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On a systematic perspective on risk for formal safety assessment (FSA)

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A B S T R A C T

In the maritime domain, risk is evaluated within the framework of the Formal Safety Assessment (FSA), introduced by the International Maritime Organization in 2002. Although the FSA has become an internationally recognized and recommended method, the definition, which is adopted there, to describe the risk, seems to be too narrow to reflect the actual content of the FSA.

Therefore this article discusses methodological requirements for the risk perspective, which is appropriate for risk management in the maritime domain with special attention to maritime transportation systems. A perspective that is proposed here considers risk as a set encompassing the following: a set of plausible scenarios leading to an accident, the likelihoods of unwanted events within the scenarios, the consequences of the events and description of uncertainty. All these elements are conditional upon the available knowledge (K) about the analyzed system and understanding (N) of the system behavior. Therefore, the quality of K and the level of N of a risk model should be reflected in the uncertainty description. For this purpose we introduce a qualitative scoring system, and we show its applicability on an exemplary risk model for a RoPax ship.

1. Introduction

In 2002 the International Maritime Organization (IMO) approved guidelines for the Formal Safety Assessment (FSA) as a method of evaluating risk in the maritime domain. The FSA has been described there as "*a rational and systematic process for assessing the risks associated with shipping activity and for evaluating the costs and benefits of IMO's options for reducing these risks*" [1,2]. However, in a recent review on the FSA, Psaraftis expresses a need for scientific discussion in the maritime domain about a number of fundamental issues concerning the FSA [3]. In particular, he sees a need for unification of the applied terminology, discussion on the development of risk models and how to report FSA studies. These findings are reminiscent of the perspective of Aven, who calls for a continuous scientific discussion on understanding, expressing and communicating risk, see for example [4,5].

The basic philosophy of the FSA is that it can be used as a tool to facilitate a transparent decision-making process. In addition, it provides a mean of being proactive, enabling potential hazards to be considered before a serious accident occurs. However, the description of the method can give an impression that the definition of the word "*risk*" does not fully reflect the way the risk is further explained and it seems that the components relevant for risk description change depending on the context.

In the context of risk analysis, presented in the FSA guidelines *risk* is defined as a combination of the probability (P) and consequences (C) of a given action [6]. Further in the guidelines, in Chapter 7 "*Risk control options*", the risk is decomposed and the uncertainty aspect of two risk components (P, C) is added as an important element of the decision process. Moreover, for the identification of risk control measures, Sub-chapter 7.2.2 suggests developing causal chains of events leading to an accident, which means that the definition of risk includes an insight into certain scenarios leading to the undesired situations. Finally, Chapter 10, "*Presentation of FSA results*", stresses the need for a discussion about the assumptions, limitations and uncertainties of a risk model.

It has been argued that the FSA, presented as a proactive, highly technical and complex method, can be misused, yielding results which may not fully reflect the relevant features of the analyzed system, see for example [7,8]. To facilitate a more coherent framing of what the FSA as a tool expects from an analysis, it may be beneficial to adopt a more systematic risk perspective, which incorporates the various aspects of the risk description. This could help to make sure that all these relevant recommendations, which are located in different chapters of the guidelines, can be properly addressed at the appropriate stages of the risk analysis.

Therefore this paper serves the purpose of adding to the discussion asked for by Psaraftis and Aven. It proposes the

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requirements for a risk perspective, which is suitable for the maritime domain and meets all the requirements given in the FSA guidelines. The proposed perspective is an extension of a concept by Kaplan and Garrick [9] which has been developed further by Flage and Aven, see [10]. This perspective relates risk to a set comprising the following: events forming scenarios leading to consequences of interest, the probabilities of the events, the consequences, uncertainty, sensitivity and background knowledge. The novelty of the approach is related to the last element of this set, namely background knowledge (BK). In the literature on risk in socio-technical systems BK is defined as a mixture of knowledge and understanding, see for example [10–12]. In the philosophical debate, knowledge is separated from understanding, and the latter is taken as the central concept of epistemology, rather than propositional knowledge, see [13]. As knowledge (K) and understanding (N) are two different concepts they represent different aspects of uncertainty related to an analyzed system. This distinction between K and N implies a revision of the scoring system for uncertainty proposed in earlier work [5,10,14]. Thus an alternative methodology for uncertainty assessment is presented for consideration in future risk studies; moreover it meets a call for research on methods to communicate uncertainties [5,3].

The remainder of this paper is organized as follows. Chapter 2 introduces knowledge and understanding and highlights the main differences between these two concepts. In Chapter 3 we elaborate on a risk perspective, which would accommodate all the requirements of the FSA. In Chapter 4 we demonstrate how to implement knowledge and understanding in a risk perspective. An example from the maritime is given in Chapter 5, which is followed by concluding remarks.

2. Knowledge and understanding

2.1. Knowledge

Knowledge is widely identified with propositional knowledge and analyzed in terms of justified, true belief. The growth of knowledge is seen as cognitive advancement and it is accomplished by the acquisition of new justified, true beliefs that satisfy the additional condition.

Knowledge focuses on believing a proposition, which could not easily have been false, which means that K is factive. To acquire knowledge about events, first the events need to exist. Second, one needs to refer to reliable sources to learn about these events.

However, there are suggestions among epistemologists to take understanding rather than propositional knowledge as the central concept of epistemology, see for example [15]. It is argued that the main goal of our cognitive process is not to acquire knowledge as justified true beliefs but to advance our understanding. Moreover, propositional knowledge is an important part of understanding a phenomenon. Hence, the epistemology of understanding has to comprise an account of propositional knowledge, see for example [15].

2.2. Understanding

Getting knowledge is important, but aspiring toward understanding is more ambitious. Besides knowing the important and relevant truths that belong to the comprehensive, coherent body of a domain and comprehending the appropriate fictions (e.g. idealizations, thought experiments), understanding comprises grasping how the various truths and fictions relate to each other. Moreover, with understanding we are able to use information to (see [15]):

- argue within the framework of the account,
- apply its results to new situations,
- assess and acknowledge its limits,
- devise suitable (thought) experiments, and
- ask new questions unto which the account does not yet provide conclusive answers.

Baumberger in his recent work [15,16] lists four main features – described in the following sub-sections – which make understanding different from knowledge. These four reasons clearly indicate that knowledge and understanding are two concepts having different focuses. Moreover, each of the concepts can be related to specific difficulties in risk modeling, and it is considered useful to make the different difficulties explicit.

2.2.1. Not a species of belief

Understanding is not a species of belief. Its content cannot even be fully explicated as a collection of beliefs since it involves grasping connections between beliefs, non-belief states like questions, non-propositional commitments like categories and non-verbal symbols, as well as having certain cognitive abilities, see [15].

2.2.2. Holistic

Understanding is holistic. Knowledge can be broken down into discrete bits. It is knowledge of an individual fact, expressed by a proposition. The proposition is true; the knower believes the proposition and his belief is justified. If the content or the justification of a belief is taken to depend on relations it bears to experiences and other beliefs of the knower, this may introduce a holistic element. But even if knowledge is partly holistic, understanding is wholly holistic. It cannot be broken down into discrete bits. It is the understanding of a whole domain or topic, expressed in a more or less complex account or theory containing propositional and non-propositional elements. The account or theory answers to the facts and the understander is committed to it and justified in it.

By gaining an understanding about the system one becomes familiar with the way the system operates. This enables him to construct a model reflecting the actual behavior of the system to the extent he is interested in, simply by putting the right variables in the right order.

2.2.3. Gradual

Unlike knowledge, understanding is gradual. For any fact, either one knows it or one does not know it. But understanding admits degrees. Understanding can vary at least in breath, depth, significance and accuracy.[1]

2.2.4. Not factive

In contrast to knowledge, understanding is not factive. One can only know A if “A” is true. But one's understanding can involve propositions that are not true, and some of them may even belong to the central propositions that constitute the account of the topic. As claimed in Section 2.2.3, understanding can be more or less accurate, due to its gradualism.

Even if understanding is not factive, it must, of course, answer to the facts by accommodating the evidence. But since understanding is holistic, accommodating the evidence is a requirement on the entire theory, not on each individual element of it[2].

[1] Novices in the field as well as scientists start out with crude characterizations that properly direct them towards their topic and then refine these characterizations. Their advancement of understanding involves a move from beliefs that are strictly false but in the right neighborhood to beliefs that are closer to the truth. This development may result in true beliefs. But even an earlier step displays some measure of understanding.

[2] Hence, understanding a topic does not imply that all central beliefs that constitute our theory are true. Even mature science is full of idealizations and

There are several reasons for understanding not to be factive [16,17]

- in complex systems there are numerous causes of A which interact in complicated manners; therefore it is difficult to address all of the causes or we can determine them more or less accurately;
- when describing A we make idealizations, which can degrade our understanding but does not destroy it; and
- understanding admits degrees, meaning that with each step in the sequence we understand an analyzed phenomenon better than we did before.

In non-factive cases we have some understanding of A without knowing all facts about A, which means that despite not possessing full knowledge about A we have an understanding of A which can be enough for a reliable inference about A.

Knowledge is about facts; understanding is about the real meaning of the facts. We might know something to be true, but we need understanding to realize why it is true and what is the impact of that truth. If we know that B is a reason for an event A (we know why A happens), we have the basis for believing that A is because of B. But when we understand why A happens, we additionally obtain a grasp on how B affects A. By getting this comprehension about A we are able to

- develop an explanatory story about how B can cause or be a reason for A;
- infer about B knowing A; and
- for some A* and B*, which are similar but not identical to A and B, draw a conclusion about A* assuming B*, and give the right explanation for B* assuming A*.

As the risk is about future events, the ability to grasp explanatory relations between elements in the modeled system in order to infer about the system in the future is crucial. As we in practice do not posses facts about the future, thus our knowledge about the future states of the world implies assumptions, which come from our understanding of the world. This means that risk perspective inherently contains understanding in larger proportion than knowledge.

3. Describing risk

While often not clearly enough distinguished, there is a fundamental difference between the concept of risk and ways to describe risk. We adopt the following terminology:

- the risk concept concerns what risk means in itself, what risk "is";
- a risk perspective is a way to describe risk, a systematic manner to analyze and make statements about risk; and
- a risk metric is the assignment of a numerical value to an aspect of risk according to a certain standard or rule. Risk metrics, e.g. address the likelihood of an event occurrence or the consequence severity, or derivations such as expected values.

(*footnote continued*)
thought experiments. In contrast to the more or less crude characterizations, they are not in need of improvement and not supposed to be eliminable from scientific theories.

The FSA defines risk as a combination of the probability (P) of an accident and its consequences (C) as follows:

$$\mathrm{R} = (\mathrm{P}, \mathrm{C}) \tag{1}$$

As a risk metric the FSA proposes a risk index (RI), which is defined more explicitly as a product of P and C:

$$\begin{aligned}\text{Risk index} &= \text{Probability} \times \text{Consequence } \log\ (\text{risk index}) \\ &= \log\ (\text{probability}) + \log\ (\text{consequence})\end{aligned} \tag{2}$$

The RI serves the purpose of being a crude risk indicator used for ranking various hazards and selecting the most relevant ones, which are then analyzed in detail. However, the same definition is often adopted among engineers to describe risk itself, see for example [18,19]. However, it easily leads to confusion, especially when comparing two situations A and B, where

- A encompasses frequent events resulting in minor consequences – single or minor injuries and local equipment damage;
- B considers a remote event of catastrophic consequence – multiple fatalities and total loss of a ship.

Even though the products of P and C in both cases are the same – following the FSA guidelines the risk indices are the same, RI=7 – these two situations differ substantially. The available information about A is most likely better than in the case of B, as A occurs more frequently – it is likely to occur once per month on one ship. B occurs rarely – once per year in a fleet of 1000 ships – or is likely to occur in the total life of several similar ships; for the adopted classification, see [2]. The amount of information available about A and B affects the level of uncertainty associated with the descriptions of A and B. Also the measures to control the risks in these two situations are probably different, as in the first case the focus might be given to P, and in the second case C might be subject to mitigation. Therefore, interpreting risk simply as a product of P and C leads to the misconception that risk is just a number, which is divorced from the scenarios of concern. Applying this perspective, much of the relevant information needed for risk management is not properly reflected or even missing [5].

Thereby, a wider concept of risk should in our view be applied, allowing a systematic and hierarchical description of the risk and reasoning in light of available knowledge and a possessed understanding about the analyzed system and its behavior.

In the scientific literature there have been numerous proposed definitions for risk; for a recent and thorough review of the risk concepts, see for example [5,11,20]. By studying the different risk definitions, regarding socio-technical systems, we found that many scientists perceive risk as a logic construct referring to future events or situations resulting in an outcome, which is definable but uncertain, which puts at stake something that humans value. This means that risk refers to the future but it is managed in the present, based on experience gained in the past.

An appropriate starting point to describe risk, which also fits in the maritime domain, has been introduced by Kaplan and Garrick [9], where risk is presented as a complete set of triplets:

$$R = \{S_i, L_i, C_i\}_C, \tag{3}$$

The triplets attempt to answer the following questions: what can go wrong in the system (Scenario – S), how likely is it that it goes wrong (Likelihood – L), and what are the consequences if the assumed scenario happens (Consequence – C)? However, describing the risk as a complete set of triplets is unattainable, simply because our knowledge on the system is never complete, and therefore the system cannot be characterized exactly, see [21]. What we actually attempt to describe is an incomplete set of triplets, called "a set of answers". This set reflects the risk in a given system according to our best knowledge (K) about the system and our understanding (N) of its behavior; however, certain triplets, yet existing, remain undiscovered and thus they cannot be captured. But if our K or N improves, new scenarios can be defined and added to the triplet, and therefore the incompleteness of the risk set which is conditional upon K and N should be recognized. Due to this incompleteness, the notation of risk shifts from “a risk is equal to a set” to “a risk is described by a set”, and the conditional dependency upon K and N is added as follows:

$$R \sim \{s_i, l_i, c_i\} | \{K, N\}, \tag{4}$$

$$\Delta \sim \{\mathrm{K}, \mathrm{N}\}. \tag{5}$$

The construct Δ represents a set comprising the knowledge dimension and the understanding dimension. The former addresses the facts, or true justified beliefs, which cannot easily be false regarding the elements of a modeled system, which are included in a risk model. The latter refers to both the facts and non-facts describing the ways in which the modeled system is explained to work.

In a more general way, adapting the definition of risk given by Aven in [21], the description of risk can take the following form:

$$\mathrm{R} \sim \{A, C, Q\} | \Delta\ . \tag{6}$$

Following this notation, risk description should contain scenarios composed of events (A), the consequences (C) if a scenario becomes true and uncertainty analysis (Q). The last one reflects the basis for assigning the probabilities for A and aims at the assessment of the effect that the limited Δ has on the outcome of the risk model. Therefore, Q also contains the sensitivity analysis and parameter importance scoring, as suggested in [22]. All the elements of risk description are conditional upon Δ, as the level of K and N determines how certain we are about A and C. As shown in Section 2, K and N are two different concepts; they represent different aspects of the uncertainty related to an analyzed system. This distinction between K and N implies a revision of the scoring system for uncertainty proposed in earlier work [5,10,14]. An alternative methodology for uncertainty assessment is presented and discussed in the following section.

In the cases where maritime transportation systems are analyzed, usually the consequences of the analysis are well defined (e.g. collision, groundings, fire, environmental pollution, loss of life). When it comes to the basis for assigning probabilities, however, this may be problematic. The main reason is that some paths of the scenario – links between events – are better understood than others, or the knowledge about certain events is better than about others. This creates uncertainties (Q) with respect to variables (parameter uncertainty) and links (structural uncertainty), which can be reduced either by gaining K or improving N. Parameter uncertainty can be addressed by improving K about parameters, getting new evidence or learning about that from available data sources if possible. However, structural uncertainty is associated with the level of understanding of the modeled domain. Thus, the influence of K and N on the level and type of uncertainty needs to be determined, along with the source of uncertainty. To provide a more comprehensive risk picture, a sensitivity analysis of the model needs to be performed, which determines the elements of a model, which if changed may significantly alter the model output. The elements, which are uncertain and the model is sensitive toward them, need to be pointed out and their potential effects on risk evaluated. This step is tantamount to parameter importance scoring, as presented by Milazzo and Aven in [14].

Adopting such a risk perspective, systematic uncertainty decomposition and treatment is allowed, which is more than just mentioning the assumptions, limitations and uncertainties of a risk model as suggested by the FSA [6]. It allows quantification of the effects of different assumptions and imprecise knowledge about variables on risk, as well as a systematic qualitative assessment of the knowledge and understanding on which the risk model is based. Moreover by distributing K and N across a risk model, we can identify the areas of insufficient K and/or N, which need further research. It furthermore provides insight into the confidence one has about the effectiveness of proposed risk control options (RCOs). RCOs working in areas where the K and/or N is limited should not be given equal weight as RCOs working in areas where the K and/or N is more extensive. Thus, appropriate reflection on K and N can have a significant impact on the kind of adopted risk management strategies.

Moreover, in some cases where K is low but N is sufficient we may find that the level of Q is low or medium. This can be the case where an analyst understands the phenomena but the facts about it are fragmented and require additional justified assumptions. This may lead an analyst to make a projection of the system in the proper direction, as he understands the phenomena; however, the magnitude of risk can be burdened with some uncertainty.

On the contrary, in the presence of high K but low N, it can happen that the Q is classified as high. This is especially the case when the available data is not necessarily applicable in the future, and the lack of understanding prevents an assessor from making a proper projection of the present state of a system into the future. This means that both the direction of projection and magnitude of risk are highly uncertain and surprises may easily occur.

However, according to the existing scoring system – see [10,14] – the level of Q in both cases discussed above is moderate. This shows that the risk perspective that is proposed here needs its own uncertainty scoring system, as a distinction between K and N is not anticipated in the existing solutions. Moreover, we show that very often K is not available at all, following the classical definition of knowledge. This means that in such cases it is N which drives risk models.

4. Incorporation of knowledge and understanding into a risk perspective

In this section we show how to incorporate K and N in a risk model through scenarios, following the risk perspective adopted. Moreover, we discuss the possible ways to describe the effect of uncertainty associated with the parameters and structure of a model on risk metric. Finally we introduce the concept of an uncertainty scoring system for a risk model, which is an extension of a system originally introduced by Flage and Aven in [10].

4.1. Scenarios

A fundamental and very likely the most important stage of any risk analysis which in turn affects all the steps following the analysis is scenario identification, meaning the proper translation of K and N into a model. Intuitively, the importance of this step seems obvious; however, it does not always receive due credit, see for example [3,23,24]. When describing risk the main focus is on understanding these scenarios, which ultimately lead to undesired events. Scenario identification is tantamount to discovering causality, which seems to be the natural way of understanding, analyzing and finally mitigating hazardous situations, which produce risks. This mindset has been successfully adopted in the nuclear power industry and the process industry; moreover it is successfully pursued in air transportation, see [25–27]. In recent years some researchers made attempts to follow this way to improve maritime safety as well, see for example [28,29].

A scenario can be defined as a realization of a chain of events – see also [6] – triggered by an initiating event (*IE*). The *IE* may cause the system to move from its predefined safe and efficient trajectory (S_0) towards the set of trajectories (S_i) which are not as safe and effective as S_0, but it does not mean they are all unsafe. The system being on its trajectory S_i travels through various mid-states (*MS*) at which transitions take place, redirecting the system towards the end states. The latter can be either an undesired event, like an accident, or safe operation of MTS, which means that the system may return at some point to S_0. A scenario encompasses various events (variables), which are linked with mathematical functions of varying complexities – from the simple Boolean logic to multivariable functions. Each scenario consists of two parts: qualitative and quantitative. The quantitative part reflects the content of the scenario, and is described by events, whereas the relations between the events are characterized by the scenario's structure, which refers to its qualitative part. This means that each single scenario requires from an analyst proper understanding of the modeled system.

For many complex systems, such as the maritime transportation system (MTS), the levels of our K and N of the analyzed scenarios vary and usually are not equally spread over a scenario, as we know and understand more about a given part of the scenario than about the others. This is especially important to realize when it comes to determining the RCOs and defining the locations for these in a risk model. If we decide to place RCOs somewhere along a path that is considered poorly understood, then their effect in the real world may be completely different from that anticipated in a model. By representing K and N along a scenario

- we identify the areas of a system that we can model accurately and the areas for which a qualitative approach is more appropriate;
- we define the weak paths of a scenario, which should be treated with caution, especially if the outcome of the scenario is sensitive to the changes along these paths;
- we decompose a scenario into smaller pieces, to avoid problematic links, and focus on modeling events which are better understood;
- we demonstrate the effect of improper K and/or N on a model's outcome.

The description of a scenario should shed some lights on the process of failure evolution, specifying the sets of associated *IEs*, *MSs* and *ESs*. There will be inevitably smaller or larger portions of the scenarios remaining uncovered; however, the uncertainties associated with these scenarios may be smaller than their counterparts associated with the set of scenarios developed on assumptions not supported by the available information.

In the first case, the analysis is based on the observation of system behavior in the past; thus it is limited to the known events, which caused the MTS failure. However, if we manage to represent properly the available knowledge and grasp an understanding of a system we can get a canvas for a predictive model determining the critical paths of the system leading to an accident in the future. Therefore, the uncertainty of this approach would be mostly associated with not observed *IEs*, *MSs*, *ESs* and links between those forming an unknown set of scenario paths.

Whereas, in the case where the description of a system is not based on evidence, nor is utilizing available information properly or is lacking understanding of the system behavior, the gap between a real system and its description becomes unidentifiable, and surprises may occur, see for example [5,30].

4.2. Quantification of uncertainty

We take a stand, that the uncertainty is a result of our limited knowledge and understanding of the modeled system, which is in line with the commonly adopted claim that the uncertainty is a function of the available information on a given system in a given situation, see also [23,31–33].

The lack of knowledge about the analyzed system usually leads to uncertainty in the model parameters, see [21,34]. But lack of understanding of the system behavior is far more critical, as through understanding an analyst is able to do the following:

- structure the model;
- make statements about the hypotheses supporting the model;
- formulate sound assumptions; and
- assess the knowledge about the model parameters.

It is relevant for a risk framework to communicate the extent of the knowledge about the phenomena analyzed, see [1,22,35]; however, the level of system understanding must also be there, as it allows structured analysis of uncertainties involved in a model of the analyzed phenomena. Besides quantification of the uncertainties we determine their nature and distribute them across the model to determine the areas of the model in which the bulk of uncertainty sits.

The description of risk can be considered plausible and useful for decision makers only to the extent that it addresses the limitations in the available K and N and demonstrates their effect on a risk metric.

There are numerous ways to address and express the model uncertainty depending on its type; for the quantitative approaches, see for example [36–38]. However, the qualitative descriptions are often postulated as well, see for example [5,10,14].

In the context of risk analysis, both types of uncertainty descriptions are needed in our view. Firstly, a crude quality check is made of the available K and N based on existing theories, information and data. This allows an initial model check, if the available level of K and N makes it possible to formulate any reliable statement about risk. As a result of this step, an uncertainty matrix can be drawn, where all the elements of a risk model are systematically evaluated and ranked, following an adopted scoring system. This step delivers answers about the degree of uncertainty, which can be classified as high, medium or low. This shall be accompanied with the sensitivity analysis of a risk model, which determines the elements of a model, which if changed may significantly alter the model output. Then, the elements, which are uncertain and the model is sensitive toward them, need to be pointed out and their potential effects on risk quantified. This step is called importance scoring.

If an element of a risk model gets a high importance score, it means that the available knowledge and understanding of analyzed phenomena significantly affect risk metrics. An attempt can be made to quantify this effect, to get an indication about the magnitude of the spread in risk metrics. By performing such an influence analysis, one may eliminate some of the potential surprises. In order to determine the effect of K and N on model outcome, the following steps are proposed:

(1) Develop a model structure along with a set of relevant parameters, which, however, can take different states or can be governed by more than one hypothesis. These alternatives reflect understanding of an analyst, and can be referred to as alternative hypotheses testing, see for example [39].
(2) Perform quantitative uncertainty analysis (QUA) of the model(s).
(3) Perform sensitivity analysis for each model (SA) to specify the variables, which are important for the model, as their variability affects the model outcome the most. The results of the SA may be different for two models, which have the same

quantitative parts (variables) but differ in qualitative description (structure).

(4) Determine parameter importance (PI), based on adopted scoring system.

(5) Report the results of uncertainty analysis QUA in the light of PI.

By applying this procedure we perform an extended quantitative uncertainty analysis of a risk model. To run the above procedure efficiently appropriate modeling techniques need to be applied, allowing for quick reasoning and model updating in light of new information, for example Bayesian Belief Networks.

4.3. Qualitative uncertainty assessment

In this section we present a scoring system for the qualitative uncertainty assessment. This system is an extension of the scoring system proposed in [5,10,14]. However, the system presented here features novelty, as it accounts for the joint effect of the level of knowledge and the quality of understanding of an analyst on the uncertainty of a risk model.

The main idea of the scoring system is to assign a qualitative description for the quality of K and the level of N to each and every element of the model (including the relations between elements) using the hierarchical description. Each element of the model and relations between the elements are evaluated with respect to the evidence, which is used to describe the element:

- the data, models and theories – these are factual and allow an analyst to formulate statements about the risk model – K; and
- assumptions, judgments and the ability to assess the level of knowledge about the element – these are not necessarily factual – N.

The following category classification is applied for the qualitative uncertainty scoring system: high, medium, low.

The presented classifiers are crude and can be case-specific and subject to judgments by the analyst; nevertheless they could serve as a guideline (see also [10]):

Quality of knowledge (K):

Good

- Data is reliable and/or
- Engineering model is accurate and/or
- Scientific theory is broadly accepted

Poor

- Data is unreliable
- Engineering model is a crude estimate
- Scientific theory is contested

Moderate

Conditions between those characterizing K as Good and Poor

Level of understanding (N):

High

- Assumption is broadly accepted among peers and/or
- Judgment is broadly accepted among peers and/or
- Assessor can well justify the ranking of K

Low

- Assumption is contested among peers
- Judgment is contested among peers
- Assessor cannot properly justify the ranking of K

Medium

Conditions between those characterizing K as Good and Poor.

Combining these two in a two-dimensional matrix, a classification table for degree of uncertainty is worked out, as presented in Table 1.

Table 1
Degree of uncertainty classification table.

	Knowledge		
	High	Medium	Low
Understanding			
High	L	L	M
Medium	L	M	M
Low	H	H	H

A high degree of uncertainty means situations where an analyst cannot formulate any reliable conclusions based on a risk model. There is no common understanding of modeled phenomena. Also, the uncertainty can be classified as high in the presence of knowledge about certain elements of the modeled system or phenomena if, at the same time, one does not know the relations between elements, or various experts would quantify the relations in different ways. This means that in the presence of knowledge but lack of understanding of the degree of uncertainty is high, as one cannot produce any reliable future projection of the present situation.

Giving as an example a maritime transportation system, we know the number of accidents (N_a) that have happened in the past, we know the volume and composition of traffic (V), and we also know the long-term and short-term trends (T) for the number of accidents in the area. These are facts – obviously to consider them as facts we shall assume for instance that the accidents are reported and recorded properly, meaning that the accident database does not contain any mistakes or cases which are double-classified and the issue of underreporting does not exist. Despite some of the above-mentioned assumptions not being true, we can still accept the existing data as facts, simply as we do not have anything else. This means that these “facts” are observable and measurable; they constitute our K about the parameters of an analyzed system and provide a solid basis for variables, which can be used in a model of the system. However, despite extensive K about crucial elements of the analyzed system, we need to have a grasp of how the amount of traffic (V) affects the number of accidents (N_a) to understand the trend (T).

To understand a phenomenon a person needs to grasp explanatory connections; this in turn requires certain abilities, for instance an adeptness in using the information one has, not merely an appreciation that things are so [18]. Thus, grasping V as a cause of N_a is not the same as correctly believing that N_a occurs because of V. Moreover, to understand this we must address the facts. If the link between V and N_a is not clear, it means that our understanding of the effect that V has on N_a is limited or does not exist.

The implication of the above is that despite our knowledge of the crucial elements of the system (V, N_a, and T), the lack of understanding of the system behavior prevents us from making a reliable inference about the future behavior of the system, if it is based only on these variables.

5. An example

This section presents an example of the qualitative uncertainty assessment of a simplified risk model for a ship carrying passengers (RoPax), which is involved in an open-sea collision. For a detailed

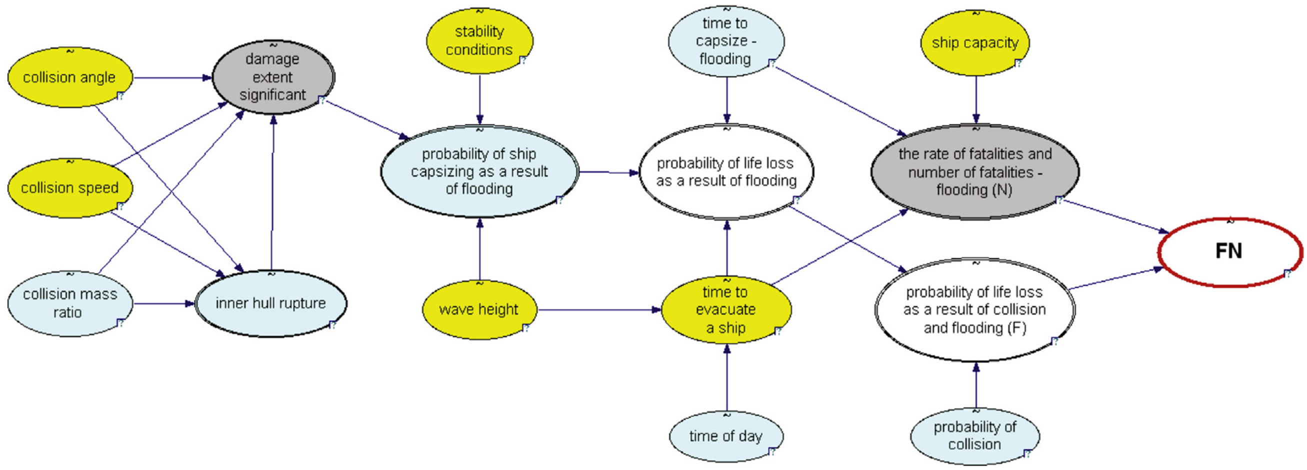

Fig. 1. Simplified risk model for open sea collision involving a RoPax ship. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

description of the model, the reader is referred to [40], whereas Fig. 1 summarizes the model.

This model estimates the risk in a certain sea area, focusing on a selected accidental scenario that, ultimately, leads to the loss of a struck RoPax ship. This accidental scenario is a breach of the inner hull of the RoPax that is struck by another ship and the consequent flooding; this can further result in the loss of the ship. The loss of the RoPax is expected if two consecutive limits are exceeded, namely crashworthiness and stability. Subsequently the corresponding probabilities of the limits being exceeded given the traffic and environmental conditions are evaluated on the basis of the model. For this purposes the following general factors are taken into consideration: the composition of the maritime traffic in the sea area being analyzed, the collision dynamics, the hydrodynamics of the ship and her loading conditions.

Ultimately, the cumulative number of fatalities (N) resulting from the accident is modeled utilizing the concept of the rate of fatalities. This rate is determined taking into account the time for evacuating a ship and the time for a ship to capsize. The number of passengers on board is modeled utilizing available data from RoPax operators from the analyzed sea area. All these, along with the associated probabilities (P) for a given number of fatalities, are depicted in a F–N diagram, which can be considered as a risk metric.

In Fig. 1 three colors are used to make a distinction among variables which are obtained from the numerical simulations (blue), those taken from the literature (yellow), those based on certain assumptions (gray) or purely conditional on their parents (without filling).

Whereas, Table 2 lists all the elements of the model, along with the central evidence, on which the elements are quantified, allowing for the uncertainty assessment.

The results of the qualitative uncertainty assessment are tabulated in Table 3. Information about the sensitivity of the model toward each parameter is added. This information is obtained quantitatively from the modeling environment where the risk model was developed; however, the translation into a qualitative scale needs to be made by an analyst. By combining the uncertainty score with the sensitivity score a metric for parameter importance is obtained. This metric informs an analyst about the weak elements of a risk model, which either needs improvement, or if this is not possible analysts should be very open about them.

Moreover, with this metric an analyst can elaborate on the locations for the effective and feasible RCOs. Precisely, he can specify where not to place RCOs, as their in these particular elements of the model may be questionable.

For instance, based on the risk model or RoPax, as presented in Fig. 1, we would like to know what are the best, effective and feasible options to control the risk. Let us assume that the results of our crude analysis suggest that the most effective way to reduce the risk metric to an acceptable level is to (see [41])

- reduce the collision angle (α);
- reduced the time to capsize (T_caps);
- decrease the probability of an accident (P_a).

Moreover, we learn that α needs to be reduced to a certain range to reduce the damage extent, which causes flooding of a RoPax or P_a should be lowered by an order of magnitude or T_caps should be extended by 20%. Then it is up to the analyst or decision-makers to

- specify whether the changes are attainable;
- specify the actions which are needed to make the changes; and
- prioritize them by their feasibility and the anticipated effectiveness.

The effectiveness of RCOs can be quantified with reasonable accuracy if they address the technical part of the model, i.e. improving the crashworthiness of a ship structure, improving ship post-accidental stability resulting in a longer capsize time. It is far more complicated to evaluate the effectiveness of RCOs, which address the socio-technical aspects of the modeled system, i.e. measures to reduce the probability of an accident by influencing the way in which a ship is navigated.

If there is a need to reduce a variable, which is not understood, such as α and P_a in our example, which has medium to high parameter importance, additional studies, on the causes of accidents and the ways to mitigate them are needed. If our existing N and K do not allow for justified conclusions, though the selected RCOs are feasible their effect on the outcome cannot be measured without ambiguity, meaning that surprises may occur.

A feasible and effective action might be to increase T_caps, which means that the structure of a RoPax needs to be improved stability-wise. Moreover the effectiveness of these RCOs seems to be very high, as once they apply to the structure, in the case of a collision, they are going to absorb certain amount of energy according to the design and sustain certain extent of flooding – with a high degree of confidence.

Table 2
Central elements of the risk model for a RoPax with the evidence on which the elements are based, see [41].

	Model parameter	Source	Evidence for the parameter
1	Collision angle	Literature	Several empirical models; however, they are against understanding of this parameter, according to which this parameter can be considered uniformly distributed between 0 and 180 deg.
2	Collision speed	Literature	Several empirical model; however, none of them are "true", as the data used to developed them come from various areas and address various types of navigation.
3	Collision mass ratio	Model, data	This parameter is derived from a model which simulates maritime traffic. The model takes input data about maritime traffic recorded by Automatic Identification System (AIS).
4	Damage extend significant	Assumption	This variable is quantified through a conditional expression, which binds together variables 1, 2 and 3. The form of this expression can be debatable.
5	Inner hull rupture	Model	A detailed numerical model giving reliable predictions is applied to quantify this model parameter. Model is understood well enough and all its relevant limitations are known.
6	Stability conditions	Literature, assumption	This parameter is based on certain assumptions; scarce data available to support the assumptions.
7	Probability of ship capsizing	Model	A detailed and reliable numerical model is applied here. Main assumptions existing in the model are understood.
8	Wave height	Data	Long-term statistics on the wave heights for the analyzed sea area are used to quantify this parameter.
9	Time to capsize	Model	A reliable numerical model is applied here.
10	Time to evacuate	Literature	Recommendations given by the international Maritime Organization are utilized here. However, it is understood that this approach may lead to bias, as the recommendations provide the upper limits for the evacuation time. In reality the evacuation time can be shorter than given by the IMO. Some more sophisticated tools could be used to improve the knowledge about the evacuation process.
11	Time of day	Model	Maritime traffic simulator is utilized along with AIS data.
12	Probability of life loss in flooding	Assumption	Linear, conditional function is applied, which connects variables 7, 9, and 10. This means that the quality of this variable depends only on the quality of its parents.
13	Ship capacity	Literature, assumptions	The number of people on board is determined indirectly from the public reports provided by shipping companies operating in the analyzed sea area. Certain assumptions are made based on data from the literature.
14	Number of fatalities	Assumption	This variable is quantified through a conditional expression, which binds together variables 9, 10, and 13.
15	Probability of collision	Model, data	Maritime traffic simulator is used along with the available data about ship accidents in the analyzed sea area.

Table 3
Qualitative description of uncertainty associated with an exemplary risk model for a RoPax.

Model parameter	Analyst's quality of knowledge	Analyst's level of understanding	Parameter uncertainty	Parameter sensitivity	Parameter importance
Collision angle	L	L–M	H	L	M
Collision speed	L	L	H	L	M
Collision mass ratio	**M**	**M**	**M**	**H**	**H**
Damage extend significant	L–M	M	M–L	L	L
Inner hull rupture	H	H	L	L	L
Stability conditions	**L**	**H**	**M**	**H**	**H**
Probability of ship capsizing	M	M–H	L–M	M	M
Wave height	H	H	L	L	L
Time to capsize	H	M-H	L	L	L
Time to evacuate	M	H	L	M	M
Time of day	M	H	L	L	L
Probability of life loss	H	M	L	L	L
Ship capacity	M	M	M	L	L
Number of fatalities	H	H	L	L	L
Probability of collision	**M**	**M**	**M**	**H**	**M–H**

6. Conclusions

In this paper we present a risk perspective, which is suitable for risk analysis and decision making for the maritime domain.

The risk is about future events, but its description is based on experience gained in the past, which is a combination of our knowledge of the analyzed system and an understanding of its behavior. Therefore knowledge and understanding are inherent parts of risk description, which in our view should be reflected upon by an assessor. The distinction between knowledge and understanding is evident among philosophers; however, it has not received much specific attention among risk analysts yet. The importance of seeing these two concepts separately and its implication on the process of risk model development, uncertainty analysis and selection of risk measures have been demonstrated.

To express the uncertainty in a qualitative manner a two-dimensional scoring system has been proposed, where both knowledge and understanding are implemented. The applicability of the proposed perspective has been shown in an example where a risk of a RoPax vessel suffering a collision with other ship is analyzed.

The concept introduced here leads to systematic and transparent risk analysis, where all the requirements as specified by the IMO in the Formal Safety Assessment guidelines can be met and systematically incorporated.

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