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Designing decision support systems at the interface between complex and complicated domains

Research-in-Progress

Tina Comes
Centre for Integrated Emergency Management (CIEM)
University of Agder, Norway
tina.comes@uia.no

Antonella Cavallo
Entrepreneurship, Commercialisation and Innovation Centre (ECIC)
University of Adelaide, Australia
antonella.cavallo@adelaide.edu.au

ABSTRACT

Crises are characterized by complexity, uncertainty and their dynamic evolution. Neither the development of the situation nor the consequences of a decision can be foreseen. Therefore, crisis management requires plans and strategies that are designed to account for lacking information and sudden system changes. With the rise of ICT systems, large amounts of data from heterogeneous sources are available to decision-makers that quickly need to be transformed into understandable and reliable information. Hence, the need arises for support in collecting and processing information that can be used for the continuous revision and updating of plans and strategies as an answer to the uncertainty and complexity that they entail. We build on notions from decision theory, emergency and risk management, complexity science and systems theory to conclude that epistemological pluralism and adequate ad-hoc approaches need to be integrated in the design of decision support systems for crisis and emergency management.

Keywords

Crisis management, complexity, uncertainty, risk management, decision support, systems thinking.

INTRODUCTION

Many aspects in our lives depend on how much we know about what is going on around us – our neighbors, our environment, and many other factors that we may not even think about. Questions such as "how often should I backup the data on my computer?"; "should I go to the police and tell them that I suspect that something weird is happening next door?" or "should I move to another country?", depend to a large extent on our information, our interpretation and whether or not we believe that this information is a valid basis for making our decision. Typically, the question of what we judge as "valid" to solve the problem depends on our perception, current mind-set, emotions and the options to solve the problem that we have in mind (Lindblom, 1959). Only in hindsight, we may be able to judge if the decisions made were 'right'. Yet, many times it may not even be possible in retrospect to determine whether the decision made was optimal, as we do not know how other alternatives would have performed.

BACKGROUND: DECISION SUPPORT IN CRISIS MANAGEMENT

While decisions are hard to make in our day-to-day life, problems in crisis management are even harder due to their far-reaching consequences, high pressure and short time. Nevertheless, similar to the situations described above, crisis management strategies are mostly influenced by the available or most prominent knowledge about the risks a decision involves. This is particularly challenging, as it is impossible for humans to process all the available information prior to choice (Maule and Hodgkinson, 2002). Standard paradigms in decision theory suggest that we should seek to make *the* optimal, or at least a good decision (Hites et al., 2006; Von Neumann and Morgenstern, 1953). To do so, we need to know the outcomes of a decision although it is not factual yet, in the sense that we cannot see, observe, touch, smell or measure them at present (Teigen and Brun, 1997). Moreover, decision outcomes will evolve over time and it may not be possible to differentiate clearly the outcome of a specific decision from the outcomes of other decisions. To compare the quality of the different options we have measures that integrate expectations about the future and the potential consequences of a decision, but also individual or collective value judgments, risk perceptions and preferences need to be taken into account (Comes et al., 2012; French et al., 2009; Huber, 1997).

The most prominent techniques to support decision-making under uncertainty are rooted in probability theory. The development of these models to manage uncertainty and risk can be traced back to the beginning of the 17th century when Blaise Pascal and Pierre de Fermat applied mathematical approaches to gambling (Frosdick, 1997). Since then, the theories of rational decision-making under uncertainty have been extended to comprise expected utility theory (Von Neumann and Morgenstern, 1953) and approaches to quantify uncertainty in cases of ambiguity, imprecision and lacking information, such as robust Bayesian methods (Ruggeri et al., 2005), second order probabilities (Baron, 1987) or imprecise probabilities (Walley, 1996). Although these normative techniques are conceptually sound and well developed, they do not seem to correspond to the human perception of uncertainty (Tversky and Kahneman, 2002): there is a considerable gap between the scientific methods to quantify and our intuitive approach to handle uncertainties. In fact, many people perceive uncertainty as an element of discomfort, something temporary, that is better to get rid of (Morin 2007).

To deal with uncertain and complex situations people frequently use heuristic forms of thinking; they involve processing less of the available information, and doing so in a simpler way. These heuristics are functional, in the sense that they make complex problems tractable. However, they are prone to error, which can lead to misjudgments and failure for individuals and organizations (Buehler et al., 2002). Beyond the individual sense of discomfort, the difficulties in communicating uncertainty and risk (Klinke and Renn, 2002) have contributed to a neglect of uncertainty in decision-making and strategic planning. There has been an incentive to hide or distort uncertainty assessments - particularly in highly controversial debates such as climate change (Mitchell and Hulme, 1999) or the transformation of the electricity supply towards a low carbon system integrating more renewables (Walker, 1995).

To manage and mitigate risks in complex and uncertain situations, there is hence the need for decision support that helps overcoming cognitive biases. The greatest challenges in designing such systems are the need for flexibility to account for increasingly fast changing environments and the consideration of the human factor in both the systems simulated and the visualization and explanation of results. To describe these challenges and outline how information systems supporting decision-makers facing these challenges can be designed, this paper is structured as follows: the next section discusses the most prominent approaches to risk management and their application in crisis situations. Subsequently, we introduce the Cynefin framework to distinguish complex and complicated situations as a basis for understanding the limitations of expert systems and models. Then, we discuss two possible approaches to manage complex risks: the precautionary principle, which is widely applied today, and the use of modern ICT systems. Finally, we highlight the need for integrated approaches, provide conclusions and outline ways forward.

LIMITATIONS OF CURRENT APPROACHES TO RISKS

Definitions of risk vary depending on the context and purpose of use. Contrarily to financial applications, we understand risk in a purely negative way and understand risk as the chance of something harmful happening, i.e. risk is the exposure of something we value to a hazard event, often measured in terms of probability of that event times consequence (Smith, 2004).

Along with an increasing number of hazard events and growing exposure and vulnerability of economy and society (Asbjornslett, 2009; Wang et al., 2012), risk management (RM) has become ever more important. It aims at achieving sustained benefit within each and across all human activities, and can be understood as an integrated part of all decisions we make. RM is, however, costly and resources are scarce. To prioritize risks and allocate efficiently RM resources one characterizes the relevance of risk events (or hazards: potential triggers) according to their frequency and potential harm (Arrow, 1996). For events that re-occur frequently, statistics and similar past cases are typically available, and the respective best practice RM measures can be implemented. Rare or unprecedented events are, however, often neglected (Wright and Goodwin, 2009), which is particularly misleading if stakes are high.

Therefore, one of the most difficult fields of decision-making is crisis management: information is typically scarce, ambiguous and uncertain, and few comparable cases are available. Traditionally, crises have been managed by following standardized procedures such as the National Emergency Risk Assessment Guidelines in Australia (NEMC 2011), standards for health and safety management such as ISO14971 or the Seveso regulations for hazardous matters, which were introduced in the EU as a reaction to the Bhopal disaster (Acquilla et al., 2005). Influenced by these standards, RM usually involves the steps risk identification, analysis, evaluation, mitigation, monitoring and review (Hoffmann 1985; Klinke and Renn, 2002), which are repeated in a cyclic manner. As the starting point in this framework is the identification of all potentially relevant risk events that need to be addressed in the subsequent phases, this approach is valuable for re-occurring or at least foreseeable risks whose frequency and severity of consequences can be analyzed and evaluated so that strategies can be created to deal with them.

This approach has several limitations. First, it relies on the assumption that all potentially relevant risks can be identified and described a priori, neglecting unforeseen, emerging or misinterpreted risks (Cavallo 2012; Gilpin and Murphy 2008). Moreover, the mitigation strategies themselves are mostly not considered to be error-prone. More generally, this approach does not account for the interlacedness of complex systems: failures typically propagate, so that one single triggering event can have multiple far-reaching consequences whose impact can grow via enforcing feedback loops (Helbing et al., 2006). To acknowledge the fact that not all risk sources may have been identified and not all potential impacts can be assessed, the concept of "residual risk" has been introduced: an umbrella term covering all risks that are not part of the explicit framework (Power, 2005). It is, however, unclear how these residual risks can be managed or controlled.

COMPLEX OR COMPLICATED: HOW MUCH CAN WE KNOW?

Another way of looking at risks is the distinction between complicated and complex risks which is drawn from Snowden's Cynefin framework (Snowden and Boone 2007). The Cynefin framework characterizes the problems we are facing and the information available by distinguishing between four cognitive domains, which go from 'simple' to 'complicated' to 'complex' to 'chaotic'. The extreme domains are the simple and chaotic: while in the simple domain, a problem is characterized by available information, which is easy to access and around which there is no ambiguity; in the chaotic domain, everything is uncertain. The domains have significant implications for the way we (should) make decisions: simple problems can be solved by referring to standard procedures and best practices, while in the chaotic domain, there are no rules or guidelines, not even models or tools that can provide help, and decision makers are left to their intuition.

Here, we focus on the interface between complex and complicated domains, where (computational) decision support systems can provide help and guidance. In everyday life, complicated and complex are often used as synonyms. However, there is a semantic difference: complicated risks are those, which involve a degree of uncertainty whose core can be ascertained before an event occurs. Although complicated risks may seem hard to understand or model, it is possible to gain an understanding about the problem by referring to expert knowledge and experience. This is typically the case for any engineered system, such as power plants or airplanes. Even though sometimes at the outset, information about complicated risks is difficult to access, decision-makers are able to find means and tools to support RM.

Complex risks are different. The relationship between cause and effect cannot be understood until after the event. The World Trade Centre terrorist attack in 2001, the tsunami in 2004 or HIV are examples of complex risks. The first two examples were complex, as they were unforeseen at the time, whereas HIV's complexity stems from the fact that it is not clear yet, how to eradicate the causes of its spreading, although we can model its spreading, which is a complicated component of this risk. Depending on the degree of uncertainty entailed in RM, different approaches are needed to solve the problems and make decisions.

The approaches to RM discussed above follow a pattern for which, once a risk has been identified as such, it is either considered as simple or broken down into a list of manageable sub-problems back-tracing the linear chains from causes to effects. On this basis, action plans and mitigation strategies can be formulated.

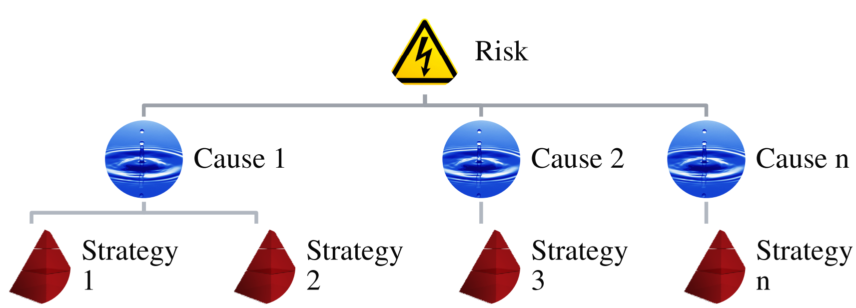

Figure 1. Decomposing risk into its elements – a breakdown structure.

The underlying assumption is that the problem can be divided into sub-problems and tasks that can be managed by specific organizations or actors independently from one another. By following the individual actions and solving each sub-problem, also the overall risk can be managed. For example, we assume that awareness campaigns, emergency kit distribution and services for the most vulnerable people will help mitigating the destructive effects of a natural hazard (and many other disasters for that matter).

Apart from these complicated risks, there are complex risks, which are harder to manage, as illustrated by the Fukushima disaster in 2011. In the first case, an earthquake triggered a tsunami, and these hazards together with the characteristics of the nuclear power plant (NPP) and its management resulted in a nuclear disaster. Here, it was not a single event, or a single reaction that led to the serious consequences, rather it was the combination and sequence of events. In hindsight, the risk analysis showed that the catastrophic outcome was caused largely by human error and misjudgment (The National Diet of Japan - Fukushima Nuclear Accident Independent Investigation Commission 2012). This example illustrates what we mean by the interface of complex and complicated. A NPP is itself an engineered system. There are blueprints of its layout, and the laws of physics enable us, in principle, to understand the outcomes of manipulations of the system. Considering the NPP as embedded in a social system – the humans running and steering the operations – adds a layer of complexity. In fact, despite operational local and international standards were in place in Japan, they were not followed – neither by the government nor by TEPCO, the company owner. This part of the risks qualifies for the 'complex' label, as they are risks, which could not have been identified before the event occurred.

Therefore, complex risks require an approach considering the different systems concurring to the risk event to happen. Eric Morin, one of the world experts of complexity used to say: "Complexity is the science of connection" Morin (2010): instead of breaking down the risk into its components, the relations between risk components and the systems to which these are attached need to be taken into consideration. Moreover, even systems that not have been considered relevant initially – such as human behavior that leads to the unexpected failure of engineered systems – may need to be connected to solve the problem. In this manner, even the system itself is continuously shaped and re-discovered during the management of complex risks. Particularly, the interactions between different systems are relevant to the risk analysis. Instead of using exclusively risk registers, the additional need to analyze risks in their network emerges.

Note that Cynefin does *not* enable us understanding the true nature of a system, which may be complex although we have not realized this (yet). The question about the nature of a system is hard to answer objectively, and "ground truths" are hardly available. Related to our understanding of the problem, the scope and framing we consider is important: building a levee that protects a community against flood of a given height is a complicated problem, which can be solved by engineers. The construction of the levee is, however, most likely only an intermediate that serves the more encompassing objective of protecting a community against climate change. In this sense, the question whether or not this goal is achieved depends not only on the adequate (technical) construction of the levee, but also on the environment, such as evolution of temperatures and meteorology, and the number of years, for which the levee is supposed to protect the community. If our focus is rather on protection, we might also ask what should or must be protected, defining infrastructures (power plants, hospitals, etc.) for which the risk should be much lower than for "normal" residential buildings.

Given the conundrum of interlaced problems we need to solve, one of the most crucial aspects in decision-making is realizing, if a problem is behaving sufficiently predictable to allow automated tools and models to be applied. The above examples show that often, we understand the true nature of the problem too late – when the system behaved in manners that we did not expect and damage was done. The question how to predict system changes given that our information is typically local and time horizons are rather short, is one of the most crucial questions in studying transitions between complex and complicated systems. How do we understand early enough that the system may not be as stable as we think it is? How can we recognize regime changes as early as possible? And how can we manipulate and influence the system such that it, ideally, stays in a stable state that we understand.

DESIGNING DECISION SUPPORT SYSTEMS

The precautionary principle: a way out?

The financial crisis, the case of the epidemic flues or the eruption of an Icelandic volcano have put in question the adequacy of our current RM protocols. The applied RM strategies have been found to be inadequate in retrospect. For example, as the swine flu stroke in Europe, most countries decided to buy significant amounts of vaccines. France alone bought 60 million vaccines, whereas Poland decided not to purchase any. In the end, France used only 5 million doses, and Poland did not have any significant raise in casualties compared to any other country which had purchased vaccines (France5.fr on 22nd April 2010). The considerable losses of airlines and industrial production across Europe in the aftermath of the Icelandic volcano outbreak in 2010 has inspired discussions about the actual danger of the ash cloud to air traffic (Gislason et al., 2011).

The use of the precautionary principle is often the symptom of decision-makers being overwhelmed by uncertainty (Cavallo 2010). The precautionary principle focuses exclusively on effectiveness: achieving a goal regardless of the cost or resources spent. By doing so, decision-makers neglect the negative side or longer-term effects that are not as obvious or urgent. Owing to time pressure and purely satisficing behavior, they do not strive to explore alternative options that may be more beneficial. This 'total risk averseness' (Kouvelis and Yu, 1997) leads to unbalanced decisions. Therefore, RM needs to balance effectiveness and efficiency.

A role for ICT systems

While in the past, modeling efforts and computational power have often be dedicated to building more sophisticated simulations or models, with the rise of social media, the role of information and communication technology (ICT) systems has changed. By understanding information systems as a means for communication and collective information gathering, processing and sharing, the complexity of a problem can be discovered earlier than ever before.

Modern ICT systems enable the consideration of goals, preferences and drivers of different stakeholders and actors. The relation between risks, decisions and goals of individuals or organizations show that complicated tasks are often embedded in a complex problem. In our levee example, the problem's complexity stems from hardly foreseeable environmental developments and the varying socio-economic environment and the goals and preferences of political decision makers and stakeholders (definition of protection levels). In this sense, a complicated problem with a specific objective can be understood as an integrated sub-problem of a complex one, and the questions whether or not the levee helps to achieve the overall goal (protection of community) and if the protection levels are appropriate make the problem complex. Again, information systems can used in to elicit these aims earlier than ever before, and they enable quick updates to changes in risk perception and preferences. While traditionally, workshops have been used to bring stakeholders and experts (physically) together, today ICT systems and social networks offer new possibilities for the collaborative design and interactive exploration risks and decision problems.

THE NEED FOR AN INTEGRATED APPROACH

When characterizing and modeling risk, we mostly rear to past events and experience. While the conclusions drawn from the cases discussed may seem apparent in hindsight, there are many complex situations in disaster dynamics that are characterized by high uncertainty and cannot be deciphered in advance because of the lack of adequate information. Even worse, we may not even know what information is actually relevant and needs to be considered (Pich et al., 2002; Snowden and Boone, 2007; Helbing and Lämmer, 2008). This complexity is not reflected in most approaches to RM, which focus on describing an event, its likelihood and its impact (Pender, 2001; Rasmussen, 1997).

Timely and adequate reactions to upcoming risk events depend on the perception of the situation (realizing that there is a crisis) and the ability to respond (controllability and adaptability of the system). Much importance has been given to the role of human beings in managing complexity: they are the most flexible elements in the system (e.g. Meadows 2002 and Snowden and Boone 2007). It follows that there is a need for the development of ICT systems and tools that interact with humans and exploit this flexibility, whilst at the same time combining their local objectives with overarching societal goals. In this manner, it can be avoided that different organizations or individuals only strive towards their "local" optima, whilst neglecting the impact of their further decisions that are made in parallel or future decisions.

RM requires a holistic analysis of the actual and cognitive implications for stakeholders to go through deeply uncertain decisions in the attempt to mitigate the disaster impact. It is important that risk plans account for social and personal factors that occur, for instance, personal views and attitudes influence how risks are estimated (Meadows 2002). Research on heuristics and biases addresses this tendency to make mistakes based on our personal convictions or wrong assumptions (Esgate, et al. 2005). ICT systems with a particular emphasis on human machine interaction can provide visualizations and explanatory reports in near-real time that enable addressing these heuristics in future.

CONCLUSION

In summary, complex systems are characterized by their dynamic development, which cannot be predicted a priori. Although some parts of the system may be complicated, the interplay between different parts of the overall system forestall the possibility to model and simulate complex risks by means of monolithic expert systems (Wright and Goodwin, 2009; Bryant and Lempert, 2010; Montibeller and Franco, 2011; Comes et al., 2013). We argued that therefore, a new concept of risk that does not focus on the event but characterizes the system itself is required. Along with this new concept of risk, an adaptation of risk management strategies is required that will involve the use of information systems in two ways. First, they enable us modeling the complicated parts of the problems, for instance by Bayesian networks or other simulation techniques. Second, they enable quick information collection, processing and sharing. In this sense, they enable controlling and monitoring when decision-makers assume that the problem is complicated and may help realizing relatively early that the situation evolves in unexpected ways as fundamental assumptions are not fulfilled. Additionally, once decision-makers realized that the situation is complex, ICT systems enable establishing connections between different systems. In this sense, they can help in increasing an understanding and exchanging information between actors or organizations whenever needed.

While first proofs of concepts and demonstrators are available (Bryant and Lempert 2010, Comes et.al. 2013, Montibeller et.al. 2011), an overall integrated participatory approach that respects the cognitive limitations of individuals, behavioral aspects and makes individual, organizational and societal goals transparent is part of our ongoing research. To this end, further workshops and interviews with end users and stakeholders are planned.

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