capsized (60 degrees). The analyzed accident scenario involves RoPax ship in DSC. The main elements of the model are: 1) the probability of being in DSC; 2) wave parameters; 3) ship loading conditions; 4) ship's response to waves; 5) the probability of capsizing of the ship in the DSC; 6) time needed for a ship to recover from DSC; 7) time needed to evacuate people from the endangered ship; 8) the fatality rate (a share of people on board that will perish as a result of the stability accident).

II.C.1. LaiDyn

With the use of LaiDyn we conduct over 17300 simulations of motion of a ship in DSC for a wide set of conditions, corresponding to a ship and environment. LaiDyn model is based on the assumption that the complete response of a ship to a given excitation is the sum of linear and non-linear parts.[41,42] Such division results from the fact that the linear computation methods are well-known. It causes the situation where the radiation and diffraction forces are presented by linear equations quite well. In this method, the main part of the first order load is calculated with the linear approximation, based on the current heading and location in relation to a wave. Defining the non-linear part, such elements as non-linearity as a result of ship shape, hydrostatics and wave force were taken into consideration.[42] Despite the ability of the software to cope with the irregular waves, for the purpose of this paper we adopt the regular wave only.

II.C.2. Parameters of risk model

Risk measure adopted in this paper is expressed as the probability of the consequences, where the latter is expressed as an expected number of fatalities, resulting from the stability accident. It can be formulated as follows:[43]

$$R \sim P(N) = \mathrm{P}(DSC)\mathrm{P}(caps|DSC)\mathrm{P}\big(N\_fatalities|(caps, DSC)\big) \tag{2}$$

where *P(DSC)* is the probability of a ship being in DSC when at sea, *P(caps|DSC)* is the probability for a ship to capsize when in DSC, *P(N_fatalities|caps,DSC)* is the probability of certain number of fatalities when capsized in DSC.

The probability for a RoPax being in DSC while in operations at sea is taken as 0.14 per year per ship. This number is derived from the experts' judgment on the reliability of machinery and electrical systems of a ship in operation.[44] However this number can be debatable, since it depends on numerous factors, like the engine type and configuration, and there is spread in the available body of literature. [45]

Another major parameter of the risk model is *P(caps|DSC),* which is determined by ship behavior in waves. This is governed – inter alia - by ship loading condition, which defines stability condition of a ship. For the purpose of this paper we anticipate four different loading conditions for the same ship draft, as presented in Table 1. It means, that the ship mass does not change (the center of buoyancy remains in the same location for all these loading conditions) but is distributed differently (the center of gravity of a ship is different for those conditions). Since the stability of a ship is determined by the mutual relation between the location of the center of gravity and metacenter (which remains in close relation with the center of buoyancy) the stability of a ship in these four loading conditions differs. For each loading conditions a set of simulations is conducted. From the time series of a simulation the relevant information about the maximum roll angle and the time of reaching it are obtained.

The ship is considered capsizing if the time of reaching the critical angle is shorter than the time of repair. Otherwise, she is considered safe. Time to repair is modeled with the use of Weibull distribution with alpha=0.5 and beta=23.[46] In a similar manner the life loss is determined, if the time to capsize is shorter than the evacuation time, we assume that the life is perished. Then, the number of fatalities (N) is estimated based on a concept of fatality rate, as follows:

$$N = \left(1 - \left({}^{haz}/_{resp}\right)\right) N_{pax} \tag{3}$$

where *haz* is the exposure time to a hazard (time for the ship to capsize), *resp* is the response time, in this case the evacuation time, N_{pax} is the number of people on board the ship. The latter is obtained from the available data published by ship operators regarding the total monthly volume of passengers transported with the use of similar ships as the one considered here. Assuming an ordered evacuation of a ship in danger, the time to evacuate the ship is modelled with the use of triangular distributions following the IMO recommendations, and a distinction is made between day and night.[47,48]

Wave and wind parameters are taken from the available statistics as presented in IMO documents[49] and combined into a three-state variable called *weather*, as presented in Table 2. The adopted distribution of this variable reflects the prevailing wave conditions for the Northern Atlantic Ocean.

The direction of the encountering waves with respect to a ship heading is modeled with the uniform distribution, where the variable is discretized in four states (180-270°, 270-360°, 360-90°, 90-180°), covering all possible directions of wave.

TABLE 1 Loading condition

Loading condition	Draft [m]	GM [m]
LC01	6.10	0.30
LC02	6.10	0.98
LC03	6.10	1.11
LC04	6.10	2.29

TABLE 2 Weather condition

Weather	Significant wave height [m]
Good	Below 3.33
Moderate	Between 3.33 and 7.34
Bad	Above 7.34

II.D. Meta-model validation

The main objectives of the validation of the meta-model are: 1) to develop trust in the model among the potential end-users, 2) to point to the elements of the model that when further improved can significantly reduce the uncertainty of the meta-model. For that purpose we run a number of tests. First, the obtained results are compared with the available data that are used to develop the model. Next the sensitive parameters of the model are found; finally the parameters that take the most of the model uncertainty are determined in the course of the value of information analysis.

II.D.1.Cross validation of the meta-model

This type of validation test is performed by adopting K-fold Cross-Validation (CV). Therein part of the data is used to develop the model, and the other part is used to check the predictive power of the model by comparing the response of the model with the recorded data. The K-fold algorithm works as follows:

1. randomly divide the data set into K subsets;
2. for each subset S:
    a. train on the data but not on the subset S;
    b. test model on the subset S;
3. return the average error over the K subsets.

The results of cross-validity analyses are presented in Table 3 with respect to a variable called *Number of fatalities* (N), which is a'priori discretized in a number of instances. Very good prediction power for the meta-model is noted for all instances of the variable but one. The lowest prediction power – the probability of delivering the correct answer (based on data used for training) - holds for the instance covering the highest number of fatalities (2500-3000) and yields 0.2. The meta-model has problems with proper prediction of this instance, for a set of conditions resulting in the fatalities falling in that range; instead it indicates the lower range of 1500-2500 as the most probable outcome, with the probability of 0.72. In other instances the probability of delivering the correct answer is between 0.82 and 0.99.

TABLE 3 The results of Cross-Validation of the meta-model

	Model						
Training dataset	Number of fatalities N	0	0-750	750-1500	1500-2500	2500-3000	Check sum
	0	**0.9999**	0.0000	0.0001	0.0001	0.0000	Σp(0)=1.0
	0-750	0.0510	**0.8163**	0.1122	0.0204	0.0000	Σp(0-750)=1.0
	750-1500	0.0000	0.0000	**0.9611**	0.0389	0.0000	Σp(750-1500)=1.0
	1500-2500	0.0101	0.0050	0.0000	**0.9246**	0.0603	Σp(1500-2500)=1.0
	Above 2500	0.0800	0.0000	0.0000	0.7200	**0.2000**	Σp(2500+)=1.0

II.D.2. The value of information analysis

The value-of-information analysis identifies the most informative variables, with respect to the output variable. It determines the variables among which the probability mass of the output is scattered. This analysis can be seen as a tool for analyzing the potential usefulness of additional information, before the information source is consulted, i.e., what the effect of observing one node would have on the other. To visualize the potential influence that two directly connected nodes have on each other the thickness of the arcs connecting them is varied.[50] The thicker arc the stronger influence. The results of this analysis are depicted in Figure 2.

II.D.3.Sensitivity analysis

The purpose of a sensitivity analysis is to investigate the effect of changes in the assigned probabilities of the network variables on the probabilities of a specific outcome variable. In a one-way sensitivity analysis, every conditional and prior probability in the network is varied in turn, keeping the others unchanged. Here a sensitivity-value approach presented by Coupé and van der Gaag is applied.[51] The level of sensitivity for all the model parameters is presented visually on Figure 2. The more intense color of the node the more sensitive the model is to the changes of this node.[25]

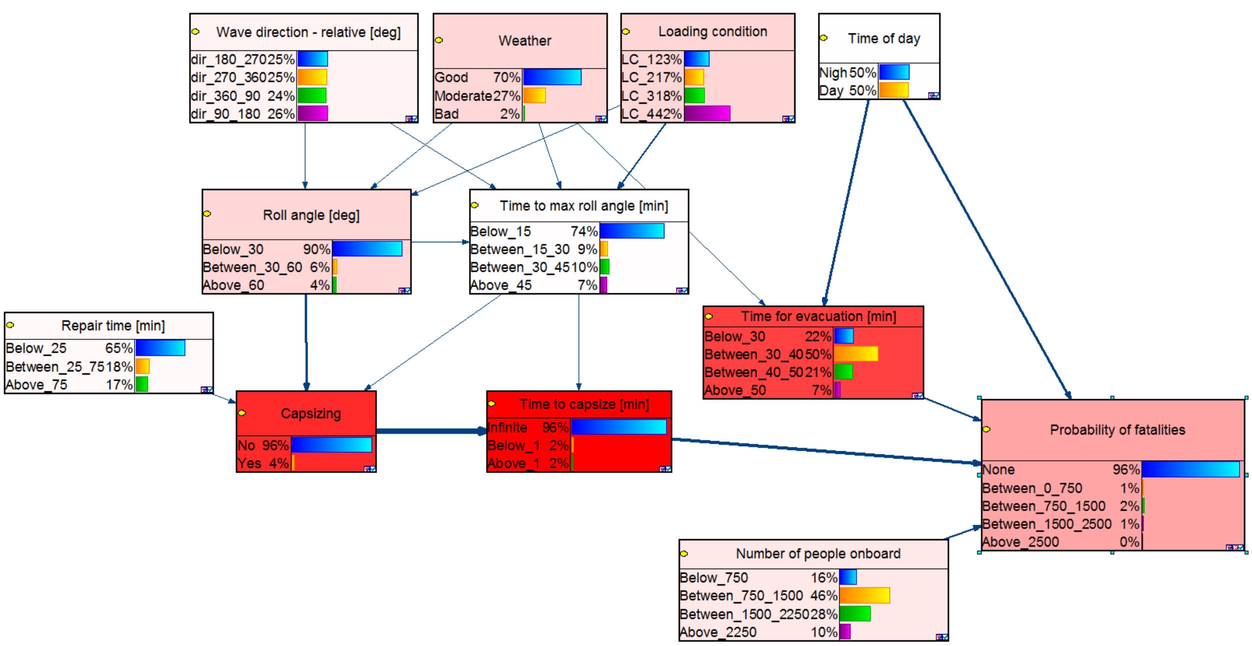

Fig. 2. Results of sensitivity and value of information analyses

III. RESULTS

To measure the risk associated with the stability accident of DSC of a ship in operation we adopt the widely agreed metric, which is a cumulative probability of fatalities that results from the above-mentioned accident. The results are presented in a form of F-N curve plotted on top of the risk acceptance criteria as depicted in Figure 3. However the meta-model presented in Figure 2 determines the probability of a given interval of fatalities (f), once the accident happens. To get the cumulative frequency per year (F), the results needs to be multiplied with the probability of DSC and the frequency of an interval (f) needs to be transformed into the cumulative frequency (F). Social risk acceptance criteria are adopted here, as proposed by IMO for RoPax and passengers ships.[11]

To inform the end-users about the quality of the meta-model and its validity, a set of analyses is performed. Their results indicate that the structure and the parameters of the model correspond with the data-set obtained from over 17300 simulations of a ship in DSC (C-V analysis). Moreover, the model is sensitive to a number of variable, the one estimating time for evacuation, a node estimating time to capsize and a node estimating the capsize event itself. This means, that small changes in any of those result in significant changes in the model outcome. However, the node *Time for evacuation* is based on guidelines, which are internationally agreed and provide rather conservative estimates, meaning that the evacuation cannot take longer than what is anticipated by our model. Other sensitive elements are *Capsize* and *Time to capsize*, which are obtained in the course of numerical simulation adopting the state-of-the-art model, thus the uncertainty associated with that node is moderate. Other nodes, like *Number of people on-board*, *Weather* or *Loading conditions* are less sensitive, however the uncertainty associated with the first two can be deemed moderate at most. The uncertainty of the latter is high though, since there is no evidence for the adopted distribution of that node.

However when we look at the results of the value of information, it is evident that there is significant influence of *Time of day* on the *Time for evacuation*, which is a sensitive node. Obviously there is also a significant influence of *Capsizing* on *Time to capsize* and *Probability of fatalities*. This means that the most of the uncertainty associated with the outcome node is passed along those paths, which are marked in bold arrows in Figure 2.

The influence of the variable estimating the probability of a ship being in DSC is not shown on the figure, however it cannot be.

Once the risk model is developed and checked for its validation, it is used to evaluate the safety of a ship in operation, where the results are presented as a set of F-N curves and plotted on top of the risk accepted criteria given by the IMO. Subsequently the results are compared with the standard stability criteria, as currently in force, for four loading conditions as anticipated by the risk model, as depicted in Figure 3. The ship is considered safe, when the risk falls within the acceptable region. On the right side of Figure 3, the actual stability parameters in eeach considered loading condition of the ship are plotted in color dots and limiting curves reflect individual stability criteria. If a dot is below the corresponding line the ship is considered safe, otherwise she is not. Comparing the risk picture with the classical stability criteria picture, it is evident, that good agreement is found for those cases, where ship fulfils the IMO stability criteria by large amount (LC4). This is the case for LC4 (however the curve goes beyond the limiting lines for some numbers of fatalities). However, for the cases where the prescriptive IMO criteria are barely met (LC1-3), the risk level is not acceptable for that ship, since the risk measure falls beyond the limiting lines of ALARP.

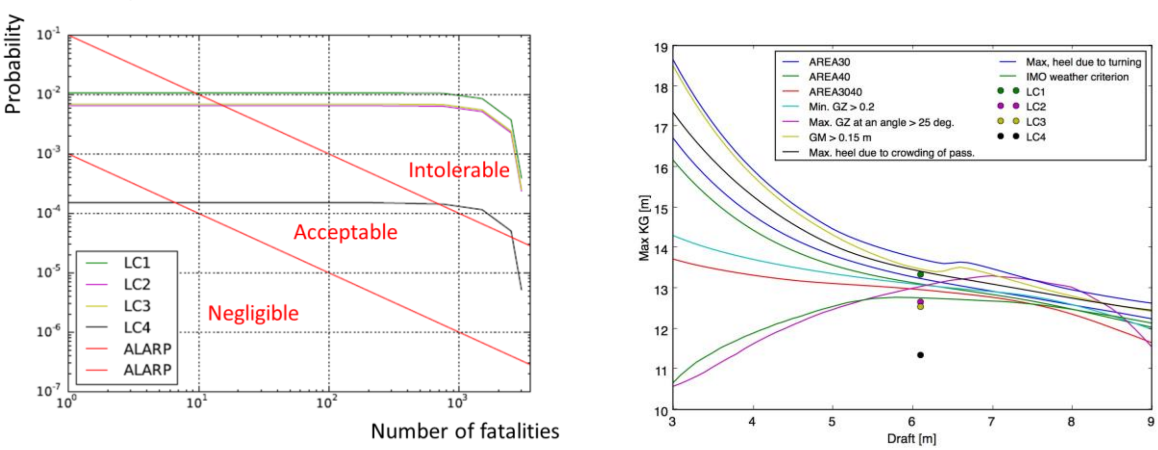

Fig. 3. The results of risk analysis for DSC plotted on top of risk acceptance criteria for ships carrying passenger – to the left; graphical representation of four loading conditions plotted on top of present stability criteria.

IV. DISCUSSION

The modeling carried out in the course of the research reveals significant merits of the applied approach. The meta-model can be utilized for innovative ships and their unusual loading conditions. The range of effects taken into account and the relation between them are exceptional. Not only is the dynamical behavior of the ship considered but also other time-depended phenomena producing the whole scenario of the studied incident.

Despite the unquestionable advantages of the implemented risk-based approach some difficulties are faced as well. First of all the BNs require the quantitative adjustment in terms of probability distributions of the applied variables which may be problematic since there is a shortage of well-established reliable models in the literature. The considered evacuation time is an important factor influencing the network outcome while this time may be predicted only roughly. There is a lack of evacuation models predicting the time required to abandon a ship with regard to actual motion amplitudes that seems to be important. Another challenge influencing the final outcome of the meta-model is ship's motion modeling. LaiDyn software was utilized which is well-benchmarked simulation tool, although it contains numerous simplifications. Due to the complexity of ship 6DOF motion it is difficult to assess to what degree the probability of breaching the predefined marginal angle of heel corresponds with the actual ship behavior in rough sea. The time spent to reach this critical angle of heel is one of the key variables in the model (*Roll angle, Time to capsize*). Reducing uncertainty about variable *Weather, Number of people on board* and *Loading conditions* will also reduce the overall uncertainty of the meta-model. However, the uncertainty associated with the first and second variables is of aleatory nature, thus can be deemed unresolvable.[52] The knowledge about *Loading conditions* is not available to us at the moment, but in principle could be gained. The uncertainty of *Repair time* depend on design and operational factors, which are not considered here, however the model is not very sensitive to that node, thus it is not of the highest priority to investigate it further here.

The influence of the uncertainty associated with the estimates of the probability of a ship being in DSC while in operation seems to be rather significant. This parameter is obtained based on the experts' judgment, which accounts for various aspects of ship operational conditions. On one hand such assessment can be considered less uncertain than if based on reliability data given by the manufacturer. On the other the value for that parameter holds for medium size container ship with one engine, thus for a double-engine RoPax this value can be lower, pulling down the risk values. Definitely this parameter needs more detailed investigation.

It is also important how the nodes are discretized, how many states do they have, and what are the bases for selecting those. This affects the results of cross-validation, and the overall performance of the meta-model.[39,53]

Last but not least, the time required for the meta-model preparation can be seemed as a drawback compared to classical stability criteria. The process of meta-model development is at the moment time-consuming since there is a need for performing a huge number of numerical simulations to obtain the probability distributions for the essential variables. However, the preparation of the data-set is an exercise that needs to be performed only once in ship's life, for a wide range of operational conditions.

Notwithstanding the mentioned difficulties the performance of the meta-model is decent and the application of the model to evaluation of safety of ship in operation goes beyond the contemporary ship stability assessment methods. The holistic approach taking into account the consecutive events creating scenarios bring the model closer to real life situation than any other.

V. CONCLUSIONS

The risk assessment of a specific accident type for w RoPax ship is presented here, which can be seen as a novel approach to evaluate the safety of a ship at sea. The probabilistic meta-model developed with the use of the state-of-the-art ship dynamics model and organized with the use of Bayesian learning algorithm indicates the level of risk associated with a given operational scenarios, accounting for the uncertainties, providing the end-user with convincing message rather than just stating that the operation is either safe or not, as it is presented in the existing methods. The latter may give a false impression of a ship being safe in a condition where in fact the risk is unacceptable. Therefore, the presented model shows its superiority over the existing approach in assessing the safety level of a ship.

Moreover, the meta-model can be further extended to comprise other scenarios of stability incidents and non-stability related failures. Besides the scientific value of the work there is some potential for its practical application since evaluation of the risk plays an important role in shipping market. The costs of insurance could be calculated on the risk basis, and then operators' contribution to P&I Clubs may vary according to the risk as well. Such direction in the safety culture development would encourage ship owners, operators and on board crew to mitigate the risk even if it remains in the acceptable margin.

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