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Maritime Operational Risk Management using Dynamic Barriers

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ABSTRACT

The safe operation of any vessel is challenged by the constraints posed through design as well as maintenance and correct operation of the available safety barriers to ensure their effectiveness. This requires a direct linkage between barrier performance and operational risk management, accounting for potential degradation of the barriers and ensuing corrective actions. Therefore, the introduction of dynamic barrier management is a powerful tool in maintaining design resilience during operation and in emergencies. It is the purpose of this paper to demonstrate the achieved progress in developing a comprehensive approach to address risk in real-time. The authors aim to show how performance information on barrier elements and their respective functions is a) collated, b) aggregated through parametric (empirical) models for identifying barrier relative importance, function criticality and in defining a set of key safety indicators, and c) is intuitively visualized for providing real-time guidance to crew and shoreside management. The practicality of this approach is demonstrated by considering watertight doors as dynamic barriers preventing excessive transient- and progressive-flooding on a cruise vessel during operation. It will be discussed how these methods can be generalized into a framework, enabling operational risk management and subsequent decision support.

KEY WORDS:

Dynamic Barrier Management; Maritime Operational Risk; Feedback-loop; Sensor Data; Real-time Response

INTRODUCTION

Today, the maritime industry is faced with the increased complexity of ship systems and ship operations as well as the trend for accelerated innovations expediting the introduction of novel technologies. These developments are putting additional requirements onto the skills of the professional seamen already exposed to stressful working conditions. At the same time, it is an expectation by society at large, that the industry shall improve their safety records and provide a safer habitat for seafarers and passengers. During the operational life of a vessel, the magnitude of risk and failure modes can vary significantly between existing vessels and new designs. Such fluctuation depends on changing system conditions, on-going activities and the operating environment. In this respect, it is crucial to be able to recognize potentially severe situations and make the right judgment for the operational decision needed to control the pertinent risk. Here, the appreciation of precursors leading to an imminent accident and the awareness of the necessary action to deal with the dangerous state are important elements that cannot be ignored. This creates demand and interest in extending the application of risk assessment methodologies, traditionally focused on design, to the complete lifecycle of a vessel, to ensure that the vessel is not only safely designed but can continuously operate within the desired safe boundaries throughout the entire operating life. In this respect, we engage the duality of ship safety, namely how we design the vessel for safety and how the vessel is operated safely. In this respect, the vast knowledge and experience potential available from the vessel's operation can enhance safety and environmental performance by not only providing the valuable lessons learnt from occurring incidents, but also contributing to building a robust feedback mechanism to the naval architects to target design improvements. For this purpose, the availability of data to analyze the operation more objectively will accelerate the discovery of quick win design upgrades in addition to having the potential to measure their impact.

After launching, the performance of a vessel is subjected to the outcomes of decisions classified in four types: *strategic*, *operational*, *instantaneous* and *emergency*. Strategic planning decisions are characterized by a long planning horizon (with time to consider risks and benefits of alternatives carefully), low decision frequency, and long-term effects. Examples are approving major modifications, choosing between alternative technologies and deciding on a maintenance strategy. Operational planning decisions are related to actions that will be taken and implemented within a shorter period, i.e. during a vessel voyage. The planning period is relatively short, however, sufficiently long to carry out some form of risk assessment. Instantaneous decisions are immediate responses executed by sharp-end operators, i.e., to follow or deviate from procedures; ignore or react to deviations from normal working conditions, etc. Emergency decisions are the decisions taken by a team in emergencies to avoid or adapt to hazardous situations (Yang and Haugen, 2015).

In such context, the lines of action are guided by the fundamental principle of safety management to maintain the organizational ability, on all levels, to timely adjust to planned and unplanned changes and out-of-range disturbances, as opposed to mere reduction of risks and unwanted events by constraining performance through more rigidly defined activities. This is achieved through (a) the early detection of deviations from design assumptions about how safety hazards are expected to be controlled and (b) generation of necessary actions, or decision-support information, to timely restore the system into a safe state. This constitutes, amongst others, the basis for management of safety barriers, the purpose of which is to maintain the system in the safe state by stopping the development of an accident. To this end, timely and accurate information about barrier performance becomes critical (Hollnagel, Woods and Leveson, 2006). For the sake of clarity, safety barriers are physical and/or non-physical means (ranging from technical elements such as hardware and software, to operational activities executed by humans, or a combination such as a complex socio-technical system) with the intent to prevent, mitigate or control undesired events or accidents (Sklet, 2006). Hence, in preparing for the operations phase, the integration of information systems and tools that can be applied during operation is essential for verifying the performance as well as monitoring the status of the barrier elements. The latter is a paramount prerequisite for establishing a feedback loop between the design and operation. At the same time, it is equally important to carry over the information on the boundaries of safe operations inherent by design to the operator. A safety barrier ability to tolerate perturbations affected by hazards and related conditions whilst operating in a stochastic environment at sea includes the dormant constituents provided through design, as well as active ones, which require to be properly managed during operation. The target performance is set from the design phase, whilst for the operation phase the aim is to perform at a level as close as possible to the design intent. Consequently, the opportunity is presented to identify barrier criticality that serves to utilize the resources efficiently and raise the level for setting new targets to demonstrate the effect of continuous improvement. Furthermore, the feedback loop is traced back to the design process for improving the next vessel series by modifying the barrier or strengthening the barrier for the existing vessel (King, Van Welter and Svensen, 2016). What has also been recently realised is that in anticipation of safety deterioration over the lifecycle, for example the deterioration of stability-margins through weight growth high up in the vessel, somewhat arbitrary margins are being allowed during the design and building phase to cater for such deterioration. Clearly, there is room for improvement here, in need of operational information.

So far, preserving barrier integrity on a real-time basis is challenging because of limitations in assuring that objective information is continuously collated for establishing and maintaining barriers. Advances in instrumentation, industrial networks, equipment and supervisory control systems will help to integrate information between the sharp- and blunt-ends, which can be translated into actionable intelligence for a unified understanding of any barrier status across the entire organisation. Accounting for the above, the paper is structured as follows: Section two outlines the implementation of a parametric model to monitor and assess flooding risk in real time enabling dynamic barrier management with the water-tight doors as the barrier function. The section focuses on how to (a) identify the boundaries of safe performance, (b) make these boundaries known and visible to decision makers, and (c) ensure that decisions taken do not drive performance towards the boundaries, using a concrete application as a showcase. Section three explains how the methods can be generalized into a framework, which can be used for operational decision support, and section four provides concluding remarks.

MANAGEMENT OF WATERTIGHT DOOR BARRIER ELEMENTS IN OPERATIONS

Passenger vessel losses are being reduced on a year to year basis, driven by continually evolving regulations and the evolution of a more robust safety culture (Dobie et al., 2018). This is consolidated by initiatives within the cruise industry to develop and improve basic principles, best practices and procedures with the ambition to become the safest form of travel in the world (Kulovaara, 2015; CSSF, 2020). Nonetheless, loss of damage stability due to flooding still represents the largest proportion of vessel losses and human casualties, which demands continued attention (EMSA, 2019). To this end, recent advances in sensor technology and predictive data analytics provide a means to address this challenge, enabling continuous assessment and management of flooding risk, through monitoring of key risk-drivers (variables) as well as the performance of available safety barriers. The watertight doors as barrier elements to prevent flooding are visualized together with their functional purpose (maintain watertight integrity) in a simplified bowtie diagram in Figure 1, where capsize/sinking are the unwanted events to be averted.

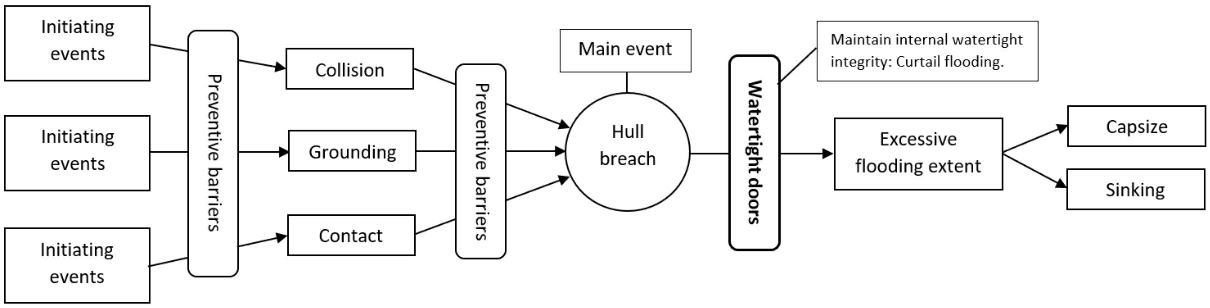

Figure 1: Simplified bowtie diagram illustrating watertight doors as safety barriers with function to maintain watertight integrity.

A sensor-driven monitoring application requires interfacing between various on-board alarm and control systems as well as the deployment of advanced software tools and platforms onshore for data acquisition, storage, transfer and analysis. Essentially, the software tools need to be linked to and reflect the dynamic processes of watertight door operation, whilst system specific standards ensure uniform exchange of information along the blunt- and sharp-ends. In the following section, an outline of a parametric model for real-time assessment of flooding risk is provided, enabling dynamic management of the water-tight door barrier elements. Next, it is described how collection of data and signals from sensors, instruments and systems associated with watertight doors via direct monitoring can be preliminarily processed locally and selected analyses of the results are transferred online so that the blunt- and sharp-ends can safely estimate a critical situation when needed.

Parametric model for live (dynamic) flooding risk monitoring

The parametric model for live flooding risk monitoring incorporates a range of variables including the watertight doors as safety barriers for flooding containment. The model is an adaptation of the framework presented in (Karolius, 2019; Karolius, Cichowicz and Vassalos, 2020), but with application in the operational phase of the vessel lifecycle. The model utilizes multi-sensor data fusion, where accumulated (historical) operational data (a priori) are combined with real-time sensor readings (evidence) to form a strengthened belief (posterior) of the observed risk with reduced uncertainty. Important sensor evidence is the status of the watertight doors and evidence on key risk-driving parameters, such as the vessel operating loading condition, wind speed and number of passengers on-board.

The model has initially been developed for the purpose of demonstration in the context of Dynamic Barrier Management, consequently various simplifying assumptions have been made as will be outlined in the following. The assumptions impose limitations on the model in capturing the risks from important variables and restrains the model from actual onboard application without more comprehensive considerations. Nonetheless, the model is sufficiently adequate for the purpose of concept demonstration. Firstly, the model incorporates only collision damages. Grounding damages may, however, easily be implemented using applicable distributions (Zaraphonitis et al., 2015). Secondly, the vessel loading condition, trim and heel have been assumed even keel and upright. This may be supported by the fact that large cruise vessels operate on a very narrow trim range (Paterson and Atzampos, 2017), as well as required to be operated upright without any significant heel ($\pm 0.5°$). Additional trim ranges may be included in the damage database if found necessary. A more serious implication is that the effects from waves have been disregarded. It is important to stress that the effects from waves may critically impair vessel survivability, especially in relation with open watertight doors, which calls for more detailed consideration in future developments. The watertight doors may also leak or collapse under the floodwater pressure, whereas the initial assumption herein is that – if a door is closed, it will provide full functionality as a floodwater boundary. Future developments may be enhanced by incorporating probabilistic models for the consideration of waves as well as leak and collapse pressure heads, similar to Karolius (2019) and Karolius, Cichowicz and Vassalos (2020).

The developed model represents flooding risk as the probability of vessel loss following collision damage, inherently related to large scale economic and environmental consequences as well as inevitable loss of human lives. The problem of flooding risk is therefore two-fold and involves breach- and loss probability (probability of getting a hull breach and subsequent vessel loss). This may be illustrated in the event tree seen in Figure 2, which forms the basis to formulate the initial risk model governed by the probability of loss following a collision incident and subsequent breach using the chain rule of conditional probability as represented by Eq. 1.

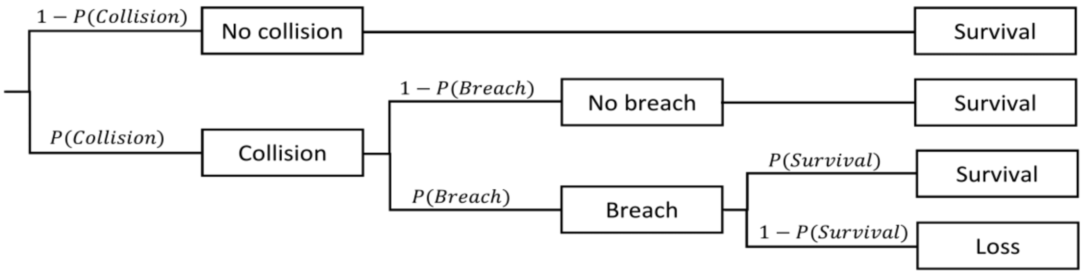

Figure 2: Event tree representing the casual chain resulting in vessel loss from a collision incident.

$$P(Loss,\ Breach,\ Collision) = P(Loss|Breach,\ Collision)\ P(Breach|Collision)\ P(Collision) \quad \text{Eq. 1}$$

A marginal probability of collision, *P(Collision)*, may be obtained from applicable collision statistics, or more realistically, the observed traffic density from available navigational instruments, such as the radar or AIS system may be utilized to infer an updated (strengthened) belief of collision probability conditional on the number of potential collision sources, i.e. *P(Collision|Traffic)*. For initial demonstration of the model, however, we have assumed a collision probability of 1. The ensuing risk from the model is consequently conditioned on the fact that a collision has taken place, a notion in line with the probabilistic damage stability framework found in SOLAS (IMO, 2006a). Applicable models for accounting for the actual traffic density, such as the *AISyRisk* model developed by DNV GL in collaboration with the Norwegian Coastal Administration (NCA, 2018), may readily be incorporated in future developments.

The breach probability following a collision, *P(Breach|Collision)*, reflects a range of variables such as the speed and heading of the vessels involved in the collision incident. However, aiming for a dynamic risk measure in operation, these variables are unknown and not yet realized, and it must be assumed that the variables may take any values from their marginal distributions. Vessel structural soundness (crashworthiness) would also affect the probability of getting a hull breach following a collision incident but would be invariant during operation (determined in the design phase), e.g. additional stiffeners or higher tensile strength steel would reduce the probability of a hull breach following a collision. For initial demonstration, and similar to the probability of collision, a breach probability of 1 has been utilized (i.e. any collision result in hull breach).

A breach opening in the hull following a collision incident may translate into a range of possible initial damage extents (in terms of lost compartments open to sea), depending on its position and extent of damage as illustrated in the event tree in Figure 3. Using the event tree, we may reformulate the risk model governed by the probability of loss following a collision incident and subsequent breach, resulting in a specific damage extent *i* by Eq. 3. The total loss probability is then given by the summation of all the *N* possible damage extents as in Eq. 4.

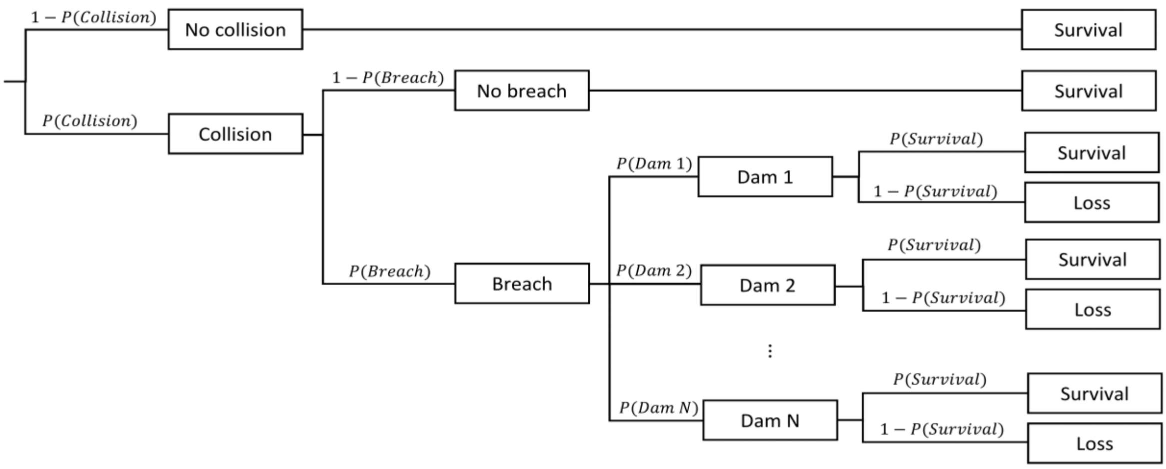

Figure 3: Event tree representing loss from collision, from various possible damage extents.

$$P(Loss,\ Dam\ i,\ Breach,\ Collision) = P(Loss|Dam\ i,\ Breach,\ Collision) \cdot \cdots$$ Eq. 3
$$\cdots \cdot\ P(Dam\ i|Breach,\ Collision)\ P(Breach|Collision)\ P(Collision)$$

$$P(Loss,\ Breach,\ Collision) = P(Breach|Collision)\ P(Collision) \cdot \cdots$$ Eq. 4
$$\ldots \cdot \sum_{i=1}^{N} P(Loss|Dam\ i,\ Breach,\ Collision)\ P(Dam\ i|Breach,\ Collision)$$

The probability of vessel loss conditional on a specific damage extent i, may be represented by the compliment to the survival (s[1]) factor from the SOLAS probabilistic damage stability framework (Eqs. 5-9) (IMO, 2006a). The probability of a specific damage extent *i* taking place relates further to the p factor from the same framework (Eq. 10). However, a non-zonal Monte Carlo (MC) sampling approach in line with Zaraphonitis et al., (2015, 2017) has been implemented to identify the probability of occurrence for various damage extents, where pertinent distributions presented in Karolius (2019) have been utilized. Regardless, we may still refer to this as a p-factor, and substituting accordingly for the p and s factors, and assuming a collision and breach probability of 1 as discussed above (Eq. 11) results in Eq. 12.

$$P(Loss|Dam\ i,\ Breach,\ Collision) = 1 - s_i$$ Eq. 5

$$s_i = \text{minimum}\ \{s_{intermediate,i}, s_{final,i} * s_{moment,i}\}$$ Eq. 6

$$s_{intermediate,i} = \left[\frac{GZ_{max}}{0.05} \cdot \frac{Range}{7}\right]^{\frac{1}{4}}$$ Eq. 7

$$s_{final,i} = K\left[\frac{GZ_{max}}{0.12} \cdot \frac{Range}{16}\right]^{\frac{1}{4}},\ K = 1\ if\ \theta_e \leq \theta_{min}, K = 0\ if\ \theta_e \geq \theta_{max}, else\ K = \sqrt{\frac{\theta_{max}-\theta_e}{\theta_{max}-\theta_{min}}}$$ Eq. 8

$$s_{moment,i} = \frac{(GZ_{max}-0.04)Displacement}{M_{heel}},\ M_{heel} = maximum\{M_{pax}(N_{pax}),\ M_{wind}(V_{wind}),\ M_{survival\ crafts}\}$$ Eq. 9

$$P(Dam\ i|Breach,\ Collision) = p_i$$ Eq. 10

$$P(Collision) = P(Breach|Collision) = 1$$ Eq. 11

$$Risk = P(Loss,\ Breach,\ Collision) = \sum_{i=1}^{N}(1 - s_i)p_i$$ Eq. 12

From the above equations for the s-factor, it is evident that it is case specific, and depends on various risk-drivers, such as the loading condition of the vessel (draught, *T*; vertical centre of gravity, *KG*), number of passengers carried (N_{pax}), as well as the imposed wind speed (V_{wind}). Whereas SOLAS aggregates the risk (or attained index A) for the intended operational envelope (*T*, *KG*) and specified limiting wind speed as well as the worst case (maximum) number of passengers allowed, the real-time information may be utilized for an actual risk representation. Thus, Eq. 12 may be rewritten as in Eq. 13.

$$Risk = P\big(Loss,\ Breach,\ Collision, N_{pax}, V_{wind}, T, KG\big) = \sum_{i=1}^{N}(1 - s_i)p_i$$ Eq. 13

In its current form, the risk model does not account for the watertight door barrier elements, and the various p-factors presently only represent the initial extent of damage, i.e. the compartments being compromised and open to sea as a direct result of the damage breach. The internal watertight compartmentation of the vessel, including the various internal openings will in combination with the residual floating position be decisive for how the floodwater propagates from the initial damage extent, throughout the vessel, and are in fact sub-events of the

[1] s_i: probability of surviving a given flooding scenario *i*

respective initial damage extents. Realisations of progressive flooding extents are stochastically determined, governed by the respective watertight opening progressive flooding probability, which is given by the summation of the various ways in which progressive flooding may take place as illustrated in the event tree in Figure 4. The event tree may be used to formulate a model for progressive flooding probability as given by Eq. 14. As a result of not incorporating the effects from waves, the probability, *P(Submerged),* is governed by a deterministic process, where progressive flooding is possible only if the opening is submerged by the residual waterplane. *P(Open)* denotes the probability of an opening being open in any given time (opening frequency), and *P(Crew fail)* And *P(Sys. fail)* are the failure probabilities for the crew and door system respectively (governed by crew/system reliability).

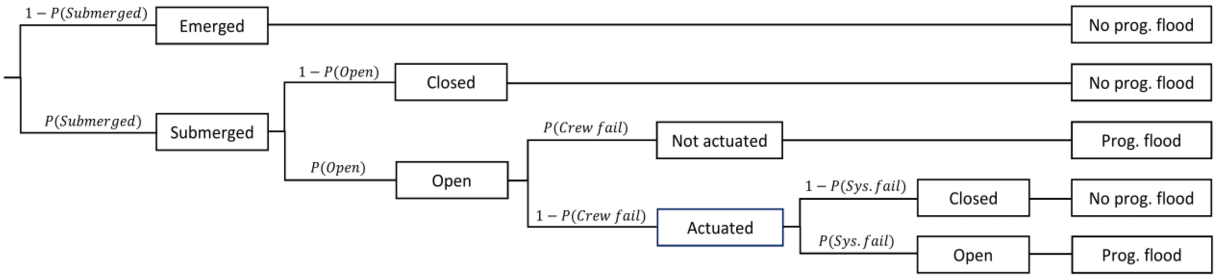

Figure 4: Progressive flooding event tree.

$$P(prog.flood) = P(Submerged)P(Open)[P(Crew\ fail) + P(Sys.fail) - P(Crew\ fail)P(Sys.fail)] \quad \text{Eq. 14}$$

Having established a model for the progressive flooding probability, *Uncertain Graph Sampling* (UGS) as presented in Karolius, Cichowicz and Vassalos (2019) has been implemented in the model to sample possible progressive flooding realizations originating from the respective initial damage extents (source nodes). The realization of various progressive flooding extents is illustrated in Figure 5, clearly showing the progressive extents as sub-events of the initial damage extents. The figure further shows that only the proportion of cases where the initial damage extent survives the initial *Stage 0* ($s_{int} \neq 0$), are proceeding to *Stage 1*, resulting in progressive extents.

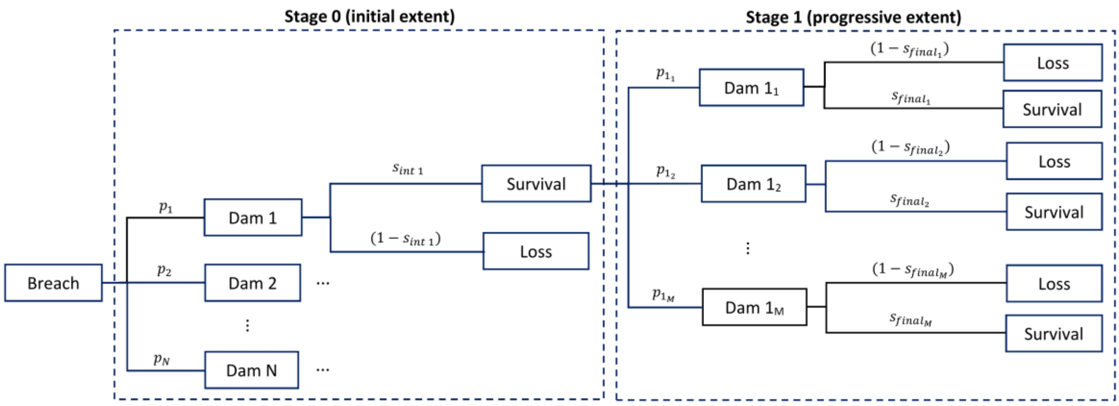

Figure 5: Event tree representing progressive flooding realisations from each source (initial damage extent).

For demonstration of the model, only one intermediate stage has been considered (initial extent of damage), a result of assuming all non-watertight structures unprotected and immediately flooded if submerged. However, in reality, non-watertight structures (e.g. A-class fire rated structures) might restrict flooding for shorter periods of time, resulting in more severe intermediate situations in the flooding evolution between the initial and final (progressive) extent, than is presently considered. This should be addressed in future developments of the model. Using the event tree in Figure 5, the final risk model may be formulated as in Eq. 15 and is now a function of the *N* watertight door barrier elements status (represented by $P_{prog.flood} = \{P_{pf_{door1}}, P_{pf_{door2}}, \cdots, P_{pf_{doorN}}\}$).

$$Risk = P\left(Loss, Breach, Collision, N_{pax}, V_{wind}, T, KG, P_{prog.flood}\right) = \cdots \quad \text{Eq. 15}$$

$$\ldots = \sum_{i=1}^{N} p_i \left[1 - s_{int\,i} + s_{int\,i} \sum_{j=1}^{M} p_{i_j} \left(1 - s_{final\,i_j} \right) \right]$$

Online implementation for barrier exploitation

Sample vessel

The presented risk model has been implemented for demonstration on a large (225,300 GT) modern cruise vessel currently in operation. Main particulars of the sample vessel are summarized in Table 1. The vessel internal compartment connectivity comprises a total of 1,088 openings, covering doors, hatches, etc., whereas 63 of these are defined as watertight barrier elements (24 Sliding-watertight doors, 26 Light-watertight doors and 13 Semi-watertight doors). The remaining openings have been assumed unprotected and to progressively flood regardless of open-closed status if submerged. The watertight door barrier elements are categorised in accordance with IMO MSC.1/Circ.1380 (IMO, 2011), which set restrictions on usage of the doors while operating at sea and are therefore directly influencing the opening probability, and subsequent flooding risk of the vessel. The various categories are summarized in Table 2.

Table 1: Particulars of the sample vessel.

Parameter (symbol)	**Value**	**Designation**
Length between perp. (LBP)	330.0	[m]
Breadth (B)	47.0	[m]
Depth (D)	22.5	[m]
Gross tonnage (GT)	225300	[-]
Number of passengers (-)	6780	[persons]
Number of crew (-)	2100	[persons]

Table 2: Opening allowance categories in accordance with IMO MSC.1/Circ.1380.

Category	**Description**	**No. of doors**
A	Doors allowed to be kept open at sea	21
B	Doors should be kept closed, but may be opened during the period for personnel carrying out work in the vicinity of the door	10
C	Doors should be kept closed, but may be opened to permit passage	32
D	Doors should always be kept closed at sea	0
Sum		63

Damage database

The sample vessel assumed (design) operational loading-condition envelope in terms of *T* and *KG* has been modelled by a Beta-Beta bivariate distribution with a bounded, valid, range below the required limit curve (IMO, 2006b), as well as the maximum summer load-line draught. The model for the vessel operational enveloped is given by Eqs. 16-19.

$$P(KG,T) = P(KG|T)P(T) \qquad \text{Eq. 16}$$

$$P(KG|T) = \frac{(x-a)^{\alpha-1}(b-x)^{\beta-1}}{B(\alpha,\beta)(b-a)^{\alpha+\beta-1}}, \quad \alpha = 5.2, \quad \beta = 1.8, \quad B(\alpha,\beta) \rightarrow Beta\ function \qquad \text{Eq. 17}$$

$$a = -1.6241T + 36, \quad b = -1.6241T + 38.5 \qquad \text{Eq. 18}$$

$$P(T) = \frac{(x-c)^{\alpha-1}(d-x)^{\beta-1}}{B(\alpha,\beta)(d-a)^{\alpha+\beta-1}}, \quad c = T_{MIN}, \quad d = T_{MAX} \qquad \text{Eq. 19}$$

The survival factor, s, is governed by the residual stability margins post damage (*GZ*, *Range*, *Heel*), which would entail assessing the residual floating position of the vessel for all the damage cases in combination with the complete operational envelope (all possible initial loading conditions). This undertaking would not be feasible (time-expensive process), especially so in real-time. For this purpose, the various stability parameters have been pre-calculated for a range of specified initial conditions and stored in a damage database. In actual (real-time) operations, relevant damage cases are simply sampled using the UGS method in combination with the observed evidence from sensors, looked-up and matched with the damage database, and the corresponding s-factors calculated and aggregated through the risk model. The operational envelope of the vessel, including fifteen initial conditions chosen to represent the damage database are illustrated in Figure 6. Actual risk values, representing the observed sensor evidence (*T, KG*) are interpolated between its respective relevant four initial conditions from the damage database.

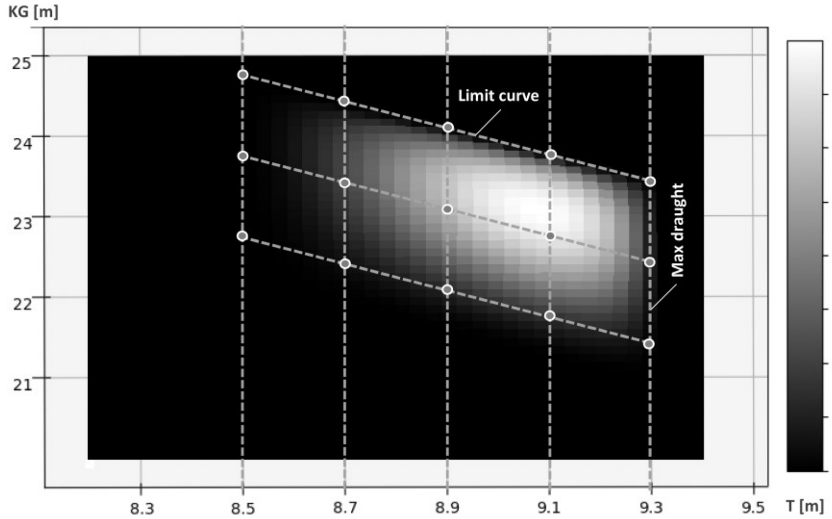

Figure 6: Vessel operational envelope, with initial conditions representing the damage database

Safety Baselines

For quantification and benchmark of the operational risk performance, acceptable safety levels need to be established to represent the boundaries of safe performance. In the following section, two safety-baselines will be suggested and outlined, namely; *Expected risk*, which is based on the operational design envelope of the vessel, and *Limiting risk*, which is based on the limit curves as required by the probabilistic damage stability framework found in SOLAS (IMO, 2006b). The former governs the aggregated expected risk of the vessel based on the (assumed) design operational envelope as illustrated in Figure 6 and represents the proportion of time the vessel is operated within each of the defined initial conditions in the damage database. Since this is an expected risk, the actual operational risk will be varying around this value, nevertheless, provides an indication and benchmark for proportions of time the expected baseline is exceeded. The latter is an aggregation of the risk representing only the initial conditions in the upper boundary (representing the limit curve) and may be used to represent an area of unacceptable risk. Both baselines have been calculated assuming the doors in their intended position in accordance with their opening allowance categorization. The relevant variables governing the expected- and limiting risk-baselines are summarized in Tables 3 and 4 respectively, where the various initial conditions proportions have been identified using MC sampling (using 1 000 000 samples), as illustrated in Figure 7.

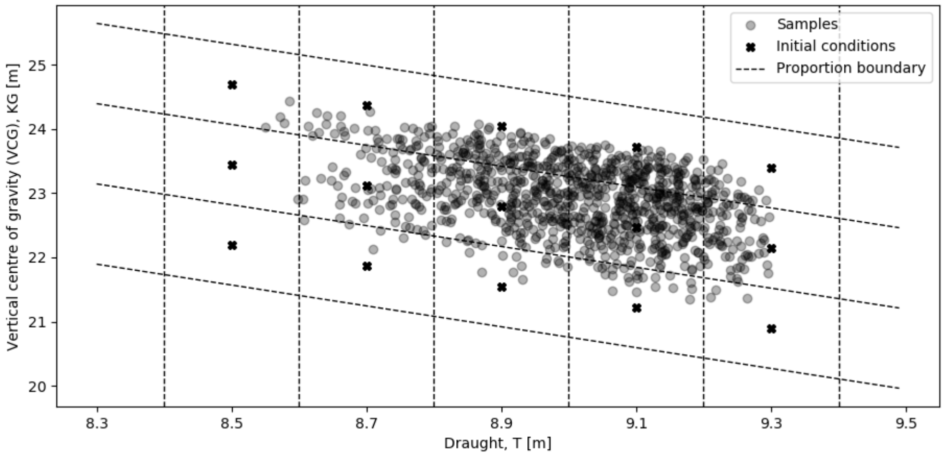

Figure 7: Identification of proportions for the various initial conditions by sampling (figure shows only 1 000 samples).

Table 3: Variables used to calculate expected risk baseline.

Init. cond. i	T [m]	KG [m]	P_i	$Risk_i$	$P_i \cdot Risk_i$	Exp. N_{pax}	Exp. V_{wind} (*) [m/s]
INIT 1	8.500	24.695	0.00177	0.35452	0.00063	6650	8.860
INIT 2	8.500	23.445	0.00373	0.34759	0.00130		
INIT 3	8.500	22.195	0.00024	0.35046	0.00008		
INIT 4	8.700	24.370	0.03839	0.34971	0.01343		
INIT 5	8.700	23.120	0.07981	0.34121	0.02723		
INIT 6	8.700	21.870	0.00518	0.33563	0.00174		
INIT 7	8.900	24.045	0.10520	0.34973	0.03679		
INIT 8	8.900	22.795	0.21937	0.33977	0.07454		
INIT 9	8.900	21.545	0.01438	0.33445	0.00481		
INIT 10	9.100	23.721	0.13218	0.33352	0.04409		
INIT 11	9.100	22.471	0.27500	0.32816	0.09024		
INIT 12	9.100	21.221	0.01801	0.33491	0.00603		
INIT 13	9.300	23.396	0.03314	0.30408	0.01008		
INIT 14	9.300	22.146	0.06907	0.29937	0.02068		
INIT 15	9.300	20.896	0.00451	0.29606	0.00133		
				Exp. Risk	0.33300		

(*) World-wide expected wind speed at 80 m height

Table 4: Variables used to calculate limiting risk baseline.

Init. cond. i	T [m]	KG [m]	Pi (*)	$Risk_i$	$Pi \cdot Risk_i$	Exp. N_{pax} (**)	Exp. V_{wind} (***) [m/s]
INIT 1	8.500	24.695	0.00571	0.36690	0.00209	6780	14.00
INIT 4	8.700	24.370	0.12358	0.36219	0.04476		
INIT 7	8.900	24.045	0.33861	0.36220	0.12264		
INIT 10	9.100	23.721	0.42545	0.34630	0.14733		
INIT 13	9.300	23.396	0.10666	0.31742	0.03385		
				Lim. Risk	0.35068		

(*) Normalized proportions, (**) Maximum number of passengers, (***) Wind speed required by SOLAS Reg. II-1/7-2 (P = 120 N/m^2)

The progressive flooding probabilities have been calculated using Eq. 14, supported by reliability data as summarized in Table 5, where the respective failure probabilities have been taken as the averaged failure probability (e.g. Figure 8 for the door system) assuming weekly testing in accordance with Reg. II-1/21 of SOLAS (2009) (IMO 2006b), and using an exponential reliability model given by Eq. 20.

Table 5: Reliability data for the calculation of the progressive flooding probability.

System	$\boldsymbol{\lambda}$ [failures per hour]	$\boldsymbol{P_{fail_{avg}}}$
Door (NSWC, 2010)	0.00005	0.00419
Sensor (Cadwallader, 1996)	0.00001	0.00084
Crew (Smith, 2005)	0.00020 (*)	0.01660

(*) Assuming an emergency stress situation, however, disregarding the time it would take to close the doors.

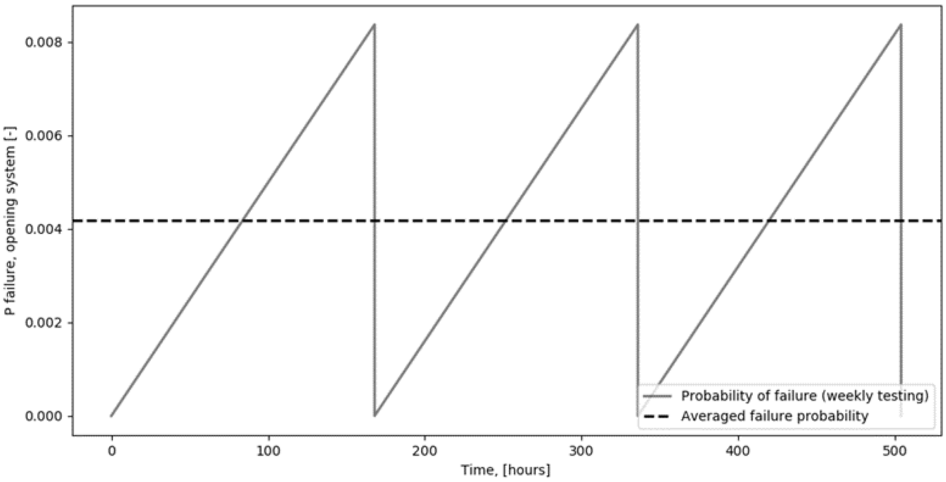

Figure 8: Average failure probability for the watertight door system, assuming weekly testing intervals and an error rate of λ = 0.00005.

$$P_{failure}(\lambda, t) = 1 - e^{-\lambda t} \quad \text{Eq. 20}$$

The two baselines are illustrated in Figure 9 for a specific time-period and time-instance, where a simple colour coding has been applied to each of the “risk-areas”. Green (or light grey) is assigned to the area below the expected risk-baseline, i.e. negligible risk, yellow (or grey) for the area above the expected risk-baseline, i.e. acceptable risk, while red (or dark grey) is assigned the area above the limiting risk-baseline i.e. unacceptable risk. This provides intuitive and valuable information to the operators for continuous benchmarking of the risk-performance through time. It is important to note that the baselines presented herein are suggestions only, developed mainly for demonstrating the methodology and to provide visual examples of how the methodology may serve to inform the operators. Applicable and acceptable safety levels or baselines in an actual onboard application would need to be determined by the operators.

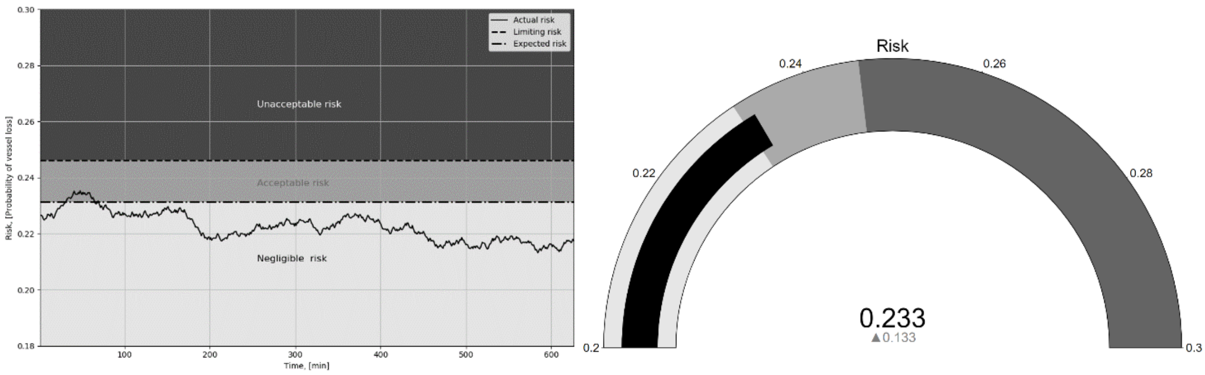

Figure 9: Dynamic (live) risk in time period (left) and time instance (including delta-risk from last time-step) (right). Note that appropriate boundaries should be defined by operators.

Onboard application

The risk model has in the following section been applied to the sample vessel during operation in a time period of 6 months, as illustrated for the various variables in Figure 10. The sampling rate of the vessel loading condition variables, T and KG, were obtained with daily intervals, while wind speed on hourly intervals. These values have therefore been extended to a sampling rate per minute by linear interpolation, as to enable to apply a higher and more realistic sampling density for the watertight doors usage. Actual door opening data was not available for the sample vessel and has been randomly sampled using assumed probability distributions for opening-rate as well as opening-duration, for a realistic representation. The distributions are given in Eqs. 21-22 respectively, with different parameters for the various door opening allowance categorization (see Table 2). The figure includes three of the 63 watertight door barrier elements for illustration (3 lower graphs), representing the various opening allowance categorizations, where it can be seen that the category A door is kept open most of the time, at long durations, and only closed for shorter durations for testing and maintenance. The other categories are kept closed for longer durations, and opened at a much higher rate, with short durations for passage in addition to testing and maintenance as would be expected. The door of category B is assumed to be kept open at a higher rate and at longer durations, as it is allowed to be kept open while performing work in the vicinity of the door. On average, doors of category A are kept open 99.9% of the time-series, doors of category B are kept open 1% of the time-series, while doors of category C are kept open 0.2% of the time-series.

$$P(Rate) = Normdist(\mu, \sigma), \quad \mu_A = 50,\ \sigma_A = 5,\ \mu_B = 250,\ \sigma_B = 5,\ \mu_C = 200,\ \sigma_C = 5 \qquad \text{Eq. 21}$$

$$P(Duration) = Gammadist(\alpha, \beta), \quad \alpha_A = 2,\ \beta_A = 4,\ \alpha_B = 2,\ \beta_B = 10,\ \alpha_C = 2,\ \beta_C = 2 \qquad \text{Eq. 22}$$

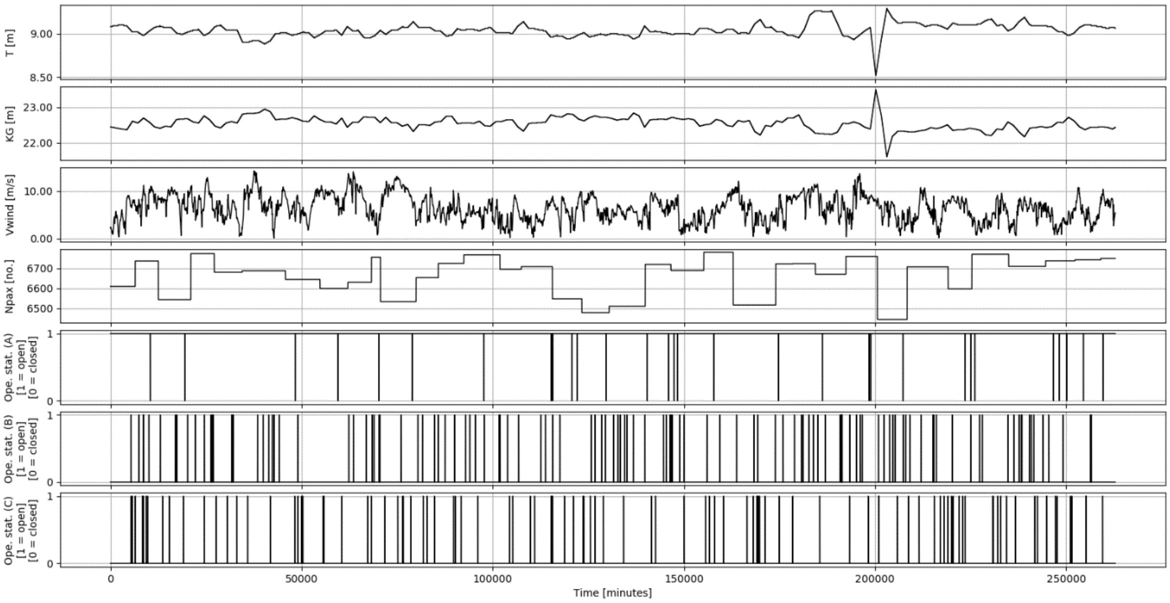

Figure 10: Time series for relevant variables over a period of 12 months of operation.

The complete risk-monitoring (profile) of the vessel during the 6-month timeline obtained from applying the developed risk-model are seen in Figure 11, including the proposed baselines. The figure clearly illustrates a time-varying risk, where the key risk-driving parameters, such as the vessel operating condition, wind speed and number of passengers carried are the governing factors and highlighted with arrows in the figure for a selection of instances. Various sudden variations are seen, representing larger change in passenger count while in port (actual port stay is excluded from the risk profile). Other larger variation comes from operating the vessel at different loading conditions, and we clearly see one large spike in risk, where the ship operates on a shallow draught, large KG condition resulting in an excessive wind profile, and subsequent moment. This scenario is exceeding the limiting risk baseline, however not the limit curve as required by SOLAS. The reason is that our limiting risk baseline is based on the aggregated risk representing the limit curve rather than the worst-case risk on the limit curve, which is approximately 0.30. The additional risk due to door operation is less obvious, and a result of correcting for the reliability measures (Table 5), i.e. the probability that a door will remain open and allow progressive flooding is very small, even if it is kept open for a period of time. This is a result of applying reliability values adopted from other industries as well as not accounting for the time aspect in closing the doors. We may, however, zoom in on a specific area (lower right of figure 11) of the timeline for more detailed assessment. Here, various spikes are clearly seen in the risk as a result of various doors kept open for shorter time periods but increasing with number of doors kept open simultaneously. Since reliability measures is difficult to quantify (especially so for the crew), a more informative presentation for the vessel operators would be the flooding risk if the doors would remain in the current open position (crew failure rate of 1), as seen in Figure 12. The figure clearly illustrates large spikes in the risk for various combinations of multiple open doors (number of open doors shown in the figure is those category B and C doors open in addition to the already open category A doors).

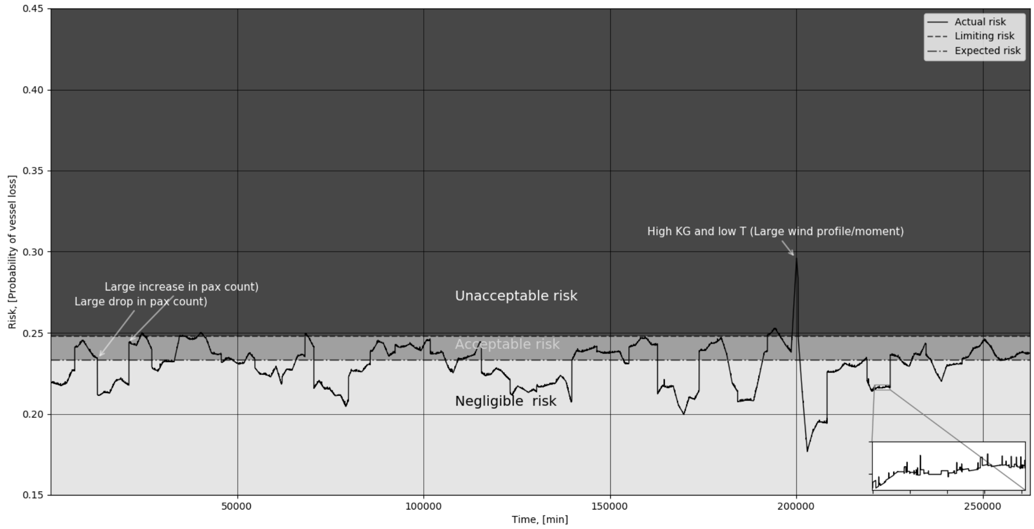

Figure 11: Risk-profile for vessel for 6 months operation – Crew failure probability: P_{fail} = 0.0166.

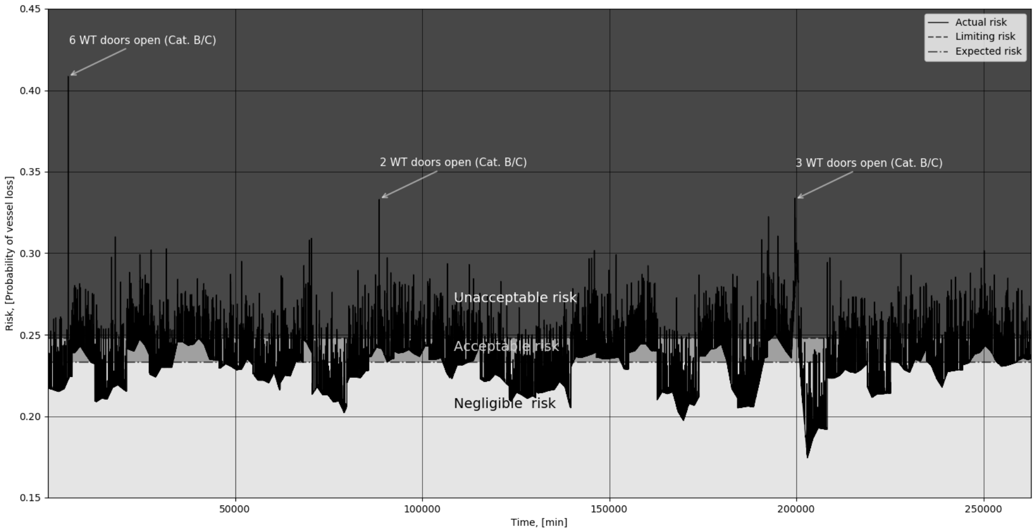

Figure 12: Risk-profile of a vessel for 6 months operation – Crew failure probability: P_{fail} = 1.0.

Real-time guidance to blunt- and sharp-ends

The above demonstration of real-time risk monitoring is well aligned with the dynamic barrier management philosophy, enabling continuous assessment of changing system conditions, capturing how the flooding risk is influenced by the status of individual doors, combinations of door status, as well as door statuses in connection with the identified risk drivers. The latter ensures that the on-going activities and the operating environment are accounted for. This ensures the recognition of potentially severe situations by benchmarking the observed risk against the identified risk-baselines, enabling the operators to intervene and bring the operation back to a safe state. It provides a pro-active approach by answering questions like; When and in combination with which other variables could/could not doors be opened? Which doors could/could not be opened simultaneously? This facilitates transparency of the processes contributing to the flooding risk and serves to avoid an accident trajectory to be aligned accidentally.

Having a detailed assessment of barrier status and events in combination with the ensuing change in risk enables the identification of critical combinations of variables, e.g. why did we have a sudden spike in risk (ΔRisk)? and what variables and doors were involved? Combinations of variables resulting in limit exceedance may trigger logging of such events. The change in risk, ΔRisk, related to a specific door being opened may further be assigned to that specific door (summation of delta risk), which over time would enable to benchmark individual doors, and its overall risk contribution within a specific period of time.

The collection of the time-series data permits the identification of precursors that may lead to an imminent accident and brings awareness of the necessary actions needed to counteract. Excessive opening frequency is one such precursor, indicating that the vessel has been exposed (susceptible) to large scale flooding, if the vessel where to encounter a collision incident. As such, the monitoring and subsequent assessment enables implementation of corrective actions in future operations. The availability of data to enable more in-depth analysis of the operation would further optimize alternative design solutions, where alternative internal door arrangements could be identified to avoid excessive door usage in operation. Collated data would further provide the basis for guidance, training and awareness to new and existing crew members on overall door usage, or more specifically high-risk doors that should remain closed and be especially considered during maintenance and testing.

PROPOSED FRAMEWORK FOR MARINE OPERATIONS DECISION SUPPORT

Although the barrier management philosophy has proven to be successful in treating operational risks in many industries, such as offshore, oil and gas as well as process, by bringing many fragmented approaches together, still, the practice is to apply fixed intervals for barrier maintenance without considering dependencies and continuously updating model parameters with real-time data. For increasing asset operability and optimal resource utilization, Pitblado et al. (2016) provided a conceptual application of dynamic barrier management in the offshore, oil and gas industries. From their view, the generic bowtie structure could be integrated into three separate calculation loops, including direct and indirect indicators of barrier performance as well as barrier importance developed by a representative quantitative risk analysis model to infer barrier status and track barrier impact on risk levels in real-time. The first loop is related to the initial barrier conditions and updated current status, the second is associated with barrier performance and the respective quantitative assessment of the prioritized maintenance decisions, whereas the third is concentrated on optimal risk control by operational safety decisions. It is a holistic approach that through a smart combination of inspection, condition monitoring, preventive maintenance, audit, sensors, process control, incident records and big data analytics enhances the identification of relevant trends to barrier observation and management. It is understood from the reviewed article, that the conceptual approach utilizes real-time data into simple mathematical models for an indication of barrier performance, which is consequently augmented to advanced calculation tools for predicting and estimating the criticality as well as safety impact of operational conditions.

Within a maritime context, safety critical functions together with their barriers are instrumented (i.e. alarm and condition monitoring systems) to warn of any abnormalities and initiate the necessary remedial action. Such information and other data collected from a specific vessel, fleet of vessels or from other available sources may be applied to determine optimal solutions and enable more real-time and well-documented decisions. For this purpose, real-time monitoring of barriers, processes, controls and systems produces frequently new values of observations that correspond to defined needs (i.e. status during the vessel's voyage, fleetwide benchmarking of crew actions). Certainly, data collation demands a selective procedure on what information to collect, extract (albeit to its availability), how to identify as well as categorize anomalies, translate those into failure precursors and correlate the latter to operational risks. Then, the focus is on aggregating the gathered information which concerns the imperative of quantitative modeling. The result from the model provides an estimation of the risk over time that exhibits the current condition of the associated barrier, process, control or system. It is noted that the model is characterized by a "dynamic" behaviour since it is continuously updated with the monitored values to encapsulate the changes and other possible effects in the complex operating environment, as will be demonstrated in section three. Such models provide continuous decision-making support to operations for both sharp-end (i.e. identify constraints to maintenance activities without jeopardizing the vessel's survivability) and blunt-end (i.e. perform fleetwide benchmarking and trending for the assembly of training programs as well as improvement of procedures). Figure 13 illustrates that operational risk management and the respective decisions depend on the audience needs. The real-time risk evaluation encompasses the dynamic interplay between technical, operational, organizational and human elements that are essential for preserving barrier integrity and prevent accidents from flourishing (Yang, Haugen and Paltrinieri, 2018).

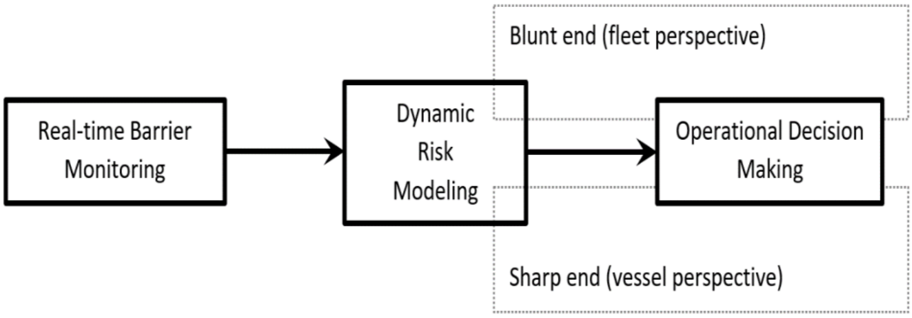

Figure 13: Highlighting the interplay between the sharp and blunt ends. Adapted from Yang, Haugen and Paltrinieri (2018).

The relationship between causes and effects can be vividly outlined through a bowtie diagram which converges in a central unwanted or top event (see for example Fig. 1). Fault trees are used to build the left side which traces a causal path (multiple threats/hazards and escalation factors, e.g. collision/grounding) backwards from the top event, whereas the right side is built with event trees which explores the different outcomes (consequences, e.g. capsize/sinking). An essential element is the placement of barriers on both sides, which are aimed at preventing or eliminating the unwanted event on the left and mitigating or recovering the unwanted event on the right. Although a bowtie is an abstract representation of complex situations, it is an effective way to understand and communicate risks to an audience as well as structure a risk-based audit for implementing and maintaining barriers. In case that the barriers are instrumented, the monitored data can be funnelled to disclose current status (dynamic bowtie) (De Ruijter and Guldenmund, 2016).

Transforming information and data into barrier performance knowledge is a step-wise process that evaluates relevant functions, identifies functional failures (failure modes), function criticality, failure mechanisms (degradations), failure symptoms and how application of sensor data can enable monitoring and enhance the control of selected functional failure modes as well as replace or support traditional maintenance tasks. To address the corresponding major accident hazards, the data flows and sensor systems need to have traceability (feedback-loop) and consider the condition of barriers preventing escalation of incidents (structural and watertight integrity, corrosion protection, oil spillage collection, fire detectors, fire water system, structural fire protection, piping, cables, means of access, alarms) (Astrup, King and Wahlstrøm, 2015). Most importantly, the effect of continuous improvement becomes evident by the establishment of control loops at different levels and presenting barrier performance knowledge on a real-time basis to the sharp- and blunt-ends (Figure 14).

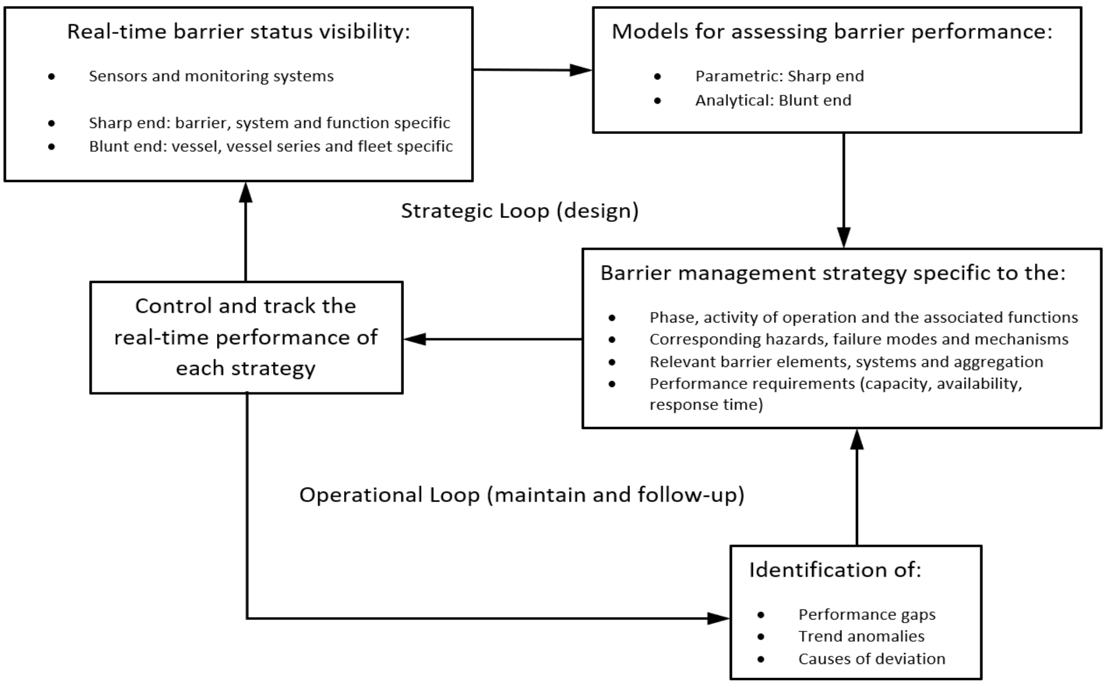

Figure 14: Integration of strategic and operational feedback loops for dynamic barrier management. Note that the operational loop is common to blunt- and sharp-ends.

It is pointed out that the attention is not focused only on the barrier, but also on the collective construct (barrier management strategy) which is aimed at meeting the challenges of a specific dynamic process and actively cope with any change in operational conditions. Therefore, the barrier management strategy considers the set of arrangements to realize the activity level albeit to the specific operation phase change, whilst the relevant hazards together with safety critical elements are identified. Consequently, the appropriate barrier functions that control the escalation of the unwanted event are selected. This selection can be performed either through a risk assessment or by engineering judgment, which is traced back to major hazards threatening vessel safety in order to continuously verify that the barriers are provided to meet the regulated performance requirements. Hence, decisions can be supported by how the effect of changes during operation is reflected under the existing barrier conditions that are in place and without having to perform time-consuming modeling tasks. The availability and vulnerability of key prevention and protection systems can be assessed with respect to required functionality against each of the identified hazards. The latter can be avoided through removal of the source of a hazard (without introducing new sources of hazard), breaking the sequence of events leading to realisation of a hazard. Where hazards cannot be avoided, vessel design and operation should be aimed at prevention where practicable by reducing the number of leak sources (flanges, valves, vibration monitoring, etc.), removing or relocating ignition sources, simplifying operations, avoiding complex or illogical procedures, amongst others (Astrup, King and Wahlstrøm, 2015).

It should be acknowledged that the materialization of the feedback loops in Figure 14 needs to be experienced at multiple levels of granularity depending on the recipient, where the status of individual barrier elements is associated with systems, functions and the vessel's overall risk picture. This entails that the sharp-end is interested in keeping track of the current (including failure) status of barrier elements presented in the format of traffic lights (individual alarms on the console of a safety or control system), as well as aggregating element status to some system, function or installation (aggregation of alarm statuses from different safety or control systems for a barrier function into a panel) without any criticality considerations. However, for facilitating some form of decision-making in evaluating the criticality of barrier systems and functions, it is most appropriate to identify indicators for a selected or representative set of barrier systems/barrier elements and aggregate (the status of) these indicators up to some risk measure through a parametric model (risk barometer or risk gauge on a visible dashboard). The implementation and monitoring of these safety performance indicators (leading – what, when and why will happen / lagging – post-mortem analysis) can be easily achieved and followed-up at all levels, since measurement is a vital part of a management process and it provides the cornerstone for sustaining and improving the robustness as well as effectiveness of a Safety Management System. To guarantee convergence with the blunt-end, especially in the wake of disturbances and external influencing factors, detailed probabilistic models (analytical) that link together all barriers would allow realization of the full barrier function optimization potential. This requires detailed models of all barrier functions and associated systems/elements (for instance modeling bowtie structures with Bayesian networks which are furnished with real-time data) that can reflect different states of the barrier elements, as well as the effect of compensating measures. Ideally, all this information should be reflected in some overall risk model that takes into consideration the status and criticality of each element and all dependencies and interactions between these elements, to be able to estimate the overall risk (Astrup, King and Wahlstrøm 2015).

As shown from Figure 15, real-time monitoring of barriers together with advanced software tools and open standards available for enterprise application integration play a decisive part in providing better capability to the sharp and blunt ends for predicting outcomes that are relevant to their respective scope. Data acquired from the monitoring systems are used by the sharp-end to maintain barrier status within reasonable bounds of a reference point; whilst integration and visualization across different barrier systems through a comprehensive mobile and web dashboard displaying up to date values of barrier performance are available to both sharp- and blunt-ends for tracking and extracting useful reports from a common database. The availability potential of ship connectivity not only empowers seamless synergy between those on-board and ashore to effectively and actively contribute towards continuous improvement, but also allows for the collective multidisciplinary team to generate predictive actions to effect control and optimization in a future time based on the current state. To this end, advanced data and analytics that were not previously available are now providing forward thinking players very powerful sources of competitive advantage using various artificial intelligence or simulation based or mathematical modeling techniques. The ability to process large data sets and use algorithms to more accurately predict the time-projected states of barriers more correctly, to identify the most probable outcomes in the future, is exactly what dynamic barrier monitoring can enable. Finally, the blunt-end can provide valuable information to the sharp-end for operational decision making. Although long-term storage typically will be in a shore-based data centre, it is useful to keep a certain data history on-board the vessel, delegating local analysis and decision support as well as aggregation and compression to avoid unnecessary usage of a ship-shore communication link which may be costly to use and not always available. To keep track of data and to structure the storage and processing of sensor data, there is a need for a unique identification of sensors as well as the components systems and functions subject to monitoring by the sensor (Astrup, King and Wahlstrøm, 2015).

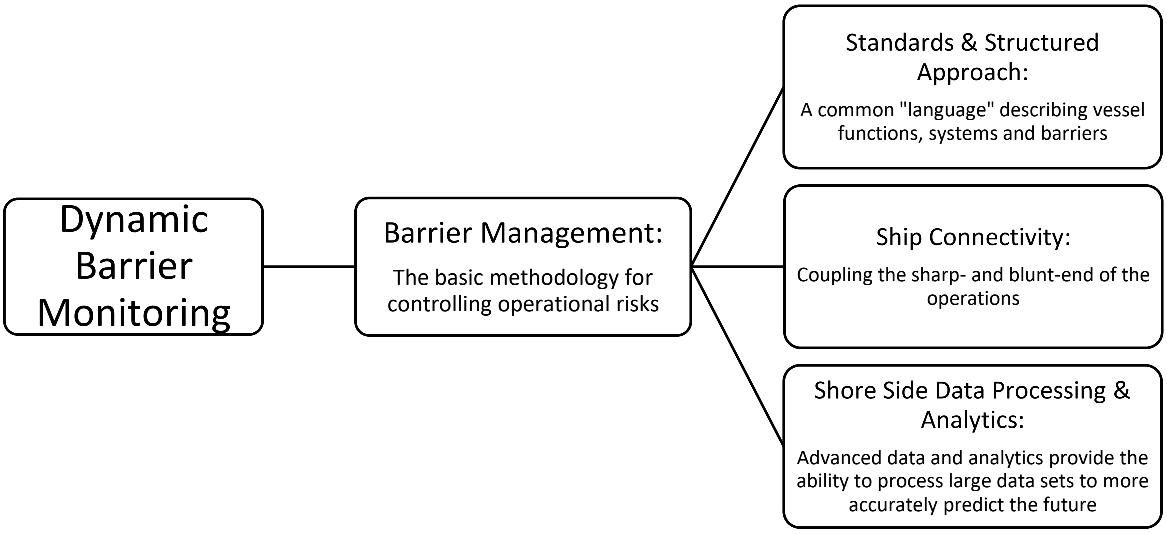

Figure 15: Dynamic barrier management basic constituents for a maritime application. Source: Astrup, King and Wahlstrøm (2015).

CONCLUDING REMARKS

Ship complexity is increasing, margins are being optimized and the drive towards greater performance is relentless. It is for these reasons that the operator's environment must adapt as technology advancements grow far beyond the capability of human skill to monitor, effectively balance and prioritize all the inputs. At the centre of this change is to leverage sensor data for comprehending the situation and present the operator with information that the actions taken are appropriate. Upon this recognition, one contribution from the paper has been to demonstrate how the framework for operational decision support can be implemented in operation where the watertight doors act as barrier elements, preventing excessive transient- and progressive-flooding on a cruise vessel during operation. In this respect, the main achievements can be summarized as:

- The outline of a parametric model for incorporating watertight door operation in combination with various risk driving variables.

- This enables continuous assessment of changing system conditions and captures how the flooding risk is influenced by the status of individual doors, combinations of door status, as well as door statuses in connection with the identified risk drivers.

- This ensures the recognition of potentially severe situations by benchmarking the observed risk against the identified risk-baselines, enabling the operators to intervene and bring the operation back to a safe state.

- It provides a pro-active approach, facilitating transparency of the processes contributing to the flooding risk and serves to avoid an accident trajectory to be aligned accidentally.

- Continuous monitoring and assessment enable implementation of corrective actions in future operations and enable more in-depth analysis of the operation to further optimize alternative design solutions, and would provide the basis for guidance, training and awareness.

- The model has known limitations, as discussed, and needs further consideration before onboard application can be realized. Nonetheless, the model successfully demonstrates real-time risk monitoring from watertight door operation, well aligned with the dynamic barrier management philosophy.

- Future developments may be enhanced by incorporating probabilistic models for the consideration of waves as well as leak and collapse pressure heads, similar to Karolius (2019) and Karolius, Cichowicz and Vassalos (2020).

Another objective has been to generalize the approach within a framework for operational decision support using dynamic barriers. This can be summarized as follows:

- The use of dynamic barrier management in ship operations is based on identifying hazards and their respective barriers, which are instrumented with sensors in order to provide information about barrier status.
- The development of a parametric model allows the effective prioritization of information about barrier performance, that is compared to defined criteria and indicators.
- The real-time monitoring of barrier status is paramount for furnishing better capability to blunt and sharp end operators for predicting outcomes that need targeted attention. This seamless synergy is empowered through ship connectivity, whereas the ability to process lots of inputs continuously is orchestrated by advanced analytics.
- To keep track, storage and processing of the data, a unique identification of sensors and barriers is required, thus, a common language needs to be enforced. This is an area where current work is ongoing and expands from the sensors, barriers, functions, models and datasets. Doing so, a clear picture would be created of what information can be continuously collated for establishing and maintaining barriers.

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