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Risk Management challenges in large-scale energy PSS

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Abstract

Probabilistic risk management approaches have a long tradition in engineering. A large variety of tools and techniques based on the probabilistic view of risk is available and applied in PSS practice. However, uncertainties that arise due to lack of knowledge and information are still missing adequate representations. We focus on a large-scale energy company in Denmark as one case of current product/service-systems risk management best practices. We analyze their risk management process and investigate the tools they use in order to support decision making processes within the company. First, we identify the following challenges in the current risk management practices that are in line with literature: (1) current methods are not appropriate for the situations dominated by weak knowledge and information; (2) quality of traditional models in such situations is open to debate; (3) quality of input data and representation of the results to the decision makers play an important role. Second, we introduce a selection of alternative, so-called "post-probabilistic", risk management methods developed across different scientific fields to cope with uncertainty due to lack of knowledge. Possibilities for overcoming industrial PSS risk management challenges are suggested through application of post-probabilistic methods. We conclude with the discussion on the importance for the field to consider their application.

Keywords: Product-service system; risk management; uncertainty; risk management tools; probabilistic challenges

1. Introduction

In order to achieve global competitiveness and sustain profitability, most manufacturing industries are transforming from a product-centric to a service paradigm [1]. The paradigm shift brings the notion of providing customers with accompanying services and systems, instead of only selling products. This has been studied under product-service systems (PSS) [2]. Initial interest under the PSS research domain focused on potential improvements in sustainability, from economic, environmental and societal point of view, as well as on better satisfaction of increasingly heterogeneous customer preferences [1].

A special case of PSS are industrial product–service systems that focus on business-to-business market and investment goods based industries [3]. For instance, in the defence and aerospace industries, their application has typically been achieved through performance-based contracts, yielding a life cycle perspective of the equipment [3].

As reviewed in [4], the PSS research field has significantly grown over the last two decades as one of the most promising business models for industrial companies. In particular, uncertainty management and decision making emerged as important topics since they have a significant impact on the overall strategic value of the asset delivered [5]. Furthermore, coping with uncertainty and risk is recognized as one of the main challenges in industrial PSS [6]. Yet, limited literature on the topic is available.

In our case study, we focus on a Danish large-scale energy company as one case of the current industrial PSS risk management best practice. Furthermore, we analyze their risk management process and investigate the tools they use in order to support decision making processes within the company. We investigate challenges and limitations of such risk and uncertainty representation.

Given the importance of proper decision support, exploring alternative approaches for dealing with uncertainty due to lack of knowledge is essential. We provide insights from so-called "post-probabilistic" approaches and discuss them briefly in the context of industrial PSS.

This paper aims to contribute to the understanding of the PSS risk management state-of-the-art, to highlight the

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importance for the field to go beyond traditional approaches in risk management and to introduce approaches that promise to overcome current challenges in practice. The paper is structured as follows. A brief view on the classical rational comprehensive way of thinking in decision making is presented in Section 2, including its limitations and reasons for considering extensions. In section 3, we describe our case study, a large-scale high tech infrastructure project. We investigate and classify Primavera tool challenges when used in risk management as a decision support tool. Section 4 offers possibilities for overcoming some of the identified challenges through the usage of alternative, post-probabilistic approaches. This is followed by the discussion in Section 5. Conclusions and future research directions are elaborated in the final Section 6.

2. Uncertainty and decision making in industrial PSS

Product-service systems often involve a substantial set of actions that are characterized by high costs, large number of stakeholders, long design and operational lifecycles, and significant societal impacts. The global transition towards service paradigm challenges the way we manage systems and in particular risk management has a significant role. A better understanding of service uncertainties as well as more research in the domain is needed [7]. Furthermore, uncertainties in PSS create complexity associated with the difficulty of identifying and quantifying causal links between a multitude of potential risks and specific adverse efforts [8]. When the knowledge base is weak, even simple relationships can carry high uncertainties [9]. Transparency in our reasoning, both in risk analysis and decision making, is therefore essential.

Uncertainty, its representation and the associated decision making are increasingly important in a variety of scientific fields, for example project management, environmental sciences as well as engineering. Both researchers and practitioners share thinking that decision advice should be accompanied by an uncertainty analysis which clarifies the quality and reliability of the conclusions. Uncertainty analysis has a long tradition and a range of quantitative analytical approaches to deal with uncertainties of stochastic nature is available [10].

Traditionally, probability based approaches have been used in engineering practice [11]. A review in [12] provides an overview of these methods and [13] offers application examples in PSS. However, large scale PSS are often bringing novelty, uniqueness, and first-of-a-kind solutions to an engineering problem [14]. Such situations are dominated by weak information and poor available knowledge. That is why theoretical and practical challenges emerged connected to the axiom in probability based approaches which denotes that precise measurements of uncertainties can be made [15]. This leads to limited applicability of traditional risk and uncertainty management approaches. Such methods heavily rely on expert judgement, prior experience and previously collected data, which is not available in these situations [16].

On the other hand, the classical rational comprehensive way of thinking aims to identify the best decision to be made [17]. The assumption in this case is that there exists an ideal decision maker who is able to compute with perfect accuracy and is fully rational. However, the concept of Bounded Rationality [18] argues that decision makers seek a satisfactory solution rather than an optimal one. Some of the reasons are: available time to make a decision, cognitive limitations and limitations caused by the tractability of the decision problem.

Second, our current knowledge base is partial, incomplete, and in some situation conflicting. In his study [19], Flyvbjerg observed that the main challenges of large-scale systems are inadequate, unreliable or misleading information. Using traditional quantitative risk management approaches in such situations that by their design require previously collected information is questionable.

Third, ambiguity refers to the fact that there are different ways in which factual statements may be interpreted by different individuals [9] and in case of multi-stakeholder decision making ambiguity increases significantly. Different studies, e.g. [20], show that other methods than probability-based approaches are required.

Fourth, [21] critically reviews and argues that traditional approaches succeed only if some rather controversial assumptions about the nature of uncertainty are accepted, such as that all uncertainty is stochastic. He further provides reasons for rejecting these assumptions when it comes to dealing with situations that we have limited information about and limited understanding of the system we analyze.

Different studies, e.g. [22]–[24] demonstrate violations of probabilistic assumptions if used to address uncertainty due to lack of knowledge. Additionally, an overview of the publications on this topic and the need to more fundamentally revise the approaches is available [25].

Because of these reasons, we analyze our industrial PSS case study and document concrete challenges in risk management practice when using current best practice tools.

3. Large-scale high tech infrastructure case study in the energy sector

The various ISO standards [26] and different professional and regulatory guidelines [27] represent a significant progress in risk management practice. However, it is still open to debate how applicable, appropriate and effective those guidelines are [28].

In order to document current challenges in industrial PSS risk management practice, we conducted an exploratory in-depth case study [29] with a case company involved in designing and deploying large-scale high tech infrastructure in the energy sector. Their risk management is recognized as one of the best practices due to their advanced way of dealing with risk and uncertainties throughout the process, tools and decision making they adopted and further developed. We conducted 18 interviews with their senior project risk manager, as well as analyzed the implementation of a complex, quantitative engineering design and deployment project risk model in Primavera. The key insights of the interviews and the analysis are:

Quality of probabilistic models: The key challenges occurred around the issue of model size and complexity. The engineering activities at hand generated a large number of activities and resources that needed to be modelled, including their dependencies, each of which was analyzed in terms of schedule risk. A large number of probabilities and probability distributions are required to run risk assessment simulations, e.g. regarding the duration of each task. Quality issues arose as to how representative the model actually is of the underlying project/system. It was difficult to justify simplifications that were made during the modelling process, particularly regarding the impact on the outcome of the risk assessment.

Quality of data and results: Data used to generate probabilities and probability distributions is perceived to play a critical role in the outcome of the risk assessments. While some probability distributions were developed based on similar past projects, others relied on expert opinion and group consensus, based on various elicitation techniques. However, their representation in the system are identical, and do not reflect the quality or reliability of the input data. The software tool also requires them to be put in as fixed probabilities and / or probability distributions, even when the precise estimates are not available. Additionally, various mathematical and computational tools are used during the simulations, without always fully appreciating their prerequisites or limitations.

Use and integration of results: Most analyses rely on advanced mathematical concepts employed during the simulation and computation of the risk assessment. Their meanings and implications cannot be fully appreciated without a deep understanding of the tools and methods used. The same applies to the origin and quality of the data, which can often no longer be judged from the results presentation.

Finally, existing tools **do not explicitly address the "gaming" aspects** of tailoring risk analysis approaches to produce the desired results, or interpret results one-dimensionally to suit a particular preconceived notion of desirable outcome.

4. Post-probabilistic risk management methods

It is important to make a distinction between uncertainties that can be treated through probabilities and uncertainties that cannot. We acknowledge the large merit of probability based methods when it comes to uncertainties of stochastic nature, but we also point out limitations that lead to the need for frameworks beyond probability when it comes to uncertainties due to lack of knowledge.

Post-probabilistic approaches collected across different domains are here systematically presented in three groups and represent an extended overview of the methods collected by [30]. From each group of methods we briefly describe those methods that have potential to better address industrial PSS risk management challenges discussed in Section 2. We further provide an overview of the fields in which these methods have been broadly discussed and used.

4.1. Imprecise probability

Imprecise probability [31] expands the possibilities of established probabilistic risk quantification to reason more reliably with limited information on actual probability distributions. The approach allows decision makers to review and discuss coherent and plausible ranges of probabilities. Given that probabilities cannot be known precisely if the modeller has only partial information at hand, imprecise probability suggests constructing probabilistic measures of interest as precise (or imprecise) as available data allows, in the form of intervals.

a) Coherent upper and lower probability

In Coherent upper and lower probability, the major novelty is the idea to drop a central assumption of Bayesian theory, which states that uncertainty should always be measured by a single (additive) probability measure. There is a large number of arguments which support the concept of Coherent upper and lower probability and why it is needed [32]. Given that it does not require unjustified assumptions which is the case with traditional approaches as argued in Section 2, the usage of this method nicely builds on top of [21] argumentation.

One well-recognized application of imprecise probabilities is in the domain of Artificial Intelligence. The methods have also been introduced and applied to the following fields: (1) Civil/structural Engineering [33], [24]; (2) Risk, resilience and vulnerability of critical infrastructures [34]; (3) Environmental risk assessment [35]; (4) Offshore oil and gas installations [36]; (5) Risk assessment of radioactive waste repositories [37].

b) The Dempster-Shafer theory of evidence

The Dempster-Shafer theory of evidence originates from the work of Dempster [38] in the context of statistical inference. Later on, it has been formalized by Shafer as the theory of evidence. In their study, [39] pointed out that the Dempster-Shafer theory of evidence, as a technique for modelling reasoning under uncertain, imprecise and incomplete information seems to have numerous advantages over the more traditional methods of statistics. The main feature of the Dempster-Shafer theory of evidence is the possibility to include additional judgments in evidential reasoning. This permits the theory to measure and take into account the weight of evidence, which arguably also addresses the argument about ambiguity from Section 2.

The Dempster-Shafer theory of evidence has also been applied to a certain extent in the fields of face recognition [40], statistical classification [41], target identification [42], medical diagnosis [43], risk assessment and applied biomathematics [44] and climate change [45]. A more complete overview of the research directions is available in [46]. Significant progress was made in signal processing by implementing imprecise methods thinking for reliability analysis [32].

4.2. Semi-quantitative methods

Semi-quantitative methods represent quantitative methods that are combined with additional qualitative information.

From the various semi-quantitative representations that are developed in different fields (see for example [47], [33], [48]), we here present the NUSAP Scheme [49].

c) The NUSAP Scheme

The NUSAP Scheme [50] can again be seen as an extension of established probabilistic modelling of uncertainty. It adds qualitative information to the uncertainty and risk analysis in a structured manner, informing the modelling, analysis and decision making process by making issues such as data origin, quality and key assumptions transparent. The acronym “NUSAP” stands for Number, Unit, Spread, Assessment and Pedigree, the five elements that constitute an information set regarding uncertainty in the method. Connected to the partial information available argument from Section 2, it is important to note that the NUSAP Scheme makes the background knowledge as well as assumptions transparent. That allows clear and easier communication with parties involved in decision making process.

Some of the experiences in applying the NUSAP system for environmental uncertainty assessments are summarized in the work of [51]. An example how the NUSAP method could be used in oil and gas industry is available in [52] or for uncertainty communication in environmental assessments in [53].

4.3. A family of related conceptual approaches based on Exploratory Modeling

A family of related conceptual approaches is based on Exploratory Modeling that uses computational experiments to run simulations. It represents the third group of post-probabilistic methods. The underlying idea is that instead of determining the best predictive model and solving for the risk mitigation procedure that is optimal (but fragilely dependent on assumptions), when dealing with uncertainty due to lack of knowledge it is wiser to seek among the alternatives those actions that are most robust, i.e. lead to at least a satisfactory result under a large number of possible future development scenarios. Considering the argument about limitations of a rational decision maker from Section 2, these set of methods represents a completely new way of thinking: instead of traditional “predict and act” paradigm, they bring “monitor and adapt” one. Here we introduce Robust Decision Making.

d) Robust Decision Making

Robust Decision Making (RDM) has been developed over the last 20 years, primarily by researchers associated with the RAND Corporation [54]. The RDM framework uses multiple views of the future to support a thorough investigation of modelling results that helps to identify a policy/plan/design [55], [56], that: (1) is robust; (2) avoids most situations in which the policy/plan/design/system would fail to meet its goals; and (3) makes clear the remaining vulnerabilities.

Since its development, RDM has been applied to strategic planning problems in a variety of fields, including climate change [57], complex systems [58], economic policy [59], flood and water risk management [60].

5. Discussion on PSS risk management challenges and post-probabilistic methods

Arguably, challenges that decision makers face in the fields where post-probabilistic approaches have already been applied are in many ways close to the ones that are often seen in industrial PSS. For instance, such decisions are characterized by a large number of stakeholders involved, weak available information, significant impact on the further process and overall system performance and have a significant societal impact. We focus on the decision analytic part and the way in which these methods work and what kind of insights they produce in the context of PSS development.

Post-probabilistic approaches introduced in this paper all aim to address challenges documented in the case example in Section 3. First, each of them represents a different modeling approach. In order to overcome probabilistic modelling limitations, alternative methods need to be considered when dealing with uncertainty due to lack of knowledge. Arguably, it might sometimes be possible to reduce uncertainty through more research. However, that might lead to additional and hidden costs of data gathering plus there are dangers associated with waiting for the results of this additional research. Deadlines and time pressures often impact decision making process dynamics.

Second, the quality of input data has been recognized as a very important part of risk and uncertainty analyses that impacts final results and therefore the final decision. Again, investing into more quality data might be too costly or too time consuming, so methods that offer decision making support with available data are essential. Some post-probabilistic methods, such as the NUSAP Scheme, address this issue in more depth. The others, such as the Dempster-Shafer theory of evidence, allow integration of multiple information sources with accompanied degrees of belief for each of them. The key with all the methods is to use all the pieces of information available (quantitative and qualitative) and not to make unjustified assumptions.

Third, equally important as to perform adequate analysis and get reliable results is to properly understand and use those outputs. Improvements compared to traditional approaches are in the following:

1. Imprecise probability methods allow computation of natural language statements [61], such as ‘A is more probable than B’ or ‘if not C then A is very likely’. By allowing experts to express their opinion in this way, we are able to gather more background knowledge than when forcing them to articulate unjustified precise estimations.

2. Semi-quantitative methods more thoroughly tackle the problem of communicating complex uncertainty analysis with decision makers, but some of them are also developed for communicating with lay public (the NUSAP Scheme).

3. The last group of post-probabilistic methods drops the "predict and act" thinking and introduce a “monitor and adopt” paradigm. These models change decision making more fundamentally and have produced reliable results in the fields such as water management [60], climate change [62] and policy related research [63] .

6. Conclusions and future research

Risk management tools are widely spread to support the decision making process in PSS. The PSS risk management practice has so far relied on probability based methods when treating uncertainty. Challenges with those methods emerged with the clear appreciation of uncertainty due to lack of knowledge and lack of information, rather than focusing on modeling uncertainties of stochastic nature. Through our case study we point out the challenges with such modelling, questionable quality of data used and therefore produced results, and difficulty of representation of the results to the decision makers.

Such challenges have triggered the development of alternative approaches in other fields. The methods introduced in this paper rely on the idea that imprecision and adaptivity correspond better to the weak information available which is the case in many PSS.

This is the first paper, to our knowledge, where alternative approaches of risk management are introduced to the field of PSS. Our objective is to inform future discussions on how and where these methods can be applied. We analyzed the case study and correlated possibilities of post-probabilistic methods with challenges identified.

In order to demonstrate the full benefit of such implementations real case studies are needed, as well as illustrative examples/synthetic cases. Future research in that direction would not only allow better treatment of uncertainty due to lack of knowledge, but would also broaden our understanding of decision making support in such situations. It is essential in our view for the field to consider these relatively recently developed methods, as well as their application potential when looking for more appropriate solutions to analyzing and quantifying uncertainty in industrial PSS.

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