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POST-PROBABILISTIC UNCERTAINTY QUANTIFICATION: DISCUSSION OF POTENTIAL USE IN PRODUCT DEVELOPMENT RISK MANAGEMENT

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1. Introduction

Uncertainty represents one of the key challenges in product development (PD) projects and can significantly impact a PD project's performance. Risks in PD lead to schedule and cost over-runs and poor product quality [Olechowski et al. 2012]. Risk management is one response for the identification and management of risks. Acknowledging the increasing societal and business criticality of product development projects, there is a need to more thoroughly explore the various fundamental approaches to describe and quantify various types of uncertainty as part of the overall decision making process.
Decisions made by PD managers and engineers have a significant impact on the strategic value of the asset delivered, and these decisions depend on the quality of information on which they are based [Eweje et al. 2012]. Uncertainty plays an important role in decision making. Decision making quality improves if uncertainty is carefully addressed (e.g. [Prelec and Loewenstein 1991], [Riabacke 2006]).
In the risk management community there is a strong argument that at least two distinct types of uncertainty have to be taken into account: aleatory and epistemic. Epistemic uncertainty arises due to lack of knowledge and can be reduced by collecting and acquiring new knowledge. This is in contrast to aleatory uncertainty that is of stochastic nature, and therefore cannot be reduced, but can be well-modelled and described by probability distributions. In addition to uncertainty, ambiguity needs to be considered that addresses the different ways in which factual statements may be interpreted by different individuals [Klinke and Renn 2002].
[Flyvbjerg 2007] observed that the main challenges of large projects, including PD projects, are inadequate, unreliable or misleading information; and conflicts between decision making, policy and planning. It has been proven by empirical studies (e.g. [Levi 1990], [Sahlin 2012]) that the amount and quality of information behind probabilities and utilities is an important factor when making decisions, in other words, people tend to make different decisions if they are aware of the amount and quality of the data on which probability and utility assessments are based. Arguably, the key challenge in PD risk management today is that uncertainty quantification relies solely (or at least heavily) on probabilistic models. While these are appropriate to describe aleatory uncertainty, they are fundamentally ill-suited to model epistemic uncertainty. In this paper, we will explore novel post-probabilistic uncertainty quantification models that promise to better address epistemic uncertainty, and their possible application in the context of PD risk management.

2. Context of the study

Product development projects represent a very complex set of actions. Complexity in the sense of PD

risks refers to the difficulty of identifying and quantifying causal links between a multitude of potential candidates and specific adverse efforts [Renn et al. 2011]. PD projects are also characterized by high costs, large number of stakeholders, long design and operational lifecycles (sometimes on the order of decades) and significant societal impact. Therefore, the way we manage product development projects is very important. Particularly, risk management can impact a project's performance significantly. Even simple relationships may be associated with high uncertainty if either the knowledge base is missing or the effect is stochastic by its own nature [Klinke and Renn 2002], and uncertainty typically increases with complexity of a project. For this reason, transparency in decision making process is crucial.
Probability based risk methods have been broadly used for quantifying and assessing risks. Those methods have shown to be reliable tools when we have an uncertain, but broadly familiar situation. In cases where there is existing knowledge, information or experience regarding possible threats for a PD project, we are dealing with situations dominated by aleatory uncertainty. We can identify possible outcomes and run simulations on representative data sets. Classical example would be Monte Carlo simulation [Kujawski and Angelis 2009], for example to predict project cost based on using scaling parameters (such as weight, range or functionality) for comparable projects. Such quantitative techniques require numerical data while available information related to uncertainty factors is not, in many cases, numerical. Rather, this information can be introduced through natural language statements. Even though probability based tools have a long tradition, their limitation is that fundamentally, projects are often unique [Flanagan and Norman 1993].
In their study, [Aven et al. 2014] showed that probabilities can always be assigned under the subjective probability approach, but the origin and amount of information supporting the numbers are not reflected by the numbers produced. Their example clarifies that one may subjectively assess that two different events have probabilities equal to, say, 0.7, but in one case the assignment is supported by a substantial amount of relevant data, whereas in the other by effectively no data at all. This is the main argument in the critique of the probability based approach to dealing with epistemic uncertainty.

Table 1. Characteristics of tame and wicked problems [Atie and Andra 2008]

Characteristic	Tame problems	Wicked Problems
Relationship of problem and solution	The clear definition of the problem also unveils the solution	No agreement exists about what the problem is. Each attempt to create a solution changes the problem
Ability to evaluate quality of solution	The outcome is true or false, successful or unsuccessful	The solution is not true or false – the end is assessed as "better" or "worse" or "good enough"
Stability of the problem	The problem does not change over time	The problem changes over time
Scope of the task	The task is completed when the problem is solved	The end is accompanied by stakeholders, political forces, and resource availability. There is no definite solution
Stakeholder alignment and clarity of values	There are shared values as to the desirability of the outcomes	There are not shared values with respect to societal goals

Many of the issues that occur during the design processes are due to a lack of knowledge. A major weakness of risk management is that the methods used so far do not capture epistemic uncertainty. For the remainder of the paper, we will use the framework of Wicked and Tame Problems [Atie and Andra 2008] (see Table 1). We argue that Tame problems are dominated by aleatory uncertainty, and therefore existing uncertainty quantification methods are appropriate. Conversely, we argue that Wicked Problems are dominated by epistemic uncertainty, are not adequately addressed by existing risk management methods and therefore require novel, post-probabilistic uncertainty quantification methods.
Based on the challenges outlined above, a growing number of expert risk analysts and researchers find the dominating probability-base approaches for assessing risks and uncertainties to be too narrow (see,

e.g. [Aven and Zio 2011]. Therefore, alternative, post-probabilistic approaches for representing and describing risk and uncertainties have been suggested:

- Imprecise probability (IP) [Walley 1991]
- The Dempster-Shafer theory of evidence, proposed by [Dempster 1967] and closely linked theory of random sets [Nguyen 2006]
- Possibility theory [Dubois 2006], which is formally a special case of IPs and random sets theories
- Semi-quantitative approaches, for example NUSAP Scheme [Funtowicz and Ravetz 1990]

The main question we will discuss in the remainder of this paper is: How can we use post-probabilistic uncertainty assessment techniques to better support decision making processes in PD projects with data we have? Furthermore, what we are developing are hypotheses how post-probabilistic methods could better address epistemic uncertainties in PDs. Since PD projects are characterized by both Tame and Wicked problems, we argue that risk management must deal with lack of knowledge more systematically and strategically.

To correlate all the parts that have been introduced above, in Table 2 we merged our hypothesis with the examples from product development.

Table 2. Examples of PD problems and challenges to manage problems depending on the method type

	Tame problems	Wicked problems
Examples form PD	• Solving apparent technical issues • Incremental improvement of existing product • Daily disturbances • Lack of experts from the field	• Supplier problems • Regulation and/or law changes • Stakeholders disagreements • Unclear or fluid requirements • Design of large-scale socio-technical system (e.g. energy generation and distribution)
Dominant uncertainty	Aleatory uncertainty	Epistemic uncertainty
Dominant uncertainty quantification method	Probability-based method	Post-probabilistic method
Challenges of risk method	Probability based methods: • Compliance to existing standards • Balancing risk management effort with expected return • Integration of risk management results into decision making processes • Selection of appropriate quantification method, and associated skills in organization	Applying (ill-fitting) probability-based method • Escalating computational complexity in large projects • Quality and reliability of "translation" of natural language statements and epistemic uncertainty into numerical values Large effort for questionable decision support Project managers' view and biases Applying post-probabilistic methods: • Novelty issue: Implementation and skill development • Need to operationalize theory to industrial practice • Interpretation of results and integration into decision making process

3. Introduction to selected post-probabilistic theories

3.1 Imprecise probability

During the last three decades, a number of mathematical structures have been developed that relax the strong axioms of probability theory (Kolmogorov's axioms) and, by that, allow capturing epistemic in addition to aleatory uncertainty. This group of theories is referred to as the "theories of imprecise probabilities". Imprecise probability (IP) is a generic term for a range of mathematical models that measure chance or uncertainty without sharp numerical probabilities (e.g. "can be", "for example", interval-valued). These models include belief functions, Choquet capacities, comparative probability orderings, convex sets of probability measures, fuzzy measures, interval-valued probabilities, possibility measures, plausibility measures, and upper and lower expectations or previsions [Walley 1991]. IP admits that probabilities cannot be known precisely if the modeller has only partial information at hand. They suggest constructing probabilistic measures of interest as precise (or imprecise) as available data allows.

The major novelty in the concept is to drop a central assumption of Bayesian theory, which states that uncertainty should always be measured by a single (additive) probability measure. Unlike the Bayesian "dogma of precision", in order to characterize the uncertainty of an event with imprecise probabilities, we need both lower and upper probabilities.

There are a large number of arguments which support the concept of imprecise probabilities. The following list is taken from [Kozin and Petersen 1996] and illustrates from the practical point of view why imprecision in probabilities is needed:

- to reflect the amount of information on which they are based;
- to model a state of complete ignorance, meaning a total absence of relevant information;
- to combine several sources of information;
- to combine different probabilistic judgments generating an imprecise model;
- to treat disagreement amongst groups members over probabilities obtained by judgments in the same way as conflict between several assessments of one individual: both are sources of imprecision;
- to capture uncertainties of some problem situation more faithfully, not only due to randomness.

Football example [Walley 1996]

Consider a football game whose possible outcomes are win (W), draw (D) or loss (L) for the home team. To express its uncertainty about the outcome, the user makes the judgements:

1. Probably not W,
2. W is more probable than D,
3. D is more probable than L.

What can we say about the probabilities of the three outcomes?

The theory of coherent imprecise probabilities allows computing interval-valued probabilities based on the above partial and imprecise statistical information that is closer to the natural language, though tied to probability. The answer to the question is: P(W) = [1/3; 1/2], P(D) = [1/4; 1/2], P(L) = [0; 1/3].

If more non-conflicting judgements are provided, the bounds for the probabilities become tighter. Many other kinds of qualitative or quantitative judgements could be added to the three we have considered, for example,

4. if not D then W is very likely,
5. W is between 1 and 2 times as probable as D,
6. I am willing to bet on L at odds of 4 to 1,
7. W has precise probability 0.4.

The theory of coherent imprecise probabilities can also accommodate different reliabilities of different sources of information, if there are grounds to assume that one source of information is more reliable than another.

3.2 The Dempster-Shafer Theory of Evidence

Other theories of IPs allow deriving interval-valued probabilities given a different type of input. One of those theories is the theory of belief functions, the Dempster-Shafer Theory of Evidence (DS).

The DS theory originates from the work of [Dempster 1967] in the context of statistical inference. Later on, it has been formalized by Shafer as theory of evidence. In their study, [Beynon and Curry 2000] pointed out that DS, as a technique for modelling reasoning under uncertainty, seems to have numerous advantages over the more traditional methods of statistics. The authors emphasize that the theory has

been popularized in the literature of Artificial Intelligence and Expert Systems, but it has also been applied to certain extent in the fields of face recognition, statistical classification, target identification and medical diagnosis.
The main feature of DS is the possibility to include additional judgments in evidential reasoning. This permits the theory to measure and take into account the weight of evidence. Another key feature highlighted by [Beynon and Curry 2000] is that, unlike in possibility theory and statistical reasoning, there is no need to force our probability or belief measures to sum to unity. Hence, possibility theory can be considered a special case of DS.
The Dempster-Shafer Theory of Evidence is based on complex mathematical explanations, a discussion of which goes beyond the scope of this paper. One study by [Walley 1996], where the Dempster-Shafer Theory of Evidence has been mathematically exhaustively explained, is followed with a set of 6 examples, each mathematically grounded. The authors of this paper tried to find an example where an extent knowledge of mathematics in not necessary to follow the argumentation, but having failed to do so focus on one example of a key feature that is mentioned above.

Example: reliability analysis (quoted from [Aven 2014])

"To illustrate, suppose that a diagnostic model is available to indicate with reliability (i.e. the probability of providing the correct result) of 0.9 when a given system has failed. Considering a case in which the model does indeed indicate that the system has failed, this fact justifies a 0.9 degree of belief in such an event but only a 0 degree of belief (not 0.1) in the event that the system has not failed. This latter belief does not mean that it is certain that the system has failed, as a zero probability would; it merely means that the model indication provides no evidence to support the fact that the system has not failed. The pair of values {0.9; 0} constitutes a belief function on the propositions "the system has failed" and "the system has not failed"",

3.3 NUSAP (Number, Units, Spread, Assessment and Pedigree) measure

In contrast to previously presented theories, where today expert knowledge is required to interpret the results, a different technique was developed during the 1980s. The idea is to draw attention to the properties of numbers (which are often ignored) and to offer transparency when it comes to the quality of information. NUSAP scheme targets a broader audience and origin of the data plays a bigger role. [Funtowicz and Ravetz 1990], alarmed by the misuse of numbers in debates about nuclear safety levels and later the misuse of scientific findings by climate change "sceptics" to delay climate action, constructed the NUSAP notation. With the focus on policy-related research, they proposed that nowadays tasks should not only include the management of uncertainties, but also the assessment of quality and communication with the public.
We argue that high quality decision making does not necessarily require the elimination of uncertainty, but rather its effective management, as the NUSAP Scheme offers. The NUSAP measure can capture more background features than IPs, though, at the "cost" being a qualitative measure. Project risk management approaches must be based on coping with a lack of knowledge at least as much as on the application of knowledge [Funtowicz and Ravetz 1990]. The NUSAP measure has a large information content, but being a qualitative expression, there is no strict formal way to base decision making on it.
Funtowicz and Ravetz [1990] coined the term NUSAP as an acronym for the 5 categories of information included in their measure: Number, Units, Spread, Assessment, and Pedigree. The essential idea is that a result of any analysis, including risk and uncertainty quantification, should not be a single number, but it should be accompanied by additional information to allow decision makers to interpret its overall meaning value (here introduced through the four additional categories). The "unit" measure states whether we are talking about percentage or money or something else. "Spread" and "Assessment" is related to uncertainty. Spread is used to express the random error, and the systematic error is expressed by Assessment. The most significant novelty comes from the "Pedigree" measure, that informs on the information feed, or in other words, the origin and quality of data analysed. By providing detailed information to the decision maker on how data was collected, what the sample size and similar measures are, the NUSAP measure lets them judge the overall value and meaning of the presented data. It

eliminates uncertainty or misinterpretation whether for example a probability measure is just a guess or based on extensive simulation and testing.
There exist guidelines for the NUSAP application [Brocéliande team 2015] and the following list is quoted according to the same source.
Typical strengths of NUSAP are:

- NUSAP identifies the different types of uncertainty in quantitative information and enables them to be displayed in a standardized and self-explanatory way. Providers and users of quantitative information then have a clear and transparent assessment of its uncertainties.
- NUSAP fosters an enhanced appreciation of the issue of quality in information. It thereby enables a more effective criticism of quantitative information by providers, clients, and also users of all sorts, expert and laypersons.
- NUSAP provides a useful mean to focus research efforts on the potentially most problematic parameters by identifying those parameters, which are critical for the quality of the information.
- The diagnostic diagram, a NUSAP method, provides a convenient way in which to view each of the key parameters in terms of two crucial attributes. One is their relative contribution to the sensitivity of the output, and the other is their strength. When viewed in combination on the diagram, they provide indications of which parameters are the most critical for the quality of the result.

Example – Pedigree matrix:
The NUSAP example will focus on the explanation of Pedigree category, the major novel feature of the NUSAP method.
As illustrated in the table below, taken from [van der Sluijs et al. 2005], Pedigree can be used for coding qualitative experts' judgements.

Table 3. Pedigree matrix for parameter strength

Code	Proxy	Empirical	Theoretical basis	Method	Validation
4	Exact measure	Large sample direct measurements	Well established theory	Best available Practice	Compared with independent measurements of same variable
3	Good fit or measure	Small sample direct measurements	Accepted theory partial in nature	Reliable method commonly accepted	Compared with independent measurements of closely related variable
2	Well correlated	Modelled/ derived data	Partial theory limited consensus on reliability	Acceptable method limited consensus on reliability	Compared with measurements not independent
1	Weak Correlation	Educated guesses / rule of thumb estimate	Preliminary theory	Preliminary methods unknown reliability	Weak / indirect validation
0	Not clearly related	Crude speculation	Crude speculation	No discernible rigour	No validation

For the data types presented in the source, the validation scores are poor. Pedigree, in this case, conveys an evaluative account of the production process of information. Also, it indicates different aspects of the underpinning of the numbers and scientific status of the knowledge used [van der Sluijs et al. 2005].

4. Discussion of post-probabilistic methods in PD

4.1 Current state of the art in practice

The various ISO standards and different professional and regulatory guidelines represent a significant progress in risk management practice. However, it is still open to debate how applicable, appropriate and effective those guidelines are [Oehmen et al. 2014]. In order to apply a certain method, we need to simplify a real situation to a "practical" model. More assumptions need to be made in order to have calculable data. This is especially the case when using probabilistic methods. However, it is not justifiable to make significant assumptions when the overall level of ignorance is high. We propose using post-probabilistic methods to be transparent when there is a lack of knowledge and address those issues in a more structured manner, both qualitatively and quantitatively, instead of simply ignoring the degree and quality of available knowledge. Also, current practices need to make a step forward from relying on "manager's experience" or "expert opinion" as discussed later on, which can be seen as a simple "way out" to dealing with epistemic uncertainty.

4.2 Literature review

Post-probabilistic methods have found application in several areas, though practically all of them outside the PD and project management domain. For example, a well-recognized application of IP is the domain of Artificial Intelligence. In his study, [Walley 1996] compares four measures that have been advocated as models for uncertainty in expert systems. The measures are additive probabilities (used in the Bayesian theory), coherent lower (or upper) previsions, belief functions (used in the Dempster-Shafer theory) and possibility measures (fuzzy logic). A significant progress was made in signal processing by implementing imprecise methods thinking for reliability analysis [Kozin and Petersen 1996].

In their study, [van der Sluijs et al. 2005] showed experiences in applying NUSAP system in the Netherlands.

To understand the state of research and application relating to PD projects, we used the SCOPUS literature database. Table 4 gives an overview of key words and results. The filter was set to search within titles, abstracts and keywords of documents. In addition, key publications of authors dedicated to these methods were reviewed. Yet, no serious application cases were found. The collected papers represent suggestions and discussions on the implementation of a corresponding method into practice. No further development or adjustments of the methods were found.

Table 4. SCOPUS search to investigate application of post-probabilistic methods in PD projects

AND	Project management	Product development
Imprecise probabilit*	1 [Fletcher and Davis 2002]	0
Dempster	1 [Elst and Kiesel 2004]	1 [Li et al. 2012]
NUSAP	0	0

4.3 Comparison among fields

Professional experience and personal judgement are important for risk assessment. Product development projects are often unique. Tacit knowledge is therefore very important. As Polanyi, a research philosopher, said: "We can know more than we can tell", This is often how the way of working of experienced managers or experts is explained. There is not much transparency in such reasoning. This issue is being addressed in Artificial Intelligence, also with the help of post-probabilistic methods, and we suggest cross-sectoral learning to inform PD.

Also, similarities exist between System Reliability Analysis, where post-probabilistic methods are used, and PD: In a reliability analysis, the objective is to capture probabilities of subsystem failures, where subsystems consist of many small components. Projects, on the other hand, can be similarly divided into smaller dependent sets, and analysed regarding the risk they represent for the overall project.

4.4 A decision maker's perspective

Acknowledging risk and uncertainty assessments as decision support tools requires that the meaning

and practical interpretation of the quantities computed are presented and communicated in an understandable format to the decision makers [Aven et al. 2014].
There are three critical questions from a decision maker's perspective:

1. For a specific situation, which is characterized by a lack of knowledge, what options do I have?
2. How reliable is the first answer I get, and can I use it confidently?
3. How costly-effective is a particular analysis method?

We argue that post-probabilistic methods allow us to better address these three questions. By including additional judgements, we are taking into account all available information and yet clearly articulate what parts are not known. With the goal to faithfully represent and express the knowledge available to best inform a decision maker and to support the decision making process, the use of post-probabilistic methods can contribute to current product development practices.
Therefore, any new method that aims to complement traditionally used probabilistic methods for risk assessment, should adequately address the questions above. Both familiarisation and implementation of a method, for risk assessment analysists and decision makers, are acceptable and feasible if the benefits gained are reflected in terms of confidence and quality in making decisions.

4.5 Overall criticism of post-probabilistic methods

The key critique for alternative uncertainty representations and treatment in risk assessment is, as stated in [Flage et al. 2014], lack of operational meanings or interpretations.
Also, through their discussion [Aven and Zio 2011] tackled some researchers' concerns, an imprecise probability result is generally considered to provide a more "complicated", i.e. harder to process, representation of uncertainty. In their study they acknowledge arguments against IP, such as that simple representation should be favoured. The use of IPs goes against of the idea of simplicity, and for many, particularly "first-of-a-kind" applications, it will lead to initial confusion and difficulties. Others strongly defend the Bayesian approach and heavily criticise any other attempt to perform uncertainty analysis [Aven and Zio 2011].
Implementation of the DS theory was not readily accepted in risk community. After several iterations, it has been proven as a valid method, or at least as a mathematically sound one. However, when significant conflict in information is encountered, the use of the Dempster rule has come under serious criticism [Sentz and Ferson 2002]. Furthermore, as stated in the same report, other researchers have developed modified Dempster rules that attempt to represent the degree of conflict in the final result.
Mathematical representation of epistemic uncertainty have proven challenging. Calculating Dempster-Shafer intervals can be highly computationally expensive [Swiler et al. 2009]. Several studies, such as [Bauer 1997] elaborated on ways and methods to overcome this difficulty. Various approximation algorithms have been suggested that aim at reducing the number of important elements in the belief functions involved.
The computational complexity of the method is another concern. Arguably, even current methods are computationally expensive and time consuming. On the other hand, some are at least less complex, for example NUSAP Scheme, than some existing methods. One of the directions in current research is exactly going towards transforming these methods into more computationally usable ones, including the development of a "computational toolbox" as it exists in various commercial and non-commercial forms for probabilistic risk assessment. Other weaknesses of NUSAP, according to [Brocéliande team 2015] are the novelty of the method and limited (but significant and growing) number of practitioners who are using the method. Also, the scoring of Pedigree is to a certain degree subjective. The choice of experts to do the scoring is also a potential source of bias [Brocéliande team 2015].

5. Discussion, conclusion and future research

Risk assessment tools have been widely spread to support the decision making process. Those techniques should be capable of producing a necessary level of confidence in their results. To create this confidence, the key is to have a transparent, systematic and rational representation and analysis of uncertainty.
The PD Risk Management practice has so far relied on probability based methods when treating uncertainty. The development of probability as a measurement of uncertainty is based on an axiom that

precise measurements of uncertainties can be made [Bernardo and Smith 2009]. However, both theoretical and practical challenges have emerged. This has sparked the development of alternative approaches in other fields. The post-probabilistic methods introduced in this paper rely on the idea that imprecision correspond better to the weak information available which is the case in many product development projects.

This is the first paper, to our knowledge, where alternative approaches of risk assessment are introduced to the field of PD. Our objective is to inform future discussions on how and where these methods can be applied. Considering the criticism that we acknowledge in this paper, it is essential for the field in our view to consider these relatively new methods when looking for more appropriate solutions to analysing and quantifying uncertainty.

We acknowledge that it would be easier to follow the argumentation of this paper if the examples were from the product development field. We decided against "making up" examples that do not exist (yet), in favour of using examples that have survived the harsh review in the risk management community. What is necessary is to develop these examples through pilot applications and case studies, where the presented theories are adapted and tested in a PD environment.

References

Atie, S., Andra, S. B., "Wicked Problems and Applied Economics", American Journal of Agricultural Economics, Vol.90, No.5, 2008, pp. 1176-1191.

Aven, T., "Risk, Surprises and Black Swans: Fundamental Ideas and Concepts in Risk Assessment and Risk Management", Routledge, 2014.

Aven, T., Baraldi, P., Flage, R., Zio, E., "Uncertainty in Risk Assessment: The Representation and Treatment of Uncertainties by Probabilistic and Non-Probabilistic Methods", John Wiley and Sons Ltd., 2014.

Aven, T., Zio, E., "Some Considerations on the Treatment of Uncertainties in Risk Assessment for Practical Decision Making", Reliability Engineering and System Safety, Vol.96, No.1, 2011, pp. 64-74.

Bauer, M., "Approximation Algorithms and Decision Making in the Dempster-Shafer Theory of evidence—An Empirical Study", International journal of approximate reasoning, Vol.17, No.2, 1997, pp. 217-237.

Bernardo, J. M., Smith, A. F. M., "Bayesian Theory", Wiley, 2009.

Beynon, M., Curry, B., "The Dempster-Shafer Theory of Evidence: An Alternative Approach to Multicriteria Decision Modelling", Omega 28, 2000, pp. 37-50.

Brocéliande team, "NUSAP: Numeral Unit Spread Assessment Pedigree", Available at: <https://proxy.eplanete.net/galleries/broceliande7/nusap-numeral-unit-spread-assessment-pedigree>, 2015.

Dempster, A. P., "Upper and Lower Probabilities Induced by a Multivalued Mapping", The Annals of Mathematical Statistics, 1967.

Dubois, D., "Possibility Theory and Statistical Reasoning", Computational Statistics and Data Analysis, Vol.51, No.1, 2006, pp. 47–69.

Elst, L. Van, Kiesel, M., "Generating and Integrating Evidence for Ontology Mappings", EKAW, 2004.

Eweje, J., Turner, R., Müller, R., "Maximizing Strategic Value from Megaprojects: The Influence of Information-Feed on Decision-Making by the Project Manager", International Journal of Project Management, Vol.30, No.6, 2012, pp. 639-651.

Flage, R., Aven, T., Zio, E., Baraldi, P., "Concerns, Challenges, and Directions of Development for the Issue of Representing Uncertainty in Risk Assessment", Risk Analysis, Vol.34, No.7, 2014, pp. 1196-1207.

Flanagan, R., Norman, G., "Risk Management and Construction", Wiley-Blackwell, Oxford, 1993.

Fletcher, A., Davis, J. P., "Decision-Making with Incomplete EvidenceTitle", SPE-Asia Pacific Oil and Gas Conference, 2002.

Flyvbjerg, B., "Truth and Lies about Megaprojects", Delft University of Technology, 2002, pp. 1-27.

Funtowicz, S., Ravetz, J., "Uncertainty and Quality in Science for Policy Research", Kluwer Academic Publishers, 1990.

Klinke, A., Renn, O., "A New Approach to Risk Evaluation and Management: Risk-Based, Precaution-Based, and Discourse-Based Strategies", Risk Analysis, Vol.22, No.6, 2002, pp. 1071-1094.

Kozin, I., Petersen, K. E., "Obtaining Reliability and Safety Assessments on the Basis of Non-Probabilistic Methods", Intelligent Systems and Soft Computing for Nuclear Science and Industry, 2 International FLINS Workshop, 1996.

Kujawski, E., Angelis, D., "Monitoring Risk Response Actions for Effective Project Risk Management", Systems Engineering, 2009.

Levi, I., "Hard Choices. Decision Making under Unresolved Conflict", Cambridge University Press, 1990.
Li, L., Xiao, T., Ma, C., "Dempster-Shafer Theory Based HLA Collaborative Simulation Modelling", Gaojishu Tongxin/Chincese High Technology Letters, 2012.
Nguyen, H. T., "An Introduction to Random Sets", CRC Press, 2006.
Oehmen, J., Olechowski, A., Kenley, C. R., Ben-Daya, M., "Analysis of the Effect of Risk Management Practices on the Performance of New Product Development Programs", Technovation, Vol.34, No.8, 2014, pp. 441-453.
Olechowski, A., Oehmen, J., Seering, W., Ben-Daya, M., "Characteristics of Successful Risk Management in Product Design", Proceedings of the International Design Conference - DESIGN 2012, Dubrovnik, Croatia, May 21-24, 2012, pp. 269-278.
Prelec, D., Loewenstein, G., "Decision Making Over Time and Under Uncertainty: A Common Approach", Management Science, Vol.37, No.7, 1991, pp. 770-786.
Renn, O., Klinke, A., van Asselt, M., "Coping with Complexity, Uncertainty and Ambiguity in Risk Governance: A Synthesis", Ambio, Vol.40, No.2, 2011, pp. 231-246.
Riabacke, A., "Managerial Decision Making Under Risk and Uncertainty", International Journal of Computer Science, Vol.32, November, 2006, pp. 453-459.
Sahlin, N. E., "Unreliable Probabilities, Paradoxes, and Epistemic Risks", Handbook of Risk Theory, 2012, pp. 477-498.
Sentz, K., Ferson, S., "Combination of Evidence in Dempster- Shafer Theory", Contract, (April), Vol.96, 2002.
Swiler, L., Paez, T., Mayes, R., "Epistemic Uncertainty Quantification Tutorial", Proceedings of the 27th International Modal Analysis Conference, 2009.
Van Der Sluijs, J. P., Craye, M., Funtowicz, S., Kloprogge, P., Ravetz, J., Risbey, J., "Combining Quantitative and Qualitative Measures of Uncertainty in Model-Based Environmental Assessment: The NUSAP System", Risk analysis : an official publication of the Society for Risk Analysis, Vol.25, No.2, 2005, pp. 481-492.
Walley, P., "Measures of Uncertainty in Expert Systems", Artificial Intelligence, Vol.83, No.1, 1996, pp. 1-58.
Walley, P., "Statistical Reasoning with Imprecise Probabilities", Chapman and Hall, 1991.

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