# Prediction in a risk analysis context : implications for selecting a risk perspective in practical applications

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# Implications for selecting a risk perspective in practical applications

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**Abstract:** Recently, there have been several calls for increased attention to foundational issues in risk analysis, addressing issues like terminology, principles and theories. An important foundational issue is the appropriateness of different concepts and perspectives for analyzing risk in practical applications. Several authors have addressed this through arguments involving, inter alia, the definition of risk, the ontology of risk, and the reliability and validity of risk analysis. This paper aims to contribute to this discussion by focusing on the concept of prediction. While this term is quite frequently used in risk analysis contexts, no earlier work has specifically focused on the issue of whether risk analyses can be considered to be predictive, and if so, in what sense. Neither has this been linked to the feasibility of risk perspectives. First, two definitions of what prediction can mean are elaborated, and criteria corresponding to these definitions are outlined to facilitate the subsequent discussion. A brief discussion on system types is included, as one type of prediction is defined through the relation between the model and the modeled system. Then, the definitions of prediction and the corresponding criteria are used to consider the appropriateness of two commonly used risk perspectives, namely the 'probability of frequency' and the 'uncertainty perspective'. In the former, a risk analysis aims at estimating an underlying true risk with quantified uncertainty bounds. In the latter, a risk analysis is a descriptive account of judgments and uncertainties by an assessor. It is finally argued that the uncertainty perspective generally is more appropriate than the probability of frequency perspective for practical risk analysis applications.

**Keywords:** foundational issues; prediction; risk perspective; probability of frequency; uncertainty

## 1. Introduction

In risk research, there is a recent focus on foundational issues addressing concepts, theories, principles and terminology. The development of well-founded risk perspectives is an important issue to strengthen the theory and practice of risk analysis. A risk perspective can be understood as a commitment to a conceptual understanding and a definition of risk, which results in a corresponding approach to measure/describe risk (Aven and Zio 2014). Establishing such perspectives is important to support decision making (Kristensen et al. 2006), but also e.g. for validating risk analyses (Goerlandt et al. 2018) and for ensuring successful risk communication (Veland and Aven 2013).

Several authors have proposed new risk perspectives. Kaplan and Garrick (1981) introduced the probability of frequency perspective, extended by Haimes (2009) with a focus on the time dimension. Aven (2010) introduced the uncertainty perspective, in which uncertainties in the background knowledge for making the probability judgments are explicitly treated. Aven (2013) further extended this perspective to include an assessment of unforeseen events, surprises and black swans. Gardoni and Murphy (2014) proposed a moral perspective, which considers the risk source as a third dimension apart from the probability and consequences.

Subsequent work has developed and discussed practical methods for measuring risk according to the different risk perspectives, see e.g. Szwed et al. (2006) and Zio and Pedroni (2013) for the probability of frequency perspective and e.g. Aven (2013), Goerlandt and Montewka (2015a) and Berner and Flage (2016) for the uncertainty perspective. Other work addressing risk perspectives has proposed a conceptual approach for combining the risk ranking results according to different underlying perspectives (Goerlandt and Reniers 2017).

Several authors have addressed the adequacy of the proposed risk perspectives in theoretical discussions. Aven (2010) distinguished the probability of frequency and the uncertainty perspective based on arguments for an uncertainty-based definition of risk. Aven et al. (2011) discussed the ontological status of risk in relation to a series of risk definitions and perspectives. Aven and Heide (2009) presented an analysis of the reliability and validity of risk analysis for a set of risk perspectives, including the probability of frequency and the uncertainty perspective, using a proposed set of reliability and validity criteria. Rosqvist (2010) discussed the issue of validity of risk analysis, focusing on the assessment of biases in probability-based risk perspectives, arguing that a systematic assessment of the direction of bias can give more insights than uncertainty assessments alone. Haugen and Vinnem (2015) have provided critical comments regarding the inclusion of certain interpretations of black swans into uncertainty-based risk perspectives. Rae and Alexander (2018) presented a review of the validity and accuracy of expert elicitations, relating this to different views on risk perspectives in a risk management context.

A question that has not received much explicit attention is whether risk analyses can be considered predictive. In the literature concerning quantitative risk analysis of socio-technical systems, several authors have claimed or implied that this is the case [i]:

> 'The PSA approach aims at defining a comprehensive, integrated model […] in which the predictions […] are performed […]' (Zio and Apostolakis 1996, p. 226)
>
> 'PRA uses mathematical probability in an attempt to deliver precise predictions.' (Crawford, 2001, p. 8)
>
> 'When a QRA predicts that an accident will occur […]' (Rae et al. 2014, p. 67)

Solberg and Njå (2012) argue that due to causal determinism, predictions can be made, but that due to uncertainty and the potential for surprises, these cannot be given any truth-value. Rae et al. (2012) have criticized the view that QRA models make predictions due to lack of scientific evidence. Paté-Cornell (2012) addresses the issue of prediction in the context of black swans, finding that rare events cannot be predicted.

Given the lack of in-depth discussion on prediction in a risk analysis context, the existence of various views apparent from the literature, and the general importance of prediction in scientific contexts (Douglas 2009, Shmueli 2010), this paper focuses on this issue. In particular, it is considered if, and if yes, how, risk analysis can be considered predictive. Furthermore, the focus is on the adequacy of the probability of frequency and the uncertainty perspective in light of two definitions of prediction (common and accurate), considering different types of systems. This distinguishes our work from existing literature on the perspectives, which has focused on other issues as outlined above. Our discussion differs from these in two respects, by focusing on the issue of prediction, and by distinguishing different system types.

The remainder of this paper is organized as follows. In Section 2, two possible definitions of prediction in a risk analysis context are elaborated, and corresponding criteria outlined. Section 3 briefly introduces different system types, whereas Section 4 introduced the risk perspectives in focus in this paper, namely the probability of frequency and the uncertainty perspective. In Section 5, an analysis is made of these risk perspectives, in light of the different interpretations of prediction and the considered system types. Section 6 provides a discussion on the appropriateness of the risk perspectives in light of the findings related to the predictability. Section 7 concludes.

## 2. Definitions of prediction in a risk analysis context

As clear from the introduction, there are different views on whether or not risk analyses are predictive. However, none of the above-mentioned authors explicitly defines prediction in presenting their views. In the recent glossary by SRA (2015), prediction is not defined either. Aven and Zio (2014) argue that conceptual clarity is one of the primary needs to strengthen the foundations of risk analysis, and Johansen and Rausand (2015) find that striving for clear definitions is important to avoiding linguistic ambiguity in risk analysis. Therefore, in this Section, two possible interpretations of prediction in a risk analysis context are presented, including a definition and corresponding criteria.

### *2.1. Definitions of prediction*

Two definitions for understanding prediction in a risk analysis context are distinguished, suggested by Hodges and Dewar (1992). These have been adopted also e.g. in natural science (Oreskes 1998) and economical science (Scher and Koomey 2011) contexts.

**Definition 1. Prediction (accurate)** A prediction is accurate if i) a statement about an observable or potentially observable quantity or event is produced; ii) the modelled situation is such that predictive accuracy *can* be measured; and iii) the predictive accuracy of the model in the situation *has* been measured.

**Definition 2. Prediction (common)** A prediction is a statement about an observable or potentially observable quantity or event.

In the above, given the focus on prediction in a risk analysis, the phrase 'a statement' is taken to be a description/measurement of risk according to a systematic approach. In risk-theoretic terms, this relates to the adopted risk perspective, which is the totality of elements considered in the risk description and the adopted interpretation of the tools for measuring risk. In Section 4, two such risk perspectives are considered, namely the 'probability of frequency' and the 'uncertainty' perspectives.

It is clear that Definition 1 (accurate prediction) is much more restrictive, but the additional conditions are necessary if one aims to make claims about the accuracy of the statement. Without actually testing the predictive accuracy of the statement, it is an unexamined claim whether an accurate prediction has been produced. Because science requires warrants for claims of accuracy (Douglas 2009), condition iii) is included. In turn, if one wants to measure the predictive accuracy of a statement, it has to be possible to do so, because of which condition ii) is included (Hodges and Dewar 1992).

### *2.2. Criteria for accurate prediction*

Hodges and Dewar (1992) propose four criteria for a situation to be accurately predictable, according to Definition 1. These are briefly considered next.

**CR1. Observability and measurability**. The situation being modeled must be observable and measurable. This means that the model should be able to produce specific statements about observable quantities or events, that corresponding measurements should be made in the system, and that the model-produced statements should be compared with these measurements without adjusting the model, its inputs or outputs in this comparison.

**CR2. Constancy of structure in time**. The situation being modeled must exhibit a constancy of structure in time, i.e. one should have reason to believe that the causal structure of the situation is sufficiently constant so that measurements taken at one time can be reproduced under the same conditions at a later time.

**CR3. Constancy across variations in conditions not specified in the model**. The situation being modeled must exhibit a constancy across variations in conditions not specified in the model. This means that test measurements are relevant to future situations under which unspecified conditions vary from those that held in the test. Thus, if the model is validated with some conditions fixed, then it is valid only for future situations in which those conditions hold, unless this criterion holds.

**CR4. Ample data collection**. It must be possible to collect ample data with which to make predictive tests of the model. This means that it should be possible to make vastly more observations than there are adjustable parameters in the model.

The centrality of conditions CR2 and CR3 is stressed by previous authors (Hodges and Dewar 1992, Oreskes 1998, Scher and Koomey 2011). Without these conditions, there is no guarantee that the model is or will remain representative for the situation being modeled. If the system changes in ways that are not accounted for in the model and validation tests, or if there are conditions in the system that could affect the system behavior in ways not captured in the model, the model output cannot be considered accurately predictive.

It is important to note that the criteria for accurate prediction depend on the relation between the model and the modeled situation. Therefore, it is important to elaborate in generic terms on risk models in context of risk perspectives, see Section 4, and to consider different types of modeled situations, which is considered in Section 3 in terms of different types of systems.

## 3. Different types of systems

There are many different ways of classifying types of systems, see e.g. Blanchard and Blyler (2016). For the purposes of this paper, a distinction made by Leveson (2012), based on ideas by Weinberg (1975), is used. For simplicity and brevity, two types of systems are distinguished: systems displaying i) organized simplicity, or ii) organized complexity.

In systems exhibiting **organized simplicity**, each component (subsystem, system element) acts independent of one another, i.e. there are no feedback loops. Each component behaves in the same way when examined in isolation or as part of the overall system, i.e. the component interactions can be considered separately from the behavior of the components themselves. These systems can be studied through decomposition (analytic reduction), i.e. the components and their interactions can be studied in themselves, and the system behavior can be subsequently deduced (Leveson 2012).

For systems exhibiting **organized complexity**, the system components affect one another through non-linear interactions and feedback loops, and system decomposition is ineffective as a way to study the system. The system derives its properties from the interactions between the components, and rather than focusing on the characteristics of the components and their pairwise relationships, the system should be treated in its entirety, requiring concepts such as emergency and hierarchy, and communication and control (Leveson 2012).

These different system types are used in Section 5 a basis for analyzing the two risk perspectives presented in Section 4 in light of the predictability criteria outlines in Section 2, by investigating how the system characteristics align with the requirements of the criteria.

## 4. Selected risk perspectives and typical related risk modelling approaches

In this paper, a risk perspective is understood as a commitment to the conceptual understanding and definition of risk, as well as the corresponding approach to measure/describe risk. As outlined in the introduction, there are many definitions and perspectives on risk.

For the purposes of this paper, two perspectives are selected: the ‘probability of frequency perspective’ and the ‘uncertainty’ perspective. These are relevant as they can be considered archetypal of the realist and constructivist positions on the realist-constructivist continuum (Bradbury 1989, Shrader-Frechette 1991), see e.g. Jore and Njå (2010) and Goerlandt and Montewka (2015b). They also represent different views on how risk analyses should be used in decision making, see e.g. Aven (2009) and Rae and Alexander (2018). Also in e.g. Aven (2010) and Aven and Heide (2009), these perspectives form the basis for the analysis and discussion, so we consider the selected risk perspectives appropriate for our current purposes.

### *4.1. Probability of frequency perspective*

In this risk perspective, risk is defined and described through the triplet $<s_i,p_i,c_i>$, where $s_i$ is the i-th scenario, $p_i$ the probability of that scenario and $c_i$ the consequence of the i-th scenario (Kaplan and Garrick 1981, Kaplan 1997). The triplet thus answers the questions (i) what can happen? (ii) how likely is it to happen? (iii) what are the consequences if it happens? In this perspective, the aim of risk analysis and risk modelling is to calculate probabilities of occurrence of events and consequences.

Schematically, the risk perspective consists of events A, consequences C and probabilities P and can be summarized as:

$$\text{Risk} = (A, C, P_s(P_f)) \tag{1}$$

The basic element is a frequentist probability $P_f$, i.e. the fraction of times an event or consequence occurs in an in principle infinite set of similar situations or scenarios to the one analyzed. In practice, $P_f^*$ is a thought construct or a model parameter, an estimate which may or may not accurately reflect the ‘true’ frequency $P_f$. A subjectivist probability $P_s$, a degree of belief, is used to describe the uncertainty about the parameters $P_f^*$. For further details about these different types of probabilities, see Aven and Reniers (2013).

In the probability of frequency perspective, the risk model is considered to present an accurate estimate of the true underlying risk, based on the underlying evidence. This focus on the underlying true risk is in line with a realist conception of risk (Goerlandt and Montewka 2015b, Jore and Njå 2010), and the achievement of an accurate risk picture is seen as a criterion for the risk analysis to be valid for use in decision-making (Aven and Heide 2009). This perspective is associated with decision strategies which apply mathematical optimization of expected utility (Kaplan 1997), or which strictly apply pre-defined risk-acceptance criteria by comparing the model-based probabilities with acceptability and tolerability limits (De Rocquigny et al. 2008).

### *4.2. Uncertainty perspective*

In this perspective, the aim of risk analysis and risk modelling is to assist the assessor in describing uncertainties about the occurrence of events and consequences (Aven 2013). This risk perspective can be schematized as follows, with A and C as above:

$$\text{Risk} = (A, C, P_s, U \mid BK) \tag{2}$$

$P_s$ is a subjective probability, a degree of belief of the occurrence of A and C, conditional to the background knowledge BK, which contains uncertainties U (Aven 2013). This assigned $P_s$ is not seen as a 'true' probability, as different assessors provided with the same evidence may disagree on how to interpret it and may have different personal background knowledge (Lindley 2006). The risk assessment thus is not independent from the assessor. Moreover, probability is considered an imperfect tool to represent uncertainty and the risk description contains a systematic qualitative assessment of uncertainties in the background knowledge (Aven 2013).

This perspective on risk is an example of a constructivist view, because the focus is not on an accurate risk description, but on an assessment of uncertainties as judged by an assessor (Jore and Njå 2010, Goerlandt and Montewka 2015b). These are expressed through subjective probabilities, and through qualitative uncertainty factors, uncertainty scores through an 'assumption deviation risk' assessment, and/or a qualitative assessment of surprises relative to the quantified results based on the risk model (Aven 2013). According to Aven and Heide (2009), accurate risk estimation is not a validity criterion in this uncertainty perspective, but instead the broad consideration of uncertainties is seen as an essential feature of risk analysis.

### *4.3. Common risk modelling approaches in line with selected risk perspectives*

In both risk perspectives outlined in Section 4.1. and 4.2, systems are decomposed in terms of events and consequences. Some common risk modelling techniques are fault trees, event trees and Bayesian Networks.

Fault and event trees are used respectively to analyze the causes of an event and its consequences. These techniques model the system outcomes as a strict sequence of conditional events, each of which a probability of occurrence is assigned to. Ericson (2005) provides more details about the modeling approach. For application examples see Klanac and Varsta (2011) and Milazzo et al. (2015).

Bayesian Networks are a type of probabilistic models in the form of a directed acyclic graph, which represents a set of variables and their conditional dependencies. As with event and fault trees, they typically focus on a sequence of events and consequences, but they are more flexible and allow an explicit representation of the state of the system and its environment, and how these influence the causal sequence. More details about Bayesian inference are given by Kelly and Smith (2009), and by Fenton and Neil (2012) who focus on Bayesian Networks. Application examples are given by Ancel et al. (2015) and Luxhøy (2015).

A common feature of these modeling approaches is the focus on determining the outcome of an activity or situation, conditional to the occurrence of prior events and/or the presence of given system states. These models represent a fixed causal mechanism (in terms of structure, content and parameterization) between system states and outcomes.

## 5. Prediction in light of selected risk perspectives and system types

In this Section, the issue of prediction in a risk analysis context is analyzed and discussed. A distinction is made between the two definitions of prediction presented in Section 2. Different perspectives for performing risk analyses are considered, as outlined in Section 4: the probability of frequency and the uncertainty perspectives. In substantiating the analyses for the different definitions of prediction, reference is also made to the characteristics of the distinguished systems, introduced in Section 3.

### *5.1. Prediction in risk analysis: probability of frequency perspective*

According to **Definition 2** (common prediction), it could be argued that risk models and risk analyses make predictions in this perspective, because a statement is produced about an event or quantity. However, it is also possible to interpret this perspective so that the model focuses on fictional, non-observable quantities. This is the argument made by Aven (2010), that the focus of this perspective is not the event A as it is expected to occur in the real world, but that focus is on $P_f^*(A)$, i.e. an approximation of a true underlying probability of the event's occurrence $P_f(A)$. Such an approximation is a model construct, existing only in the model environment, but has no meaning in the actual situation being modeled. Thus, it can also be argued that the probability of frequency perspective is not predictive, as no statement is produced about an observable quantity.

As for the criteria for accurate prediction for **Definition 1** (accurate prediction), it can be argued that the situation being modeled as such is observable (**CR1**): e.g. accidents (events) and the number of people killed or injured (a quantity) are observable properties. If the probability of frequency perspective is understood to focus on the occurrence of events A (Rosqvist 2010), it can be argued that this criterion is met. However, it can also be argued that this perspective focuses on non-observable, fictional model parameters $P_f^*(A)$, see Aven (2010). In such an understanding, the criterion is not met.

Considering the criterion related to the constancy of structure in time (**CR2**), this depends on the system being modeled, as predictability is not a property of a modeling approach, but of the modeled system, as outlined in Section 2.2. For systems exhibiting organized simplicity, it is arguable that this criterion is met, as long as the system components and their interrelations remain as in the original system. This can for instance be the case for mechanical systems, such as ship structures or chemical production installations. These are engineered based on deterministic laws of nature, which are prime examples of the structural constancy required for this predictability criterion. However, systems exhibiting organized complexity do not display the required constancy of structure in time. For such systems, the nature of the components comprising the system, and/or their respective interactions, change in an interdependent manner. The considered system may furthermore undergo modifications due to interactions with its environment, because of which the system structure may change. For instance socio-economic (Scher and Koomey 2011), socio-technical (Stringfellow 2010) and hydrological and geochemical systems in the earth sciences (Oreskes et al. 1994) have been argued not to display constancy of structure in time, i.e. these systems can be examples of systems displaying organized complexity. It should be noted that systems displaying organized simplicity could also be argued not to have the required constancy of structure in time for the predictability. For instance, if a structural system (e.g. a ship structure) may require periodic surveys to ensure that the structure remains the same, e.g. because it can be subjected to unexpected external loads or damages due to unexpected construction flaws. In such cases, it may be argued that also systems displaying organized simplicity, when embedded in larger systems displaying organized complexity, may not meet the criterion for constancy of structure in time.

The criterion of the constancy across variations not specified in the model (**CR3**) is also dependent on the system. The discussion is similar as for the criterion related to the constancy of structure in time. For systems displaying organized simplicity, where the outcomes deterministically follow from the initial conditions as long as the appropriate components and their interactions are appropriately described, it may be argued that variations in the system not specified in the model will not significantly alter the model outcomes. This may be the case for certain mechanical systems, as discussed above. However, when a system displaying organized simplicity is embedded in a system with organized complexity, it may be subject to factors that are not considered in the model. Such factors could also lead to significant deviations between the model estimate and the actual outcome.

For systems displaying organized complexity, it may be practically infeasible to enumerate all factors that may inflict variations in the system. Where such factors are associated with variations altering system components or their interactions, this may lead to significant deviations between the modelled and actual outcome. If the model does not include the factors, the predictability criterion is not met.

Concerning the final criterion for accurate prediction, the need to collect ample data to test the accuracy of prediction (**CR4**), it is found that this implies significant challenges to risk modelling, irrespective of the type of system. Risk by conception refers to possible future events or quantities (Solberg and Njå 2012), so that approaches that compare the results of a risk model with historic data are in principle not addressing the right problem. Alternatively, one could use the model to produce statements of the form $P_f^*(A)$ about the occurrence of events A, and wait for sufficient events to occur for comparison. In the probability of frequency perspective, these observations would be converted to relative frequencies $P_f$. In practical cases, this would only be possible in systems in which the events occur relatively frequently (e.g. car accidents) (Aven and Heide 2009); not in cases of low occurrence probability (e.g. large-scale industrial accidents) (Rae et al. 2014). Moreover, care must be taken that comparisons between observations and model statements are meaningful, in the sense that the same system is addressed. In cases where criteria CR2 and CR3 are not fulfilled, it is likely that the system changes during the use of the risk model and observation. Then, the comparisons are of little use as the model-produced statements and the observations concern different systems. In conclusion, this criterion is not met, neither for systems displaying organized simplicity or organized complexity.

The findings are summarized in Table 1, and show a somewhat mixed conclusion. In the common notion of prediction (Definition 2), risk models and analyses can be said to predict outcomes in the probability of frequency perspective, depending on how what one understands this perspective to focus on: events A, as understood by Rosqvist (2010), or model parameters $P_f^*(A)$, as understood by Aven (2010).

As for accurate prediction (Definition 1), the analysis shows that this is not possible. For both systems, CR4 poses theoretical and practical challenges, and CR1 poses conceptual challenges depending on what one understands the analysis to focus on. For CR2 and CR3, the situation is somewhat different depending on whether systems displaying organized simplicity or complexity are considered. While in some specific cases the criteria may be met, in most cases they are not. Hence, accurate prediction is not possible.

Table 1. Risk analysis and prediction in the probability of frequency perspective

| **Definition and prediction criteria** | | **System type OS** | **OC** | **Comments** |
|---|---|---|---|---|
| **Prediction (accurate) Definition 1** | **CR1** | Y/N | Y/N | [Y] A statement is produced about an event A or quantity Q, so a prediction is made<br>[N] The analysis focuses on thought-constructed parameters $P_f^*(A)$, which are not directly observable, so no prediction is made. |
| | **CR2** | Y/N | N | [Y] For systems with organized simplicity, the structure of the components and their interrelations remains the same over time.<br>[N] Even for systems with organized simplicity, when embedded in larger systems exhibiting organized complexity, the components or their interactions may change due to external interventions.<br>[N] For systems with organized complexity, the nature of the components and/or their interrelations does not remain stable. |
| | **CR3** | Y/N | N | [Y] For systems displaying organized simplicity, the factors governing the system outcome can be knowable, and the components and relations exhaustively studied. Other factors have insignificant bearing on the outcome.<br>[N] When the system with organized simplicity is embedded in a system with organized complexity, other factors may cause deviations in the model compared to reality.<br>[N] For systems with organized complexity, the nature of the components and their interactions changes, and not all factors causing this can be enumerated. |
| | **CR4** | N | N | [N] Risk by conception refers to possible future outcomes, so past measurements have no bearing on those.<br>[N] The collection of 'ample data' is usually not possible: it certainly is not possible for rare events, and even if it may |

| | | | |
|---|---|---|---|
| | | | be for more frequently occurring events, the criteria CR2 and CR3 raise questions about the validity of those data. |
| **Prediction (common) Definition 2** | Y/N | Y/N | [Y] A statement is produced about an event A or quantity Q, so a prediction is made<br>[N] The analysis focuses on thought-constructed parameters $P_f^*(A)$, which are not directly observable, so no prediction is made. |

Abbreviations. CRi: The i-th criterion for accurate prediction, see Section 2.2.; CS: system displaying organized complexity; N: No; OS: system displaying organized simplicity; Y: yes.

### *5.2. Prediction in risk analysis: uncertainty perspective*

The analysis made for the probability of frequency perspective is largely also applicable to the uncertainty perspective. The issues addressed concerning criteria CR2 and CR3 for accurate prediction are applicable also for this perspective, and are not repeated here.

According to Definition 2 (common prediction), it is found that QRA models make predictions in the uncertainty perspective, because a statement is produced about an observable event or quantity (Aven 2010).

As for criterion CR1 for the accurate prediction (Definition 1), the situation being modeled is observable. In the uncertainty-perspective, focus in the QRA model is on the events A, without making use of non-observable model parameters such as $P_f^*(A)$. This criterion hence is met.

The analysis for criterion CR4 is slightly complicated, because the probabilities in this perspective concern an assessor's degree of belief. Such probabilities are by definition expressions of uncertainty prior observation, based on the available background knowledge. Empirical control of such probabilities is troublesome in practice, because only some artefacts (documents, statements, datasets) can be examined, not the personal experience upon which these judgments are made. Moreover, the knowledge-based probabilities change over time (Rosqvist 2010), and are conditional to multiple heuristics and biases (O'Hagan et al. 2006). To the extent that comparing subjective probabilities with real-world observations is meaningful, the issues raised in Section 5.1. about the probability of frequency perspective are relevant as well. Moreover, Rae and Alexander (2018) provide an extensive review of the validity of expert judgment, finding that expert judgment cannot in general be considered accurate measurements, but rather that their value lays in the justification experts are able to provide.

The findings are summarized in Table 2. In the common notion of prediction, QRA models can be said to predict outcomes in the uncertainty perspective. As for the accurate prediction, the analysis shows that this is usually not possible due to criteria CR2, CR3 and CR4. It should be noted in this context that in the uncertainty perspective, the aim of the risk analysis is not accurate risk estimation, see e.g. Aven and Heide (2009), but rather a broad characterization of available knowledge and associated uncertainties.

Table 2. Risk analysis and prediction in the uncertainty perspective

| **Definition and prediction criteria** | | **System type OS** | **OC** | **Comments** |
|---|---|---|---|---|
| **Prediction (accurate)** | **CR1** | Y | Y | [Y] A statement is produced about an event A or quantity Q, so a prediction is made |
| **Definition 1** | **CR2** | Y/N | N | [Y] For systems with organized simplicity, the structure of the components and their interrelations remains the same over time.<br>[N] Even for systems with organized simplicity, when embedded in larger systems exhibiting organized complexity, the components or their interactions may change due to external interventions.<br>[N] For systems with organized complexity, the nature of the components and/or their interrelations does not remain stable. |
| | **CR3** | Y/N | N | [Y] For systems displaying organized simplicity, the factors governing the system outcome can be knowable, and the components and relations exhaustively studied. Other factors have insignificant bearing on the outcome.<br>[N] When the system with organized simplicity is embedded in a system with organized complexity, other factors may cause deviations in the model compared to reality.<br>[N] For systems with organized complexity, the nature of the components and their interactions changes, and not all factors causing this can be enumerated. |
| | **CR4** | N | N | [N] Risk by conception refers to possible future outcomes, so past measurements have no bearing on those.<br>[N] The collection of 'ample data' is usually not possible. The expert judgments are usually not amenable to empirical control, and typically should not be considered accurate estimates of an underlying true value. The criteria CR2 and CR3 raise questions about the validity of the expert judgments, when considered by themselves. |
| **Prediction (common) Definition 2** | | Y | Y | [Y] A statement is produced about an event A or quantity Q, so a prediction is made. |

Abbreviations. CRi: The i-th criterion for accurate prediction, see Section 2.2.; CS: system displaying organized complexity; N: No; OS: system displaying organized simplicity; Y: yes.

## 6. Discussion

From the analysis of the risk perspectives in light of the two definitions of prediction, it is found that risk analyses, apart from perhaps specific cases in systems exhibiting organized simplicity, cannot be considered as tools for accurate prediction. Focusing on accurate prediction as defined in Section 2, the theoretical and practical difficulties in collecting ample data to confirm the accuracy of the predictions is one important reason for this. Another important limitation is the fact that for many systems, the predictability requirements of constancy of structure in time and the constancy across variations not specified in the model, are not met. These findings should in themselves not be very surprising, as also earlier authors have found on theoretical (Aven and Heide 2009, Aven 2010, Paté-Cornell 2012) or on empirical (Rae et al. 2014, Goerlandt et al. 2017) grounds that risk analyses do not provide an accurate estimate of as assumed underlying true risk. The contribution made here is through the arguments given in support of this claim, in particular through assessing whether the criteria for accurate prediction are met, for two archetypal system types and risk perspectives.

When understanding the concept of prediction as in Definition 2 (common prediction) outlined in Section 2.1, the situation is somewhat different. For the probability of frequency perspective, it can be argued that risk analyses make predictions, depending on what one finds such risk analyses to focus on (events/consequences, or thought-constructed probabilities). For the uncertainty perspective, which focus on observable events and/or quantities, it is clear that predictions are made, if this simply means that statements are produced about observable or potentially observable quantities or events, without making any truth-claims about these statements.

The analysis shows that only in cases where the criteria for accurate prediction are met, it is meaningful to consider risk analyses as being able to provide accurate risk estimates. As argued in Section 5, this may be the case for systems displaying organized simplicity in certain cases. However, even in those cases there is a lack of data to confirm the accuracy. In addition, questions whether the constancy criteria CR2 and CR3 of Section 2.2. are met when considering these system in a broader context of systems displaying organized complexity, put serious restrictions to the idea that accurate risk estimates are possible even for systems displaying organized complexity.

Hence, the probability of frequency perspective, which focuses on an underlying true risk (Aven and Heide, 2009), is not in general justifiable for neither type of system. Considering the predictability criteria, the fact that the constancy criteria CR2 and CR3 are in most systems not met, implies that the risk model will not in general account for all factors that may affect the structure of the systems components or their interactions. A focus on frequentist probabilities $P_f^*$, even when supplemented with quantified uncertainty bounds around these using subjective probabilities $P_s$, will in general not suffice to reflect all assumptions and potential surprises stemming from the changeable nature of the system. The probability of frequency perspective does not include mechanisms to account explicitly for these assumptions and surprises and to reflect on their implications of the outcomes of the analysis. Consequently, important uncertainties may not be appropriately addressed and communicated in the decision making process. Hence, we find that the probability of frequency perspective is not in general justifiable.

On the other hand, the uncertainty perspective explicitly focuses (apart from structured knowledge-based uncertainty assessments) on the underlying evidence, assumptions, and potential for surprises. The effects of the potential surprises due to the non-constancy of the system compared to the model outcomes can be assessed qualitatively, e.g. using assessment of the effect of assumptions, see Aven (2013), Goerlandt and Montewka (2015a), and Berner and Flage (2016). The explicit attention given to the deviations between the modeled results and the events as they may occur in reality, and the underlying justification for this, leads risk analysts to use risk models in a reflective manner rather than expecting the model to give the results by itself.

Focusing on knowledge claims and judgments of an assessor or a significant social group hence is more appropriate in practical use of risk analyses. Abandoning the idea of accurate prediction of events does not mean that risk models have no use in informing decisions, but their use should be in more humble ways, as suggested by several authors (Aven 2009, Paté-Cornell 2012, Goerlandt and Montewka 2015b, Rae and Alexander 2018). One way to understand risk models is as artefacts that evaluate and assess future possibilities based on current knowledge (Apostolakis 2004). Risk models thus summarize knowledge as a type of bookkeeping device, which facilitates communication between analysts, decision makers and stakeholders. A related view is that risk models present an argumentation (Watson 1994), i.e. that risk analyses can be used for presenting an argument rather than a 'proof' that a system is safe.

Another way to use risk models is heuristically, for instance as an aid to thinking. They then serve as artefacts that can raise questions, challenging the user to make an informed judgment based on the model and its limitations. The model is then not seen to provide insight directly in the situation being modeled, but rather in its own assumptions and limitations. The inquiry on behalf of the model user then allows him/her, rather than the model, to make a statement about the events/consequences. Using risk models as above, the focus thus shifts from the quantifications per se towards the justification given for these and to the arguments by analysts and stakeholders concerning the limitations of the models compared to the space of possible outcomes. Related views on the use of risk models can be found e.g. in Aven (2013) and Goerlandt and Montewka (2015a). As argued e.g. by Paté-Cornell (2012), the justification given for the pathways for failure, the likely consequences of adverse events or the effects of risk control measures support the main utility of risk analysis, namely to raise awareness among system designers, operators and stakeholders, and to enhance communication to support decision making.

For using risk models in these ways, it is clear that the uncertainty perspective is more appropriate than the probability of frequency perspective. Therefore, we find that the uncertainty perspective should in general be preferred in practical risk analysis applications.

## 7. Conclusions

In this paper, the issue of prediction in a risk analysis context has been analyzed and discussed. Opposing views have been expressed in earlier work whether risk analyses are predictive, without clarifying how prediction is understood. To avoid such ambiguities, a distinction is made in this paper between a common prediction and accurate prediction. For the latter, four criteria concerning the relation between the model and the modeled system are applied. The analysis is framed in a risk-theoretic context of different perspectives on risk, where a distinction is made between realist conceptions that aim at accurate risk descriptions, and constructivist conceptions that focus on the underlying justification as given by risk assessors. The former is exemplified by the probability of frequency perspective, the latter by the uncertainty perspective. Furthermore, to support the analysis, a distinction is made between systems displaying organized simplicity and systems exhibiting organized complexity.

The analysis of these risk perspectives in light of the definitions and criteria of prediction shows that the claim that risk analyses make accurate predictions is not in general justified. One reason for this is the theoretical and practical difficulty in collecting sufficient data to justify accuracy claims. For systems displaying organized complexity, the lack of constancy of structure in time and constancy across variations not specified in the model, are also very important reasons why the accuracy claim is untenable. While for systems displaying organized simplicity, the constancy criteria may be met in special conditions, when considering these systems as embedded in larger systems with organized complexity, the criteria may not be met either. Hence, accurate prediction is not feasible.

Nevertheless, in the uncertainty perspective, it is found that risk analyses make predictions, when prediction is understood as in Definition 2 (common prediction).

Hence, a risk analysis in the uncertainty perspective can be understood to make statements about observable or potentially observable quantities or events. However, these predictions contain no truth-value, and may be wrong.

This common definition of prediction can also be argued to be applicable to risk analysis applying the probability of frequency perspective, if the analysis is understood to focus on observable events or quantities, which is somewhat controversial.

Based on the analysis and discussion, it is found that for most systems, the uncertainty perspective is preferable over the probability of frequency perspective in practical risk analysis applications. This is because it is better equipped to deal with uncertainties arising from the lack of constancy of structure in time or the lack of constancy across variations not considered in the risk model.

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i The abbreviations PSA (Probabilistic Safety Assessment) and PRA (Probabilistic Risk Analysis) are used as synonyms of QRA. PSA and PRA are primarily used in the nuclear industry, whereas QRA is more commonly applied in the chemical industry.