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Exploring Deep Uncertainty Approaches for Application in Life Cycle Engineering

Miroslava Tegeltija[a,]*, Josef Oehmen[a], Igor Kozin[a], Jan Kwakkel[b]

[a]Technical University of Denmark, Produktionstorvet Building 424, 2800 Kongens Lyngby, Denmark
[b] Delft University of Technology, Jaffalaan 5, 2628 BX, Delft, The Netherlands

* Corresponding author. Tel.: + 45- 244-93228; fax: /; *E-mail address:* mirte@dtu.dk

Abstract

Uncertainty assessment and management, as well as the associated decision making are increasingly important in a variety of scientific fields. While uncertainty analysis has a long tradition, meeting sustainable development goals through long-term Life Cycle Engineering (LCE) decision making demands addressing Deep Uncertainty (DU). DU characterizes situations where there is no agreement on exact causal structures, let alone probabilities. In this case traditional, probability based approaches cannot produce reliable results, as there is a lack of information and experts are unlikely to agree upon probabilities. Due to the nature of LCE, this paper argues that methods to better cope with DU can make a significant contribution to the management of LCE. We introduce a set of methods that use computational experiments to analyze DU and have been successfully applied in other fields. We describe Robust Decision Making (RDM) as the most promising approach for addressing DU challenges in LCE. We then illustrate the difference between applying traditional risk management approaches and RDM through an example, complemented with the interview findings from a company using RDM. We conclude with a discussion on future research directions.

Keywords: deep uncertainty; life cycle engineering; risk; long-term planning; sustainability

1. Introduction

Over the last few decades, the life cycle engineering (LCE) research field has grown significantly. Achieving sustainable design and product development remains one of the central issues for the manufacturing industry [1], but also other domains where LCE concept has disseminated to, i.e. the food, building and textile industry [2]. Additionally, these industries dealt with a paradigm shift from a product-centric to a service paradigm, which enables customers with accompanying services and systems for the products produced [3].

It has been suggested by both researchers and practitioners that the development of LCE and in particular life cycle assessment (LCA) should keep pace with the complex and changing product development systems [4]. LCA is an important tool to assess the environmental impacts of product and service designs to support achieving sustainability. These changes lead to an increased importance of addressing uncertainty throughout the whole life cycle of a product or service. Uncertainty considerations are particularly relevant for the accuracy of LCA [5] and therefore, research in that direction is of great significance for the field.

Uncertainty assessment and management are also increasingly important (and controversial) in a variety of other scientific fields, for example climate adaptation planning, project management, as well as safety and security engineering. Uncertainty analysis and its research have a long tradition [6]. A range of quantitative analytical approaches to deal with uncertainties of stochastic nature is readily available. Traditionally, probability based approaches have been employed in engineering practice [7]. However, design

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and engineering activities often bring novelty, uniqueness, and first-of-a-kind solutions to an engineering problem [8]. The most important decision making situations in such cases are dominated by so-called 'Deep Uncertainty' (DU): uncertainties for which experts do not agree upon models to describe interactions among a system's components, and subsequently do not agree upon corresponding probabilities and possible outcomes [9]. This leads to limited applicability of traditional risk and uncertainty management approaches and the need for developing novel approaches. While there is no consensus among researchers on a single approach to cope with DU, there is the agreement that it should be modelled differently. However, the tendency in practice is still to employ traditional, probability based approaches. These traditional methods heavily rely on experts' judgement, prior experience and previously collected data, which is not available in situations governed by DU [10].

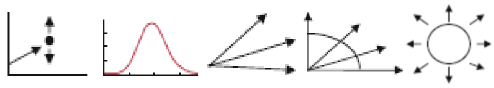
Decisions made by designers and engineers have a significant impact on the overall strategic value of the product and services produced [11]. The increasing societal and business criticality of product development projects raises a need to more thoroughly explore the various fundamental approaches to describe and quantify DU as part of LCE.

This is a conceptual paper that discusses the need to go beyond probability based tools in order to better address challenges in LCE and introduces the notion of DU and its representations. It is structured in six parts. First, the notion of DU is explained. An overview of the methods used to analyse DU is provided in Section 3. We then describe one of the methods, Robust Decision Making (RDM), in more detail in Section 4. Section 5 is a conceptual discussion, where we elaborate on RDM in contrast to traditional approaches in the context of LCE challenges through a water resource management example. Moreover, we interview the head of the risk management department in large-scale engineering company on their experiences with RDM and DU management. Conclusions and future research directions are elaborated in the final Section 6.

2. Deep Uncertainty and its representations

It is important to distinguish between uncertainties that can be treated through probabilities and uncertainties that cannot. Different taxonomies and representations of uncertainty have been developed. An uncertainty matrix was proposed by [12], which synthesised various taxonomies, frameworks, and typologies of uncertainties from different fields. The taxonomy has further been extended by [13], see Table 1. The goal of this synthesised overview is to support modelers in identifying uncertainties and communicating these uncertainties to decision makers. The typology of [12] conceptualises uncertainty as a three dimensional concept. These three dimensions are (i) the level dimension, (ii) the location dimension, and (iii) the nature dimension. Of these, the level dimension tries to capture differences in the types of scales that are used in practice when assigning likelihood to events [13]. Within this taxonomy, DU is understood as Level 4 and Level 5. This understanding is broadly consistent with [9], who defined DU as "the condition in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes."

Table 1. Synthesised uncertainty matrix by [13] and the progressive transition of levels of uncertainty from complete certainty to complete ignorance by [14].

Location	Level				
	Level 1	Level 2	Level 3	Level 4	Level 5
Context	A clear enough future	Alter-nate futures (with probab-ilities)	Alter-nate futures with ranking	A multi-plicity of plausible futures	An un-known future
					
System model	A single (deter-ministic) system model	A single (stochas tic) sys-tem model	Several system models, one of which is most likely	Several system models, with different structures	Un-known system model; we know we don't know
System out-comes	A point estimate for each outcome	A confi-dence interval for each outcome	Several sets of point estimates, ranked according to their per-ceived likelihood	A known range of outcomes	Un-known out-comes; we know we don't know
Weights on out-comes	A single set of weights	Several sets of weights, with a probabil ity at-tached to each set	Several sets of weights, ranked according to their per-ceived likelihood	A known range of weights	Un-known weights; we don't know we don't know

In their work, [14] further explain and categorise each level of uncertainty. Most of the LCE problems faced by decision makers are characterised by higher levels of uncertainty. For instance, designing a bridge or a tunnel with a 100-year lifetime involves some of the following considerations: estimating traffic intensity for the next hundred years, allowing the chosen design to adapt to any potential new installations and technologies that can/should be added to the system, estimating changes in the sea level, etc. As there is a wide range of outcomes for these alternatives that can take place, the question is how to best prepare for any combination of alternatives that my happen. The evolving, iterative, social and complex nature of LCE corresponds to a multiplicity of plausible futures, several variants for system models, a range of outcomes and associated weights or preferences regarding the various outcomes (corresponding to Level 4 or 5 uncertainty described in Table 1).

While many of the traditional analytical quantitative approaches are designed to deal with Level 1, Level 2 and Level 3 uncertainties [15, 14], it has been proven that those methods face challenges when dealing with the higher level uncertainty, i.e. Deep Uncertainty [14]. It can be argued that DU might sometimes be reduced by additional research and information gathering. However, that might lead to additional and hidden costs and delays, thus making it not feasible. This leads to the "real life" situations in LCE where actions have to be taken now, that we know are based on incomplete information and have significant impact on following processes and outcomes. We argue that DU-based approaches can offer relevant decision support to these types of decision situations.

A range of traditional uncertainty and risk management methods have been applied to Level 4 and Level 5 problems. Group processes, such as the Delphi technique [16], have helped large groups of experts combine their expertise into narratives of the future. This can be understood as a "Level 4" method, where plausible future scenarios are developed without necessarily quantifying the associated uncertainties. In his work [17] illustrates examples in risk analysis for which classical Monte Carlo methods yield incorrect answers when used to quantify higher levels of uncertainty. What IT development brought is statistical and computer simulation modelling that allow capturing quantitative information about the extrapolation of current trends and the implications of new driving forces. On the other hand, formal decision analysis can systematically assess the consequences of such information. Some more recently developed approaches, such as scenario planning help individuals and groups accept the fundamental uncertainty surrounding the long-term future and consider a range of potential paths, including those that may be inconvenient or disturbing for organizational, ideological, or political reasons [18].

However, despite this rich legacy, one key aspect remains a problem. The traditional methods briefly outlined above face challenges when dealing with long term multiplicity of plausible futures, unknown causal structures, probabilities and difficulty in identifying preferred solutions. In the following, we introduce a family of conceptually related approaches that are being used for coping with such situations, i.e. Deep Uncertainty.

3. A family of related conceptual approaches for coping with Deep Uncertainty

The DU literature rests on three key concepts:

A. Exploratory modelling: in the face of DU, one should explore the consequences of the various presently practically irreducible uncertainties for decision-making [19, 20]. This exploration uses computational scenario-based techniques for the systematic exploration of a very large ensemble of plausible futures [21, 22, 23].

B. Adaptive planning: decision robustness is to be achieved through plans that can be adapted over time in response to how the future actually unfolds [24, 13, 25].

C. Decision support: the aim of decision advise is to facilitate learning about a problem and potential courses of action, not to dictate the right solution. This entails a shift from *a priori* to *a posterior*i decision analysis. [26].

Instead of determining the best predictive model and solving for the uncertainty mitigation procedure that is optimal (but fragilely dependent on assumptions), the underlying idea is that in conditions of DU it is better to seek among the alternative decision options those actions that are most robust — that achieve a given level of goodness across the multitude of models and assumptions consistent with known facts [27]. From an analyst's and managerial point of view that means that the aim is no more to answer "What will happen?" question, but rather "Given the agreement that one cannot predict everything, which actions available today are likely to serve best in the future and keep my options open?"

A family of approaches exists for dealing with DU:

Assumption-Based Planning was developed at the RAND Corporation almost 30 years ago as a tool for improving the adaptability and robustness of an existing policy/plan/design [28]

Robust Decision Making (RDM) uses multiple views of the future to iteratively stress test one or more candidate strategies over many scenarios and refine the strategies in light of this [27]

Adaptive Policymaking was specifically developed to support the implementation of long-term plans despite the presence of uncertainties

Adaptation Tipping Points and Adaptation Pathways both approaches the timing of actions and were developed for water management [29]

Dynamic Adaptive Policy Pathways combines the work on Adaptive Policymaking with the work on Adaptation Tipping Points and Adaptation Pathways [24].

We further describe RDM as a promising approach to address the challenges in LCE under DU. RDM offers a structured way for planning under DU and it is the best known DU approach. Simulation models are used to evaluate different designs over a wide variety of different conditions. Next, using scenario discovery [30, 31], the analyst can discover conditions under which designs fail. In light of this, designs can be improved. RDM can support decision making under DU in LCE by providing recommendations that enable managers to choose and improve a design that produces satisficing outcomes across a broad range of possible future conditions.

4. Robust Decision Making to manage Deep Uncertainty

Robust Decision Making represents an approach that together with a set of model-based tools supports decision making under DU. It has been developed over the last 20 years, primarily by researchers related to the RAND Corporation [28]. The RDM framework helps decision makers to use multiple views of the future in support of a thorough investigation of modelling results that helps to identify a design that [9, 32]:

i. is robust (i.e., it performs “well enough” across a broad range of plausible futures, but may not perform optimally in any single future; as well as has little regret),
ii. avoids most situations in which the design would fail to meet its goals, and
iii. makes clear the remaining vulnerabilities (i.e., conditions under which the design would fail to meet its goals).

According to [27], RDM includes the following five steps:

1. Scoping — determine the scope of the analysis by identifying exogenous uncertainties, modelling options, key relationships, and performance metrics; construct a simulation model that relates actions to consequences.
2. Simulation — identify a candidate model to evaluate and run it against an ensemble of scenarios;
3. Scenario discovery — identify vulnerabilities of the candidate model (i.e., which combinations of exogenous uncertainties, and in which ranges, cause the design to fail to meet the goals);
4. Adaptation — identify hedging actions (modifying existing models or defining new ones) to address these vulnerabilities. Repeat steps 2 and 3 for additional candidate models;
5. Display — Plot expected outcomes of all models over probabilities of vulnerable scenarios, and choose the most robust option for implementation.

Over the years, RDM has been employed to support in strategic planning problems in a variety of fields, including climate change [33], complex systems [34], economic policy [35], flood and water risk management [36, 37].

5. Discussion of uncertainty quantification in LCE

Given the importance of decision support in LCE, exploring approaches for dealing with DU is essential. Some of the non-probabilistic methods introduced by [38] try to resolve the problem within “predict and act” paradigm in risk and uncertainty management, by introducing methods that are less reliant on probabilistic data. This set of methods corresponds more to the improvement of LCA by allowing better, more accurate estimates. Also, these methods allow the experts to provide information in data formats they feel more comfortable with (points, intervals, ratios as well as their combination), depending on the confidence level. Some studies further enhance the usage of non-probabilistic methods through comparative analyses with probabilistic approaches [39].

The approaches discussed in this paper on the other hand, drop the "predict and act" thinking altogether and introduce a “monitor and adapt” paradigm to replace it. These approaches change modelling more fundamentally and have produced reliable results in the fields such as water management [37], climate change [20], and policy related research [40]. Once crucial decisions under DU are made and additional information and knowledge are collected, traditional approaches can be employed to continue the uncertainty management in LCE.

Arguably, challenges that practitioners face in the other fields are in many ways close to the ones that are often seen in LCE. For instance, such situations are characterised by a large number of stakeholders, weak available information, significant impact on the further process and a noteworthy societal impact. We focus on the decision analytics part and the way in which these methods work and what kind of insights they produce in the context of LCE through the lens of one representative approach, RDM.

Traditionally in engineering, when dealing with lack of hard data, uncertainty analysis is based on expert judgement. Experts are asked to provide precise estimates on different activities and these estimates are the input for probabilistic analyses. The models used in these analyses need to have all the activities and correlations predetermined upfront. For a number of reasons these correlations are not always obvious and visible to the modellers.

With the latest developments in the manufacturing industry it is often not feasible to find solid ground for estimating probabilities. Even more so, subjectivity in expert judgement remains challenging [41, 42]. Furthermore, availability and quality of background information as well as a number of assumptions behind the calculations are not reflected in the results.

The current trend of achieving desirable life cycle properties (i.e., “-ilities”) further challenges the applicability of deterministic models [43]. As stated in [44], a survivable, flexible, or evolvable system should be able to sustain value delivery over time by responding to exogenous changes in the operational environment. To achieve that, we need to allow adaptivity and imprecision throughout the life cycle, and explicitly design for this.

One way to do that is to employ RDM in LCE: a large number of futures are generated based on performance criteria. First, RDM is used to sample a wider range of futures, which are subsequently assessed to see whether they are dire, benign, or opportunistic. Second, it offers a holistic assessment of the performance of generated options over the wider range of futures. The idea is that a design solution should work satisfactorily over a broad range of these possible futures. Also, RDM identifies which combinations of uncertain future stresses leads to system vulnerabilities through ‘scenario discovery’ [45, 46]. The 5-step RDM process (see above) is then repeated iteratively until a suitably robust solution is found. RDM aims to assist in the development of a solution whose performance is good enough over a wide range of futures (i.e., it is robust) rather than an optimal solution for a single specific future.

An example is presented in [45], where the authors applied RDM for a water management problem when statistical distributions of future events are poorly known, and followed the five described steps. In terms of LCE, RDM differs from traditional approaches, for instance Scenario Planning, by sampling a larger number of possible scenarios that are further evaluated. In the mentioned example, they generated 311080 possible simulations/scenarios, whereas Scenario Planning typically involves the evaluation of only a few identified scenarios. This provides more thorough analyses (for example, minimizing life cycle regret) that improve the quality of decision making in LCE, which impacts the quality of products and systems produced.

It is worth noting that such analyses are now feasible given the advances in computational methods. Moreover, RDM is complementary to other approaches [45] that bring additional information to the decision makers when managing DU.

This kind of modelling does not require unjustified assumptions and provides a structured framework for iterative refinement of future plans.

Discussion on RDM in LCE context with practitioners

Our case company is a large Danish company with extensive experience in designing and managing large engineering projects, including assessing cost and operational life cycle properties of complex, long life cycle infrastructure systems. We interviewed the head of the risk management department on his experience with RDM.

In their practice they recognized the need to look for alternative approaches that can actually manage DU. They analysed different options and decided to use RDM on one of their projects.

Several limitations were raised regarding RDM: first, in their experience, it can still be open to debate which design to choose when simulating the systems life cycle properties. RDM does not provide a "simple" answer and the analysis results must be further interpreted in the decision making process. Second, also RDM-based assessments of, say, 100-year life cycle system properties are based on current data, even if it is analysed and interpreted differently. Third, there are projects where the use of RDM is not justified, i.e. projects only involving the first three levels of uncertainty, where similar engineering solutions exist, where mostly uncertainties of stochastic nature are present, and the lifetime is rather short. Clearer guidance is needed when RDM effectively adds value to LCE decisions, and when not.

The case company agrees that there are LCE tasks in projects where higher levels of uncertainty are present and that currently employed, traditional approaches are only offering modelling capabilities corresponding to the first three levels of uncertainty. These cases are where life cycle performances of a one-of-a-kind bridge of 100-year lifetime have to be assessed, and they are dealing with first-of-a-kind solutions for engineering problems, novel technologies, new locations, more stakeholders and significantly longer lifetimes. Often, as in the water management example, traditional modelling approaches require them to make "precise" predictions based on the limited information available. That is where DU approaches can significantly support uncertainty management by more thorough analyses of possible alternative futures.

6. Conclusions

Risk and uncertainty assessment methods are widely used to support decision-making processes. Their ability to create a necessary level of confidence in the results is very important. To create such confidence, the key is to have a systematic, transparent, and rational analysis of uncertainty and the associated decision making.

There are a number of methods on hand to deal with uncertainty, so it is important to select the method best suited to the uncertainty in question. It would be desirable to have a single method capable of quantifying all types of uncertainty. Traditionally, one candidate for this task is probability theory.

The design risk and uncertainty management practice has so far heavily relied on probability based methods when treating uncertainty. We acknowledge the large merit of probability based methods, but we also point out limitations that lead to the need for frameworks beyond probability. One of the axioms in probability based approaches is that precise measurements of uncertainties can be made [47]. However, challenges have emerged from both theoretical and practical point of view. This has 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 in LCE.

This is the first paper to our knowledge where the 'monitor and adapt' paradigm is suggested for application in LCE to improve risk and uncertainty management practices. We raise the importance of distinguishing DU from uncertainty due to variance and point out complexities that it brings to decision making. Given the evidential need to go beyond probabilities when dealing with DU, we provide insights of what novel approaches offer and where they have been used. These approaches need further adapting to the conditions of LCE.

We further introduce RDM as a specific method for coping with DU in LCE. Nevertheless, in order to demonstrate the full benefit of RDM for LCE, real case studies are needed, as well as illustrative examples/synthetic cases. Future research in that direction would not only allow better treatment of DU, but also broaden our understanding of decision making support in such situations. In our view, it is essential for the field to consider these relatively recently developed methods and in particular their application potential when looking for more appropriate solutions to analyzing and quantifying uncertainty in LCE.

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