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Faith and fakes – dealing with critical information in decision analysis

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Faith and Fakes – Dealing with Critical Information in Decision Analysis

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Abstract
Decision making subject to uncertain information, whether fake or factual, in the context of management of socio-technical systems, is critically discussed from both philosophical and operational perspectives. In dealing with possible fake, incorrect and/or factual information we take the perspective that any information utilized as basis for supporting decisions, has to be dealt with in exactly the same manner - in accordance with Bayesian decision analysis. The important issue is to identify and model the scenarios through which information may cause adverse consequences and to account for their potential effects on the system representation applied as basis for decision optimization. To this end we first provide a mapping of how information affects the decision making context and a categorization of causes for information leading to adverse consequences. Secondly, we introduce a decision analytical framework aiming to optimize decision alternatives for managing systems in the context of systems representations including not only one possible system model but a set of different possible system models. As a means for assessing the benefit of collecting additional information, we utilize Value of Information analysis from Bayesian decision analysis. Finally, a principal example is provided which illustrates and discusses selected aspects of how possibly fake information affects decision making and how it might be dealt with.

1. Introduction
Public concern with the phenomenon of "fake news" has highlighted the risks and fears of information gone out of control and the associated force multiplier effects of digital connectivity in affording both the spread and the speed of disinformation. In 2016 the Oxford Dictionaries selected "post truth" as word of the year – an adjective defined as relating to or denoting circumstances in which objective facts are less influential in shaping public opinion than appeals to emotion and personal belief. In the same year, "fake news" became mainstream during the U.S. election campaign, used by Donald Trump to describe unfavorable media portrayals of himself in the media but also by various official and academic entities monitoring and analyzing the misuse of digital

platforms for the purposes of, e.g. influencing voting results or causing havoc during emergency situations (Pomerantsev and Weiss 2014, Silverman and Alexander 2016, Starbird 2017). The "threat" of fake news has in the span of several years turned into a mixture of hysteria and nihilistic skepticism. A comprehensive literature review of academic studies on the phenomenon of fake news is provided in a recent report of the European Commission's Joint Research Centre (Martens et al. 2018) which shows that there are in general two types of investigations: (i) quantitative studies that model the propagation of fake news through various media and (ii) empirical surveys of public opinion that attempt to draw conclusions about the impacts of fake news on e.g., voter behavior, ideological (re)alignment and citizen activism. The focus of the present paper is rather different; namely, we aim to provide an operational framework for how to deal with fake news in the context of ranking decision alternatives. We do not consider possible strategies of identifying whether given news is fake or not.

This paper aims to contribute to an unemotional and rational discussion on how to manage information of different degrees of "truth" in the context of risk-informed decision support irrespective of disciplinary or application domains. The introductory section provides the rationale for the proposed methodological framework through a historical, cultural and philosophical contextualization of the notions of truth, reality and their perception. It explains why a phenomenological and consequentialist approach forms the basis for the proposed framework and the motivation for our choice of operational definition of information. Thereafter, a generic system representation, which facilitates the utilization of the suggested approach for the management of information is introduced. The application of the proposed generic system representation is then illustrated and discussed in the context of a principal example where also parallels are drawn to practical cases where different categories of information are of significance.

2. A philosophical and historical view to truth, reality and their perception

2.1 Is there anything new about fake news?

Why is the phenomenon of "fake news" currently selected as an elevated societal concern even though disinformation is as old as the history of human warfare and transcends geographical and cultural boundaries? Depending on how constrained a definition of disinformation we choose to adopt, we could even argue that fake news is not a uniquely human invention but is also attested among non-human biological organisms whether as a means to take advantage of an adversary or to escape harm. Why are certain variations of "fake" information such as that found in marketing and advertising campaigns perceived as less threatening to society than a fake news tweet or blog entry about a politician or a current scientific assessment? The present societal preoccupation with fake news and related terms, e.g. post-truth, alternative facts, etc., is typically explained in terms of the risks associated with digital connectivity and the rise of 'information society'. Information has been labeled the 'currency' of the digital age; it is pervasive in all public and private spheres of life. Once largely under the control of societal institutions (governments, churches, universities), it has largely been liberated from the institutional monopolies of control – at least in Western democracies – at the price of diminishing public trust.

The spread of information through digital technology is not the only explanation; neither the most significant one. The perception of fake news as a risk with adverse consequences is largely driven by cultural and educational factors. Thus we see that the target of fake news are typically western democracies whereas the origins are typically traced to Russia or a number of small countries on the European eastern periphery. The former has both an ideological and an opportunistic motivation, a long professional experience of information and psychological operations (denial and deception) during the Cold War, and the actual technical ability to carry out such operations (i.e. a good supply of IT professionals). The latter may not be concerned with influencing ideology, but use fake news as a financial opportunity to compensate for the lack of employment or decent wages (Davey-Attlee

and Soares 2017). Fake news is not news in societies which have a long experience in state censorship and propaganda. There fake news is the reality that doesn't make it to the news. By contrast, fake news becomes news because of the surprise effect it has on a society accustomed to lack of censorship and trust in the societal institutions to represent the interests of its constituents. Culture need not be understood along national borders alone. According to anthropologist Mary Douglas writing in the context of risk perception, the selection of dangers a society decides to prioritize is an expression of the choice of social organization of that society (Douglas 1992). Thus, what a society perceives as true depends on cultural categories created along with the social relations they are used for defending. A society where the governance structure is hierarchical, i.e. where individual members are encompassed by the whole is typically enshrined in bureaucracy and tradition. It is strongly risk-averse and ignores or fears uncertainty. It needs therefore "truths" which are stable, reliable and unchanging – it needs "true facts". A society whose governance structure reflects that of a free market places value on the individual rather than the collective institution. Here uncertainty is not to be feared, rather it is perceived as opportunity. The risk portfolio of such a society is risk seeking. Individuals, not the state are responsible for their welfare (social and health benefits, education, etc.) and losses are blamed on chance or on stupidity. The ideology of "true facts" has little meaning to such cultural mentality.

Finally, the outcry of the danger of fake news illuminates a discrepancy (at least in context of Western societies) between scientific research and our education systems. It would be difficult to find scientific research after roughly the middle of the 20th century which subscribes to an objective and solid idea of truth as imagined by e.g. Plato or the positivist movement in both science and philosophy (roughly from the end of the 18th to the early 20th c.). Our educational institutions, however, have been slow and reluctant to change educational models and methods, many of which stem from precisely the positivist period, when facts and certain truths were the only serious pursuit of science, all else being labeled speculative metaphysics. As a society that values research and innovation as a means of improving life for humanity, we owe it to ourselves to examine where our prior beliefs of unshakable true facts comes from.

Finally, we wish to highlight that all current definitions of fake news miss an important semantic domain. Common to all these definitions is that fake news are intentional wrong messages sent out to the benefit of the transmitter. This omits a class of fake news, which may be sent with the intent to benefit the receiver, and thus, not necessarily malevolent. Under this class could be included moral instructions aiming to benefit a recipient which are not based on scientific evidence. In the present paper we thus adopt a broader semantic range for what constitutes "fake".

2.2 Truth, reality and perception from a philosophical and historical perspective

The concept of truth is fundamental to philosophy and science. In the context of truth, science (Gk. *episteme*) is just one branch of philosophy. Hence an inquiry into the historical development of the concept of truth provides an explanation of the motivation behind the methodological framework outlined in this paper. The question of what truth is and what makes something true is central to all five main branches of philosophy: ontology (or metaphysics) is concerned with what is true, i.e. what exists in reality; epistemology – with what can be known and how we come to acquire knowledge; logic (and subsequent modern analytical philosophy) – with the validation of truth; phenomenology – literally, with appearances (Gk. *phainomena*) or the perception of truth through experience; and ethics – with right or wrong action in respect to truth. It could be argued that historically humanity during the classical period of philosophy (e.g. Plato, Aristotle) was primarily focused on problems of truth related to metaphysics and ethics. The Enlightenment period (e.g. Descartes, Hume) was primarily interested in truth from the point of view of epistemology. The Victorian era and early 20th c. (e.g. Russel, early Wittgenstein) was preoccupied with logical problems of truth. The 20th c., when coincidentally many of the applied sciences were born, was interested in truth as it appears through our perceptual experiences (e.g. Husserl, Heidegger). Our

present position derives from the phenomenological school of thought, however, given the normative nature of decision support, it additionally accounts for ethical implications. In the context of fake information, constructivist epistemology may be used to justify the (im)possibility of objective knowledge. In Hennig (2010) explicit consideration is given to the application of the constructivist paradigm with relation to data analysis based on frequentist (objective) and Bayesian (subjective) interpretations of probability. In the present paper, we identify with the constructivist perspective of reality in so far as we see it as a manifestation of the phenomenological tradition in philosophy and in science. While it is not our purpose to define truth or what can be true but to offer an operational framework for dealing with problems where the extent of true and false information cannot be ascertained a priori, we nevertheless find it important to offer some background on the motivation for choosing a phenomenological and consequentialist basis as a rationale for the proposed framework.

2.3 On the relevance of phenomenology and consequentialism in risk-informed decision support

Phenomenological models are typically defined as models that represent only empirical observations of the physical world without resorting to a-priori assumptions. Data models or statistical models (e.g. regressions) are a kind of phenomenological model in that they do not attempt to form an explanation or theory of why given variables are correlated in a particular way, but rather aim to represent the relation among the variables. In phenomenological models truth is always subjective and dependent on the interpretation of the observer. In contrast, models of theories make a claim on the truthfulness of a proposition, which is derived on logical principles and require no evidence of observations in the physical world. The polarity truth-appearance is a legacy of the split between the pre-Socratic doctrine of flux of Heraclitus and Parmenides' doctrine of denial of the existence of change. Heraclitus held that what is real is constantly changing and that no object retains all its constituent parts or qualities from one moment to the next. Parmenides developed a logical argument against the existence of change. From the premise that it is impossible to think or talk about what does not exist, he deduced that (i) there is no coming into existence or ceasing of existence, i.e. nothing can be created and nothing can be destroyed; (ii) alteration or change is therefore impossible; (iii) movement is therefore impossible; (iv) plurality is therefore impossible. Here we have in a nutshell the two opposing views of truth – the Heraclitean notion that what is true or real is constantly undergoing change, so at no given point in time is truth or reality monolithic and absolute and the Parmenidean notion of truth as an absolute and of eternal duration. These views were further developed by Aristotle and Plato respectively and have been used to distinguish scientific, phenomenological and experimentalist view of truth and reality from the theological and analytical-mathematic perspectives. In the present paper when we apply the term truth we distance ourselves from the Platonic logico-analytical interpretation. Our approach bears a connotation to the flux doctrine of Heraclitus and to Aristotle's application of the phenomenological method. Essentially this implies the underlying assumption that the truth about a system of consideration can be established in phenomenological terms. The available knowledge about the truth of the system (what in the social sciences might be referred to as the 'lifeworld') is fundamentally subjective as we perceive it.

In taking this position we are further considerate of the applied context in which risk management or decision support take place. In this sense the operational framework is not only about truth and method but also about the ethics of the method we endorse. Given the normative purpose of risk management to provide societal decision support through a rational and transparent ranking of decision alternatives in conjunction with utility principles, our framework follows an essentially consequentialist approach. While there are different schools in the consequentialist paradigm (e.g. classical utilitarianism, hedonistic, pluralistic, actual, and expected consequentialism, and pragmatism), the common view that unites them is that normative properties of an act (we can substitute here decision) depend only on the effects, not the causes of an act (decision). It is not difficult to see why applied disciplines such as engineering or decision analysis adopt a

consequentialist approach to truth whereas basic or fundamental sciences such as mathematics, logic, philosophy, physics, etc. rely on causal explanations to validate their theories and truths.

A consequentialist approach, however, does not address the question of relevance. In analytical philosophy, the notion of "truthlikeness" is the idea that propositions should be assessed not simply in binary terms (true-false) but according to their proximity to the truth or degree of truthlikeness (Oddie 2014). It is pointed out that some false propositions might serve to get to the truth (e.g. Popper's idea of fallibilism) and that different truth propositions contribute to varying degrees to the realization of objectives. We could think of these objectives as the "truth, the whole truth and nothing but the truth". The possibility of estimating truthlikeness relies on probabilistic methods for evaluating the evidence (in the phenomenological sense – the empirical observations). In this context we can speak of degrees of belief or degrees of certainty as propositions or sets of possible worlds or truth propositions. An extensive literature has grown around the epistemological foundations of Bayesian probability. Some classical texts that discuss concepts such a s truth, belief and uncertainty from a Bayesian perspective include Ramsey (1926, 1978), Dretske (1971, 1981), de Finetti (1974, 1975), Walley (1991), and Olsson (2005). Using Bayesian probability theory we can model the probabilistic characteristics of events based on cumulative evidence. A best estimate based on evidence has more practical value to decision-making than truth arrived at on the basis of logical proof. In this sense Shannon's mathematical theory of communication (Shannon 1948) is compatible with our proposed approach as it provides essentially a probabilistic explanation of the relations between the states of two systems (sender-receiver in the context of MTC and electronic engineering; unrestricted application in the sense we propose).

2.4 Physical and semantic conceptions of information – do content and intent really matter?

In Figure 1 a system representation is given of the flow of consequences generated as a result of an exposure event. It can be observed that changes in the system state can be accounted for on the basis of adding the direct consequences (e.g. loss of life, damage to infrastructure, etc.) and indirect consequences (e.g. loss of business continuity, reputation losses, etc.). It is crucial to underline that societal risk perception regardless whether it is true or false, has impact on the system in that it has the potential to change the system's state. In other words, in the event that a system undergoes change as a result of perception, the information is equally relevant regardless of whether it is true information (objective facts) or false information (fake news or any type of intentional disinformation or misinformation or any type of unintentional error). However, as elaborated in Section 3.1 perception also importantly affects the preferences and objectives which decisions are based on. Moreover, it should be highlighted that the causes of system changes, e.g. such as natural hazards, acts of terrorism or political interference must be thoroughly understood to facilitate identification of relevant and efficient decision alternatives for managing the system and reducing risks.
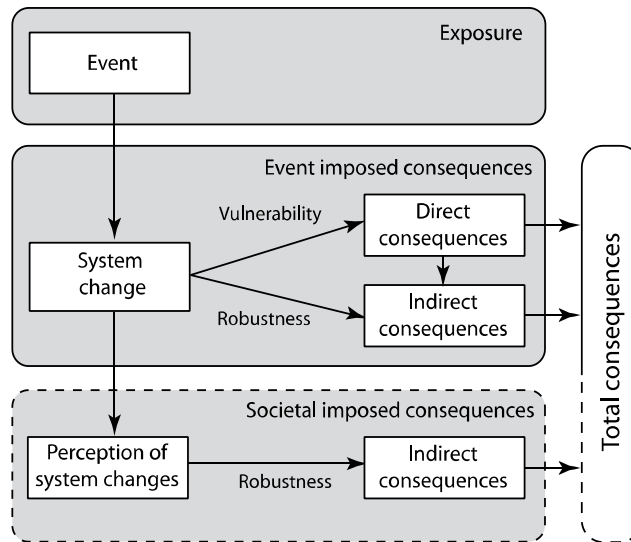
Figure 1 The JCSS framework for systems risk modelling (from JCSS (2008)).

Following Shannon's MTC, Weaver (1949) argued that the analysis of information can be viewed in terms of: (i) quantification of information in accordance with Shannon's theory for the purpose of solving technical problems; (ii) analysis of semantic problems related to meaning and truth; and (iii) analysis of "influential" problems with regard to effects of information on human behavior. Clearly, in the context of risk management in support of societal decision making, all the above are relevant.

Given the pervasiveness of the concept of information in a wide range of application areas from computer science to linguistics to biology, there is no agreed definition of information, rather a multiplicity of operational definitions that fit particular contexts. Before we say which of these definitions we prefer as befitting the context of our present inquiry, we briefly look at implications of the physical and semantic conceptions of information with regard to decision-making under uncertainty. The physical conception of information is formulated through Shannon's MTC in the context of electrical engineering. It deals with the problems of data compression and data transmission. MTC is not concerned with the content or meaning of the data, but it does provide meaning about the potentiality of meaning through the concept of statistical significance. In the words of Weaver (1949): "The mathematical theory of communication deals with the carriers of information, symbols and signals, not with information itself. That is, information is the measure of your freedom of choice when you select a message". By treating information as a physical entity, MTC postulates that a lower degree of randomness or entropy is associated with less information and vice versa.

The semantic conception of information considers the content of information through the satisfaction of three criteria: meaningfulness, consistency and truth. Those who require the first two criteria only are proponents of the theory of weakly semantic information; those who require all three subscribe to the theory of strong semantic information. Floridi (2015) distinguishes further between instructional information (which must be meaningful in order to convey the need for action) and factual information (a declarative statement which may be true or false). Floridi has come to be known as the academic authority on the newly coined branch of philosophy – philosophy of information, particularly on ethical aspects of the uses of information. He argues (2004, 2015) that truth is a defining criteria of factual information and that misinformation and disinformation regardless of intent, or the lack thereof, are not to be considered as factual information. Opposed to this view, Fetzer (2004) and Dodig-Crnkovic (2005) have argued that false information, including contradictions are also instances of semantic information by virtue of fulfilling the truth-neutral

criteria for meaningful and well-informed data. The weak semantic information school is closer to a probabilistic approach to semantic information in that it defines that in relation to a data model and its (in)consistency.

We find Bateson's (1972) definition of information best captures our proposition that information which has the potential to make a difference, i.e. generate change in a system of consideration, should be treated equally disregarding relation to truth and intent, and in accordance with Bayesian probability theory. Bateson, an anthropologist by education, but mostly known for his work in combining cybernetics with ecology, defined information as a "difference" or negative entropy: "In fact, what we mean by information – the elementary unit of information – is a difference which makes a difference." Bateson's definition captures also Shannon's basic proposition to treat information as a measure, not as the true or false proposition of a theory. It fits well with the Bayesian method of extracting meaningful patterns from data without having to specify what the meaning is. What the method offers is a ranking of which differences make a bigger or smaller difference, which is a measure of the relevance of information. As such, it is of primary concern for risk-informed decision support as even true information when not relevant will be of little value at best.

3. Problem framing and approach

Starting point for the problem framing is taken in the premise that decision ranking is normative and based on Bayesian decision analysis (Raiffa and Schlaifer, 1961) in conjunction with the axioms of utility theory (van Neumann and Morgenstern 1953). The theoretical framework for the representation of knowledge is selected as the Bayesian probability theory with due consideration of both aleatory and epistemic uncertainties, see also Faber (2005) and Der Kiureghian and Ditlevsen (2006). When attempting to rank decisions with respect to management of socio-technical systems by utilization of information as basis for knowledge building, inevitably a discourse on the concepts of knowledge, systems and truth is encountered. As elaborated in Section 2 we take the perspective of the phenomenologist and represent the available knowledge in full appreciation that this is subjective and model this probabilistically in accordance with e.g. JCSS (2008) to represent how different decision alternatives may affect achievement of the preferences of the decision maker. At this point it is important to highlight that the preferences of the decision maker often involve and depend on the perception of stakeholders concerning consideration of and choice of decision alternatives (strategies) as well as the outcomes of these. Moreover, the freedom of the decision maker to choose among strategies may also depend on the perception of the stakeholders.

3.1 Information flow in risk management

As illustrated in Figure 2 there are important dependencies and back-couplings between information, the decision maker and the stakeholders to the decision making.
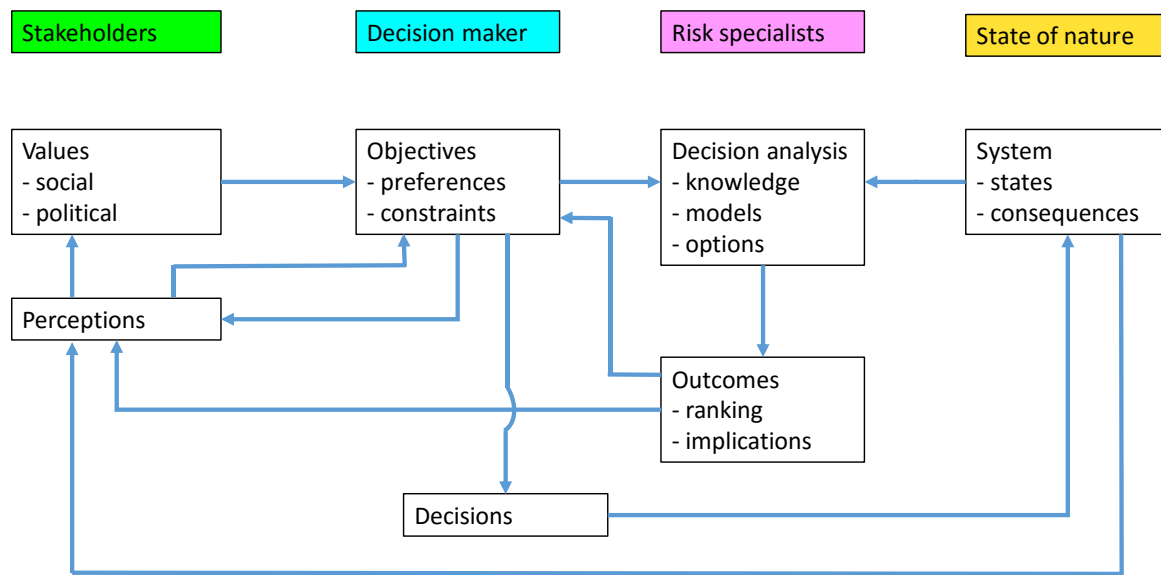
Figure 2   Illustration of the system and stakeholders in the decision making context with focus on the flow (arrows between boxes) of information affecting decision ranking and outcomes of decision making.

Whereas the general understanding of risk management and also the current practices focusses on the modelling and management of what is indicated as the system in Figure 2 (representing the role of the "True state of nature") it should be underlined that the system which ideally should be considered in the risk informed decision analysis envelopes all processes (nodes and flows of information) in Figure 2 – including the tasks of the "Risk specialist". In this manner the node with the title "System" should be understood to comprise the full contents of Figure 2.

Generally, the best available knowledge about a systems is understood to be comprised of fundamental phenomenological physical understanding and experience combined with information (often referred to as evidence) – collected and processed over time. From the mechanism of knowledge building and information flow within the context of decision making, see Figure 2, it is evident that decision making is faced with a number of important conditions of information affecting the outcome of decisions. These conditions of may be categorised as:

1) The information is relevant and precise.
2) The information is relevant but imprecise.
3) The information is irrelevant.
4) The information is relevant but incorrect.
5) The flow of information is disrupted or delayed.

It is important to note, as evident from Figure 2, that the interaction between "decision maker" and "stake holders" as well as the perception of stakeholders with regards to consequences of decisions play an important role in the formation of the preferences, objectives and available decision alternatives defining the domain of possible decisions of the decision maker. Moreover, over time the preferences of stakeholders will shape the value setting which forms the basic premises for risk management. In practical risk management it is often seen that perceptions of stakeholders may significantly affect the premises of societal decision making, not least due to the political pressures imposed by public opinions, press coverage and social media. In such cases it is not rarely seen that the public opinion exerts pressures on societal decision making to an extent where more fundamental

values on e.g. equity with respect to life safety may be violated, see also Faber et al. (2007). As emphasized in Faber at al. (2012) this calls for identification and implementation of a common rationale for the management of risks, which defines the space within which perceptions and public opinions may be allowed to affect the premises of decision making. A common rationale for the management of societal risks necessarily must be established in a dialogue between stakeholders and decision makers. Such a dialogue is challenging but may find substantial support in a structured process of risk communication and by taking benefit from risk communication protocols, where emphasis is directed on the development of informed preferences for societal risk management, see e.g. Faber and Lind (2012).

As highlighted in Section 2, we do not intend to address the specifics of risk management task related to the identification of the sources and causes of different states of information in any detail. However, a general appreciation of potential sources which may be of crucial importance to facilitate relevant and adequate system identification and risk informed decision support as described in Section 4 may be achieved by considering in particular the carriers of information, as well as the sources of risks in general. The carriers of information (transferred between the stakeholders as illustrated by the arrows in Figure 2) are in general manifold and include formalized channels and procedures defined e.g. in protocols (see e.g. Faber and Lind, 2011), informal channels such as the free press and social media, as well as technological information transmitters, such as wires and micro waves. In principle, information belonging to any of the above listed categories may be relevant for all the links indicated in Figure 2. Fake news as such may be a cause for any of the conditions of information belonging to the above listed categories 2) – 5).

3.2 Information channels and types of hazards

Especially with respect to the information flow between stakeholders and decision makers, where formal channels are not well established and for which the open press and social media play a significant role, there is an increased potential for information being distorted with the purpose of promoting particular agendas of individuals or groups of stakeholders; such cases include what is commonly referred to as "Fake News". It should however be kept in mind that other intentional and also malevolent (or well meaning) means for affecting the information flow may be relevant to consider in risk management. Such means include interferences with the information flow, e.g. in the form of information disruptions and information corruptions.

In addition to the appreciation of the different possible carriers of information and their role in the management of risks, also the different possible types of hazards should be devoted attention. In Faber (2018) four types of hazards are categorized, namely:

- Type 1 hazards: Large scale averaging, rare and high consequence events: Rare in place and time, potentially associated with catastrophic consequences. Over sufficient large scales in time and space the associated risks are predictable, which greatly facilitates their management. Typical examples of this type of hazards include geo-hazards, such as earthquakes, floods, strong wind storms, etc. In the context of the how information affects decision making as illustrated in Figure 2, technical failures of technological information carriers within systems of some size, such as power plants, wind turbine farms, etc. would belong to this type of hazards. This type of hazards have resemblance to the hazard class labelled as the "Sword of Damocles" in Klinke and Renn (2002).

- Type 2 hazards: Frequent in time and space with relatively small consequences, which is why they are commonly overseen or collectively ignored. Cognition biases such as tunneling and framing (see Kahnemann and Tverski, 1984) play important roles in this. Over sufficient scales in time and space they might be associated with devastating cumulative consequences. Moreover, their cumulative effects may trigger more disastrous consequences of the same characteristics as those of Type 3 hazards. Typical examples are emissions to the environment, exploitation of resources, extinction of species, inefficient or

inadequate regulations, inadequate budgeting, human errors, etc. Smaller biases associated with the technological transfer of information caused by e.g. inadequate control and calibration procedures as well as e.g. slightly delayed transfer of information caused by organisational inefficiency would belong to this type of hazards. This type of hazards have resemblance to the hazard class labelled as "Cyclops" and "Cassandra" in Klinke and Renn (2002).

- Type 3 hazards: Extremely rare and potentially disastrous events which are unpredictable even over large extents in time and space and for which basically no knowledge is available. May be triggered by the cumulative effects of Type 2 hazards. Examples include super volcano eruptions, impacts by asteroids, high intensity solar storms, global climate change as well as major malevolent actions. Also at small scale risk management such as e.g. for regions or communities the same type of hazards as mentioned under Type 1 hazards may belong to this group, since no sufficient averaging effects are involved.

  The management of risks due to this type of hazard cannot be planned for in the same manner as Type 1 hazards since little is understood with respect to probability of occurrence and evolution of consequences. Conditional risk assessments might be utilized to quantify speculation on the robustness and resilience of society at different scales – by basing risk assessments on certain extents of damages of the systems providing societal functionality – conditional, or "what if" assessments. Examples of Type 3 hazards of relevance for the transmission of information might include solar storms shutting down electronic communication systems at large scale, malevolent disruptions of satellite communication systems as well as interferences of GPS navigations systems. This type of hazards have resemblance to the hazard class labelled as "Pythia" and "Pandora's Box" in Klinke and Renn (2002).

- Type 4 hazards: Events triggered by incorrect information and knowledge. Examples include consciously and unconsciously omitted or manipulated information, "fake news" as well as censored and erroneous observations. The characteristics associated with events of this type of hazard may resemble those associated with Type 1 – Type 3 hazards. The management of this type of hazard may be supported by means of sensitivity analysis (see e.g. Faber et al. (1997)) and by means of inclusion of options for validation of the information and knowledge playing a significant role, for the ranking of decision alternatives. This type of hazards, as mentioned under the forgoing hazard types, may indeed play a role for all types of hazards and for this reason deserves special attention. The condition of information appears not to be specifically addressed in Klinke and Renn (2002) but could be termed "Hermes" after the god from Greek mythology, who's main role is that of a messenger.

In Section 5 we will discuss generic cases enveloping theses situations in more detail, and also draw parallels to situations encountered in practical decision making.

However, before this we first briefly introduce the Bayesian decision analysis framework for ranking of decision alternatives subject to uncertainty originally introduced by Faber and Maes (2005) and later elaborated in Glavind and Faber (2018).

4. Decision analysis in the face of uncertainty

The only available basis for decision making is our perceived knowledge of the systems we are aiming to manage; information. The representation of systems in terms of information thus constitutes a crucially important step in the context of risk informed decision analysis. The principle idea we propose here is to incorporate the possible effects of the various types of conditions of information described in Section 3.1 into the system representation through their possible implications with respect to the probabilistic representation of possible competing or alternative

systems, in addition to the normally addressed probabilistic phenomenological representations of individual most probable systems, see also Hennig (2010). Noteworthy contemporary challenges for risk informed decision support, which calls for an adequate representation of possible competing systems concerns climate change risk management (Mastrandrea, 2011) and national security in the face of hybrid warfare (Hoffman, 2009). Our proposed approach facilitates for such representations as well as adaptation and refinements (through Bayesian updating) over the course of time, as more information may be collected or otherwise becomes available.

In the remaining part of this section we will first outline a general approach to the probabilistic representation of systems and thereafter propose a decision analysis formulation which facilitates for the identification of optimal decisions with respect to risk management and collection of additional information as well as the assessment and maximization of the robustness of decision alternatives with respect to possible systems as well as system assumptions.

4.1 *General approach with respect to the representation of systems*

As outlined in Glavind and Faber (2018) the identification and probabilistic representation of possible systems may take basis in bottom-up, i.e. phenomenological models where the whole (the system) is established by combining its parts (constituents) or top-down systems modelling approaches, where the parts may be derived from information concerning the performance of the whole, or combinations of the two. The important issue, however, is that the probabilistic representations must be fully consistent with the available knowledge and that it is documented transparently which scenarios affecting relevance, precision and correctness of utilized information have been accounted for; i.e. an elaboration of the important task of system identification and documentation in risk informed decision analysis, see e.g. JCSS (2008).

To account for the scenarios affecting relevance, precision, correctness and availability of information necessitates that specific efforts are undertaken to ensure that these are established, i.e. identified and modelled probabilistically, by use of bottom-up or/and top-down approaches. To this end it is important to note that use of top-down approaches in this case requires careful consideration of which information, e.g. in terms of databases and covariates, to include as basis for the modelling. If there is no clear idea on how to select such information, the modelling will not serve its purpose. A starting point for the identification of relevant databases as well as covariates may be developed on the basis of engineering understanding and/or bottom-up phenomenological models. In this light it is immediately realized, as emphasised in Glavind and Faber (2018), that so-called data driven modelling techniques (top-down) are equally subjective as traditional phenomenological approaches (bottom-up). In addition to the identification of the different scenarios a next step is to identify different decision alternatives of relevance for management of the systems of consideration. In the present context it is of special importance to identify strategies including options for collection additional information over time and adapt strategies accordingly; this with the aim of identifying optimal as well as robust decisions.

Assuming that all relevant scenarios and decision alternatives for the management of a considered system have been identified the following steps are proposed:

1) Based on available knowledge, identify and represent possible systems probabilistically (see Section 4).
2) Formulate and undertake a prior decision analysis for the ranking of decision alternatives, accounting for the possibility of different systems.
3) Based on the prior decision analysis formulate and undertake a pre-posterior decision analysis for the ranking of decision alternatives with respect to collection of additional information and commissioning of adaptive strategies.
4) Evaluate the robustness of the ranked decision alternatives with respect to expected value of benefit (utility) contributions from system realizations.

5) Assess possibilities for improving the robustness of decisions by means of alternative strategies for collection of information and adaptive measures – and repeat step 4).

In Section 4.2 the general principles of the systems modelling and the corresponding decision analyses are outlined.

4.2 System representation and decision making

As an example a framework for systems modelling in the context of assets integrity management for technical facilities is illustrated in Figure 3.
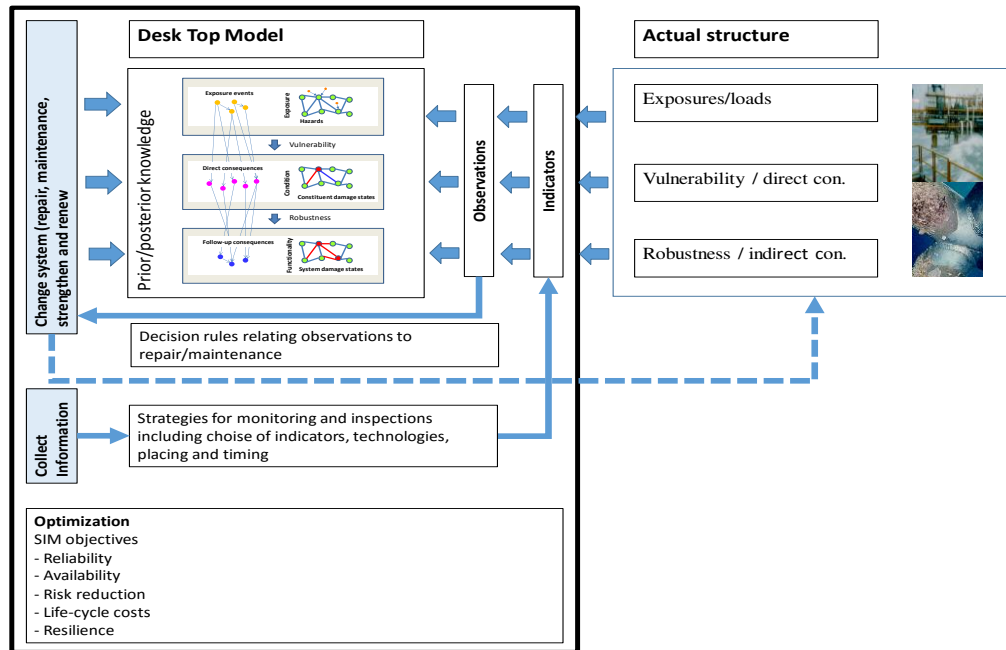

Figure 3   Illustration of systems modelling framework in the context of assets integrity management for offshore facilities (Faber, 2017).

In Figure 3 the concept of indicators is introduced as a means to incorporate information into the modelling, which is related to the performances of the system, see also Faber and Sørensen (2002) for examples. The concept of indicators provides a strong means for including information in systems modelling. In a bottom-up based modelling of the system, first the phenomenological models of the parts of the system are established and the parts are combined to the best of available knowledge to represent the performances of the system as a whole. Information is thereafter collected through indicators and utilized for a probabilistic updating of the phenomenological system model. In a data driven model the systems model is established through information collected from joint observations of indicators and system performances. Whether bottom-up or top-down modelling approaches (or combinations) are applied it is of central importance that that probabilistic system models consistently account for and distinguish between uncertainty associated with sparsity of evidence and possible model uncertainty and associated lack of fit. This is of crucial importance in the context of model optimization, where an optimal trade-off between complexity (in terms of system, constituents, and parameter models), and the associated statistical uncertainties must be identified.

Following Glavind and Faber (2018), a model $\mathbf{M}(a)$ is a relationship between input and output as a function of a decision a. In general the performance of the system is associated with uncertainty, which is why the output of the system with which we associate utility $U(a)$ in the following is random.

Accounting for the possibility that different systems are possible $\mathbf{M}(a)$ can be described as:

$$\mathbf{M}(a) = \left(\Sigma(a), C(a), X(a) \right)^T \tag{1}$$

Where the actual system is represented by the random event Σ, with possible realizations belonging to the set $\boldsymbol{\sigma}$ of n_s known components. It is assumed that each possible system realization, e.g. represented by a graph model σ_j has n_{c_j} constituents which interact together to provide the functionalities and associated utility of the system. As indicated previously different possible systems may be identified through bottom-up phenomenological considerations or as a result of top-down data driven modelling. The identification of optimal decision alternatives a must in general be undertaken simultaneously with an assumption or choice of the system s, which is realized. For a given choice of s, the performances of the constituents are represented by a set of constituents models C_s and a prior probabilistic model for all uncertainties entering these, i.e. $P'(X|s)$. It should be mentioned that all probabilistic representations in principle have temporal and spatial references, which for the sake of simplicity of notation are omitted here.

4.3 Decision analysis and robustness of decisions

The following concerns Step 2 in Section 4.1, namely the formulation of a prior decision analysis for the cases where the system is unknown. Starting with the normally considered case where the considered system may be regarded as known, following Raiffa and Schlaifer (1961) and von Neumann and Morgenstern (1953), the optimal decision is identified from the maximization of the expected value of utility, i.e.:

$$a^* = \arg\max_a E'\left[U(a) \right] \tag{2}$$

Accounting for the possibility of uncertainty associated with the system itself (Faber and Maes (2005) and Hennig (2010)), the principal decision event tree can be formulated as illustrated in Figure 4, (adapted from Faber and Maes, 2005).
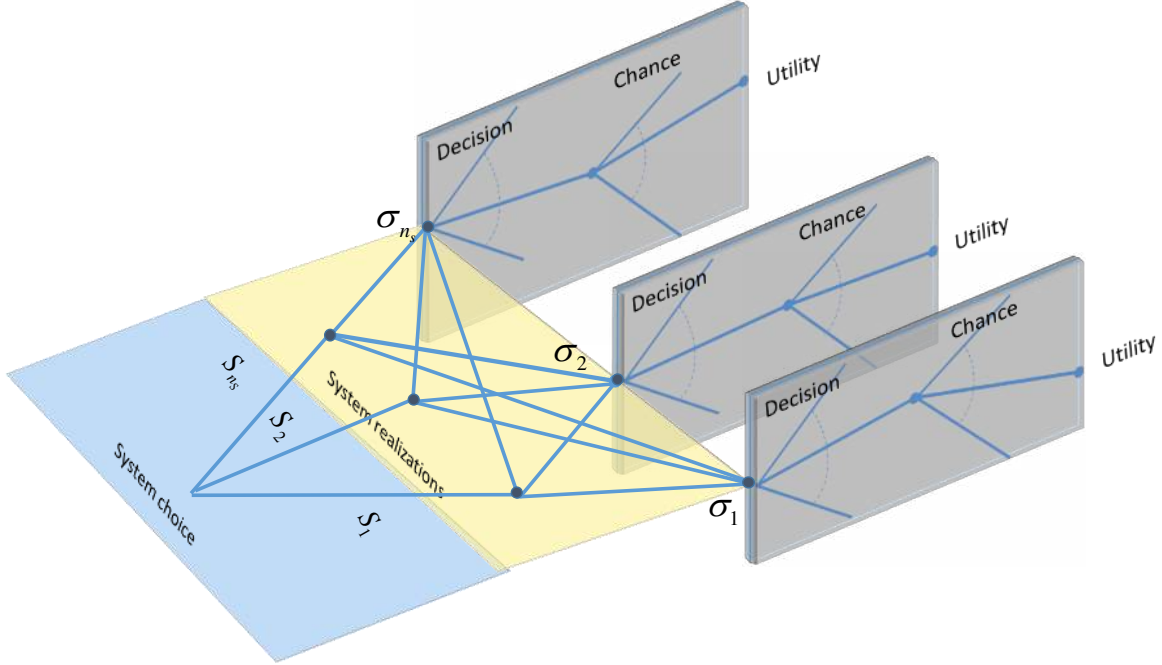
Figure 4   Illustration of the decision event tree applied in prior decision analysis of systems with uncertain possible system realizations (adapted after Faber and Maes (2005)).

In Figure 4 the variable s_i represents one choice of system representation out of a set of system representations and σ_i represents a realization of the real system. The optimization of decision alternatives is further complicated by the fact that some of the decision alternatives within **a** may only be relevant for one or some of the competing system representations. The optimization of decision alternatives must thus be undertaken jointly with a choice of system representation.

The optimization of decision alternatives, including system choice, may now be written as (Faber and Maes, 2005)):

$$(s^*, a^*) = \arg\max_s \left(P(\Sigma = s) \arg\max_s \left(E'_{\mathbf{X}|a}\left[U(a, \mathbf{X})\right]\right) + E'_{\Sigma \backslash s}\left[E'_{\mathbf{X}|\{\Sigma \backslash s\}}\left[U(a^*, \mathbf{X})\right]\right]\right) \tag{3}$$

Where a^* is determined in accordance with Equation (2). In Equation (3) the robustness of the decision with regard to the choice of system may be assessed as the ratio of the first term to the sum of the two terms. This ratio, which will take values between 0 and 1 (1=robust), indicates how sensitive the decision is with regard to the possibility that the optimization is undertaken under an erroneous system assumption.

Ultimately, model building should be seen as an integrated part of the decision optimization. On one hand, it is important that the model captures all relevantly possible systems and their uncertainties; on the other hand, there is no need for a model to be accurate in the domains of "reality" which are irrelevant for the decisions subject to optimization. By embedding the model building operation inside the optimization of decision alternatives, the available knowledge may be fully utilized to optimize the utility associated with the system under consideration, and thus consistently rank decision alternatives.

4.4 Value of Information Analysis

We now turn to Step 3 from Section 4.1, namely the formulation of a pre-posterior decision analysis for the purpose of identifying how additional information may support the choice of system s and the corresponding optimal decision alternatives a.

The decision event tree for this case is shown in Figure 5.
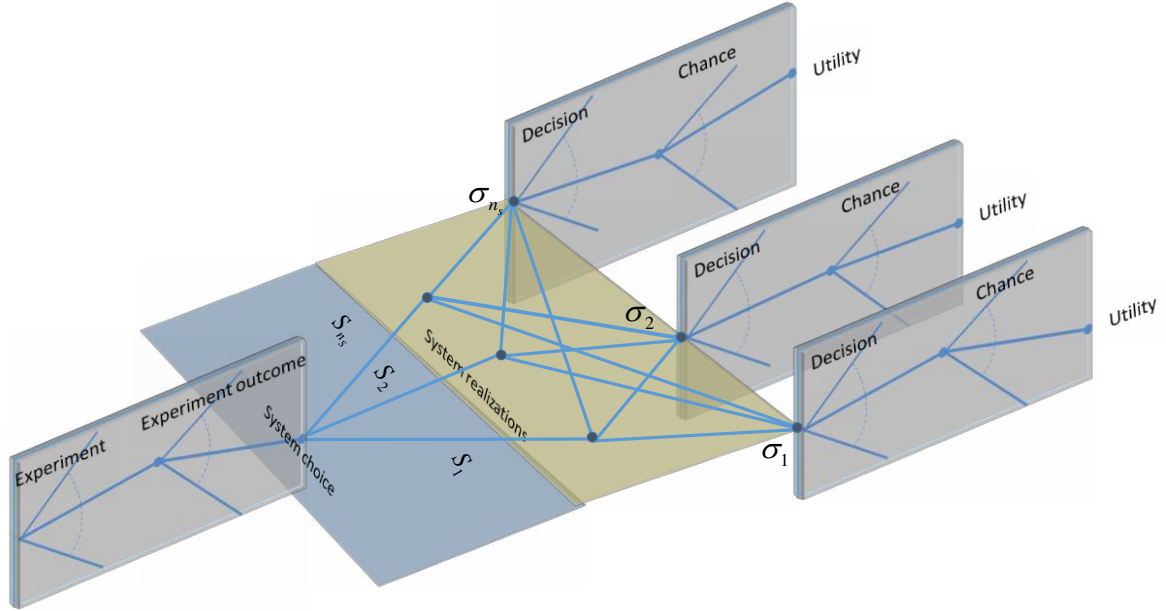

Figure 5   Illustration of the decision event tree applied in pre-posterior decision analysis of systems with uncertain possible system realizations.

The pre-posterior decision analysis for the optimization of the joint problem, which considers optimization of collection of additional information e, selection of system s to optimize decision alternatives for, and finally optimization of these decision alternatives $\mathbf{a}$, may be formulated as:

$$(e^*, s^*, a^*) =$$

$$\arg\max_e E'_{\mathbf{Z}} \left[\arg\max_s \left(P(\Sigma = s | \mathbf{z}) \arg\max_a \left(E''_{\mathbf{X}|a} [U(a, \mathbf{X})] \right) + E''_{\Sigma \backslash s} \left[E''_{\mathbf{X}|\{\Sigma \backslash s\}} [U(a^*, \mathbf{X})] \right] \right) \right] \tag{4}$$

Where $\mathbf{Z}$ represents the uncertain outcomes of the experiment strategies with realizations $\mathbf{z}$, and E'' indicates that the expected value operations are undertaken based on an updated probability assignment for the possible different realisations of $\mathbf{X}$, i.e. $P''(X|s) = P'(X|s, \mathbf{z})$.

From Equation (4) it is seen that new information will affect both the assignment of probabilities to the different possible system realization and the probability assignments for all the state variables $\mathbf{X}$ for given choice of system s.

Step 4 and Step 5 from Section 4.1 may now be invoked successively until decision alternatives are identified which at the same time are (closed to) optimal and also adequately robust with respect to possible competing systems and system assumptions.

In Glavind and Faber (2018) the approach outlined in the foregoing concerning the joint identification of system representation and optimal risk management options is illustrated on an example considering evacuation planning of offshore oil and gas production facilities in the event of an emerging storm. The reader is referred to this example to obtain more detailed information concerning how multiple systems and various types of uncertainties are modelled and treated in the decision making process.

5. On the application of the suggested approach

Taking basis in the foregoing discussion of information and how information might affect decision making presented in Section 2 and Section 3, together with the generic framework for decision analysis subject to uncertainties – including deep systemic uncertainties – as presented in Section 4, we now consider a very simple principal example to discuss some of the implications of different categories of information on decision analyses and how these analyses may be adequately synthesized.

Decision problems subject to uncertainty often involve information belonging to Category 1 (i.e. relevant and precise, see Section 3). Examples of this type of information include the event that a bridge has survived an earthquake with damages below a tolerable level, a welded joint in an offshore structure has not failed after 20 years of fatigue loading and the reduction of the concentration of pollutants below critical levels in a groundwater reservoir, after the implementation of an environment preservation policy limiting emissions from industrial activities.

Information may however also be associated with uncertainty in the form of imprecision; in which case the information belongs to Category 2. There may e.g. be uncertainty associated with the level of observed damages of the bridge, measurement errors associated with the sizing of fatigue cracks as well as errors associated with the measured concentrations of pollutants. In either cases the decision event tree to be considered in the decision analysis is of the general character illustrated in Figure 6.
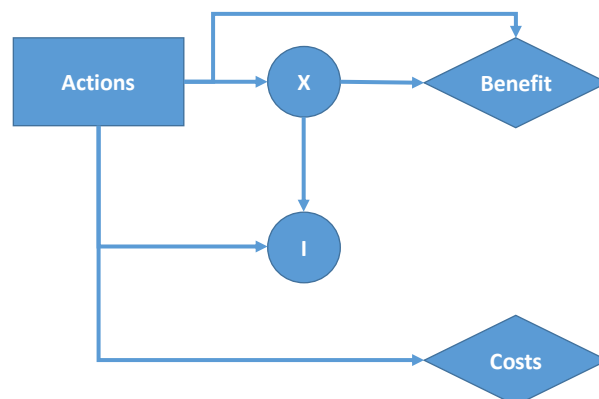

Figure 6   Illustration of principal decision analysis when Category 1) and Category 2) information **I** about a system subject to uncertainty represented by **X** is collected.

In Figure 6 the flow of actions is 1) to collect information $\mathbf{I}$ (at a cost) and based on the collected information to identify a decision which affects the perceived state of nature $\mathbf{X}$ in such a manner that the benefits are maximized.

It is important to keep in mind that the information collected, i.e. $\mathbf{I}$ may not always be relevant for the decision analysis. It can originate from another system than the system considered, i.e. $\mathbf{X}^*$. In descriptive statistics such information is often referred to as "outliers" – in fact originating from a population of events, different from the population of interest. Considering the case of the bridge damaged by earthquake, information regarding the damage state might relate to past overloading and not the recent earthquake, in the case of a welded joint, the information collected from an inspection may e.g. concern a slag inclusion originating from the welding process, rather than a crack induced by fatigue loading and finally with respect to a measured pollutant the information concerning the observed concentration may relate to a fluctuation in the natural environment instead of emissions from industrial activities . In such a case the information collected has no relevance and decisions made or adapted on the basis of the collected information would be suboptimal.

The question is then – what to do to mitigate the adverse consequences of irrelevant information? The answer is simple – but only comes with considerable efforts. What is needed is to account for all possible systems leading to the information applied in support of the decision ranking. In the considered example this means that the decision analysis also must account for possible alternative systems which might be a cause for irrelevant information. Such a representation is illustrated in Figure 7.
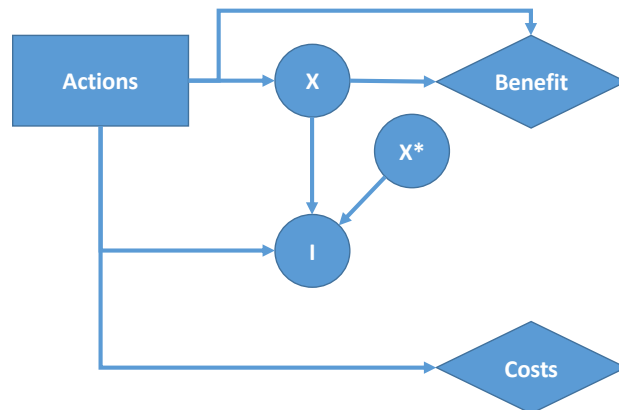

Figure 7   Illustration of principal decision analysis when Category 3) information $\mathbf{I}$ about a system subject to uncertainty represented by $\mathbf{X}$ or $\mathbf{X}^*$ is collected.

In decision analysis the probability that the information originates from system $\mathbf{X}$ or system $\mathbf{X}^*$ must be represented consistently in accordance with the best available knowledge. Indeed the information originating from system $\mathbf{X}$ and system $\mathbf{X}^*$ might be similar or in some cases even identical which underlines the difficulties associated with the immediate identification of the systems. Given that the existence of the systems have been realized the decision problem is then adequately analysed on the basis of Equation (3).

The fourth principal case concerns when the information is relevant but not correct, i.e. Category 4) information. Incorrect information may be caused by gross errors, e.g. in the collection or processing of information - or by intent. If gross errors are at hand the nature of the errors may be assumed to be random. Examples of gross errors include use of imprecise or defect equipment and misreading of data from tables.

Considering again the aforementioned examples, the information concerning the presence of damage to the bridge, an observed crack in the weld or the detection of particular pollutant in the

groundwater might be correct but can also be incorrect. Also the opposite holds, e.g. when damages, cracks or pollutants are not observed. In statistics such gross errors are considered in hypothesis testing and denoted Type 1 and Type 2 errors, respectively. In integrity management of fatigue sensitive details these types of errors are commonly modelled through the concept of the probability of indications or the probability of detection, see also Straub (2004).

As mentioned earlier, Category 4) especially – but in principle also Category 3) information may be due to intentional manipulation (i.e. "fake news") – in which case it might be expected that the information is tailored to achieve a specific objective. Intentional manipulation of information may concern in principle any of the information flows illustrated in Figure 2, however, most often when reference is made to "fake news" it especially refers to the flows of information to stakeholders, with the objective to modify their perception and thereby change the premises for decision making; i.e. the set of decision alternatives available to the decision maker as well as her preferences.

The principal decision analysis to account for manipulated information in the decision analysis is illustrated in Figure 8.
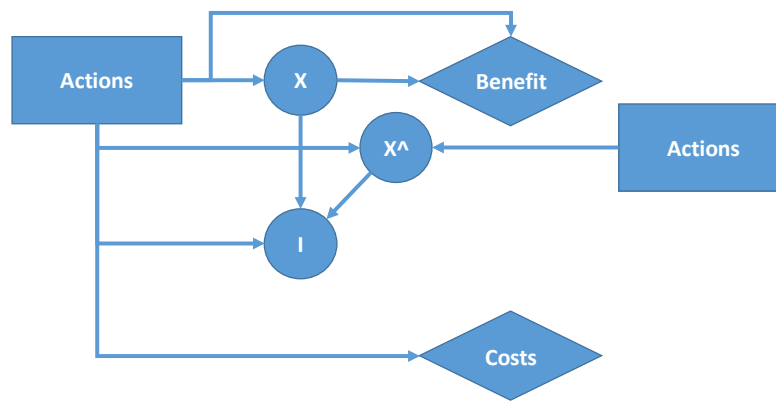

Figure 8   Illustration of principal decision analysis when manipulated Category 4) information I about a system subject to uncertainty represented by X is collected but where the information collected may originate from another system $X^\wedge$.

In Figure 8 a decision node is added compared to Figure 7 to highlight that in addition to appreciating the possibility that the information is not correct, actions are also considered for the management of the system which is the cause of the manipulation. Clearly the various possible causes for the occurrence of different categories of information may occur in combinations, and these must also be accounted for.

The final information condition concerns disrupted or delayed information, i.e. Category 5) information. This particular information condition is relevant to account for in decision analysis and systems modelling, whenever transmission of information may affect the system states and consequence generation. Again it is instructive to consider possible causes for disruption and delay of information as basis for the identification and inclusion of these types of events in the decision analysis. In practice, various types of technical failures play a significant role for this category of information, however it is important to notice that information disruption and delays are often seen as immediate consequences of events of natural hazards or larger industrial accidents. Finally, also cyber attacks should be mentioned as a cause for this category of information.

As a last point - the principle of "motive, means and opportunity" should be kept in mind. The information which is available in any decision making context should always be appreciated as the "chosen" information, which is why cognitive biases, in addition to the availability of resources of

the entity facilitating the information, might play an important role for relevance, precision and correctness of information.

From the foregoing discussion it is observed that information and its characteristics with respect to relevance, precision and correctness affect decision ranking in complex and dynamic manners – and it is evident that the management of information must be an integral part of decision support for the management of socio-technical systems.

6. Conclusions

In the present paper we address the premises for the interpreting and representing knowledge and information in the context of societal risk informed decision making. We find that the constructionist perspective to the representation of truth forms not only a philosophically sound but also a consistent and operational framework for this. Models developed and utilized for risk informed decision support must be understood as propositions, there is not one correct model but rather an ensemble of possible models which all must be accounted for in the context of the decision making.

Moreover, we provide arguments supporting that the process and approach to develop risk informed decision support does not depend on the source of hazards, nor the perceived intents of sources to do harm. Any possible underlying intent, just as any other system model assumption, represents a premise for the understanding and identification of possible efficient means for risk management. Such premises may and will also affect stakeholder perceptions of risks and have impact on the objectives for decision making as well as on the ranking of decision alternatives. However, this impact should not be presumed and included in the development of risk informed decision support. Risk informed decision support should rather be utilized as a vehicle to develop informed preferences of stakeholders, enhance the transparency of decision making processes and facilitate efficient management of risks in coherency with fundamental societal values.

We emphasize that indeed any risk management problem is nothing but a problem of information management and that focus should be directed on the flow of information and causes for different classes of conditions of information. Understanding and modelling the flow of information is of crucial importance for the identification of the system which is subject to management. To address these risks we propose a framework for the classification of conditions of information. However on this particular topic there is still substantial potential for research and improvements on methods and strategies for their management.

In support of decision making subject to possible multiple relevant system candidates, different types of hazards and classes of conditions of information we outline a scheme for decision analysis in which the system modelling is integrated into the decision optimization. Based on this approach we describe how the robustness of decisions may be quantified to assess the significance of possible system candidates and system modelling assumptions with respect to decision rankings. Finally, a principal example is provided illustrating selected aspects concerning how the condition of information may affect and be accounted for in risk informed decision making.

It is hoped that the present contribution will provide value in the further development of informed and preference coherent decision making in the management of societal risks, provide basis for identification of future areas of research and not least direct focus on the key concepts which must be carried into the curricula of future risk educations.

7. Acknowledgements

8. References

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