Probabilistic Risk Management in Project Portfolios

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Abstract

We discuss a novel method for business risk handling in project portfolios under strong uncertainty, where we utilise event trees including adverse consequences together with mitigation costs and expected effects, where consequence and event probabilities and costs are represented by random parameters. The method has been developed to support large-scale real-life applications of portfolio risk management, where the properties of the probabilities and values are entered by domain experts with often very limited knowledge of probability theory, and we demonstrate how this can be accomplished with minor information loss. The method is currently in use in one of the world's largest telecom equipment manufacturers which has a vast project portfolio of tenders, with each successful tender subsequently becoming an order in the order book portfolio.

Keywords: Risk analysis, Decision analysis, Imprecise probability, Dirichlet distribution, Elicitation

1. Background

Many big project-driven business organisations have a large number of activities, tenders, and project proposals that could be considered and managed as a project portfolio. Business risks are unavoidable and many times they could even be beneficial in the sense that the "only" thing an organisation have to do is being better at managing the risks than its competitors. In this paper, we discuss a method for business risk handling regarding project portfolios under strong uncertainty. By strong uncertainty, we mean that there are not only uncertainties regarding whether the risks in the portfolio might occur or not, but there are also severe uncertainties regarding the parameters, i.e. the numbers associated with the probabilities and costs for each risk occurring. Impreciseness has been dealt with in a variety of ways for quite a long time using, e.g., capacity theory, sets of probability measures, interval probabilities, evidence and possibility theories, fuzzy measures, preference rankings, extended elicitation methods and higher-order probability theory, and others (cf. e.g., [1], [3], [8], [13], [2], [10], [12]), but the computational complexity can be high, which we discuss, for instance, in [5]. We therefore suggested a method in [4], utilising binary event trees for the modelling of problems but using intervals and qualitative assessments instead of precise numbers. However, this by itself has turned out to be insufficient for our purposes, which is why we in this paper have augmented our earlier interval-based method with an extended belief mass interpretation of the output intervals. In [6], we introduced a belief calculus for evaluating structures with these properties, i.e. foremost a way of determining the beliefs in various parts of expected utility/value intervals given interval input. In the original formulation, we were unable to assess risks in trees more than one level deep, nor employ a larger set of distributions. This paper describes how to combine this portfolio approach with the abilities of the method in [6] to determine the belief in risk portfolios where there could be sequences of (conditional) events and mitigations together with various belief distributions. Using this combined method, one of the world's largest telecom equipment manufacturers can analyse the degrees of belief there is the value of different mitigation efforts for alleviating adverse forecasted risks of each project in their project portfolios. The turnover of the manufacturer is around 25 billion EUR/year, and the reduction in losses attributed to a more efficient risk handling in the portfolio is estimated to $1-2\%$ of the total order value.

2. Risk Portfolio Modelling

The set of risks in a project is called a risk portfolio. Each risk is then modelled as a probabilistic tree, where each event has two outcomes: the risk occurs or it does not. The decision is to mitigate a risk or not. If it is mitigated, then the probability of the risk occurring decreases (or is eliminated altogether), and the cost of the risk occurring might also decrease. Thus, the handling of each risk can be described with a decision tree having two alternative courses of action, to mitigate (action A_1 leading to an event E_1) or leave the risk unmitigated (action A_2 leading to an event E_2). Each event then has two possible outcomes, either the risk occurs or it does not. In both the unmitigated and mitigated scenarios, the cost if the risk occurs is specified, while the cost if it does not occur is zero (excluding the mitigation cost). Costs are positive, i.e. they should be minimised.

A risk tree in our model is thus a decision tree in which there are only two alternatives, to mitigate or not. These are exclusive and exhaustive; the risk occurs or it does not with probabilities p and $1-p$ respectively. The value of

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not occurring is zero, i.e. the evaluation operates on a ratio scale. The objective is to minimise the total expected cost of risks in the portfolio. To model uncertainty, the input and output intervals in our model consist of lower and upper bounds as well as midpoints, which are represented as parameters for distributions of belief over the involved probabilities and cost values. These second-order belief distributions are then combined using basic combination rules (addition and multiplication) for random variables. This is the risk handling model in [4], which has now been extended with the belief calculus described in [6], yielding a multi-level portfolio risk handling method. In this new method, sequences of conditional risks can be modelled. In multi-level trees, a consequence node in which a risk occurs (c_i) can now in itself be an event node, thus yielding conditional event chains (e.g. only if a flood occurs that results in an overtop, there is a risk of a later mudslide).

The structures we are considering are thus binary risk trees, where each event node is represented by a binary risk, i.e. a pair in which a risk does or does not occur with probabilities $p(c_i)$ and $p(\bar{c}_i) = 1 - p(c_i)$ respectively. The cost of occurring is $v(c_i)$ and the cost of not occurring is zero $(v(\bar{c}_i) = 0)$. c is here either a direct consequence (cost) or a new binary risk.

There are distributions over the random variables p and v. This aggregation is calculated using the ordinary convolution of two densities and an analogous operation for the multiplicative case. Thus, the pair $F(p), G(v)$ is a description of the probability distribution and the cost distribution, where F and G are distributions over the random variables p and v, respectively, expressing the beliefs in p and v. The general properties of F and G are formally described in [6] but have the same properties as second-order probability distributions over p and v. Different distributions must be utilised for probabilities and values. This is necessary because of the normalisation constraint for probabilities, requiring them to sum to one for a set of exhaustive and mutually exclusive events in the model. To account for the uncertainties involved, we normally use Dirichlet distributions for probabilities and three-point distributions for values or costs in the general model, but the particular choices in the method in this paper are discussed below.

Given this representation, the multi-level portfolio evaluation is based on the resulting belief distribution over a generalised expected utility over the variables p and v, i.e., the resulting distribution over the portfolio expected value/utility above. It also takes mitigation measures into account and compares the portfolio entries prior to mitigation efforts (or sets of mitigation efforts) with post-mitigation values, including the mitigation effects and the mitigation cost. Mitigations are here modifications to one or more risks in which a set of new risk descriptors (new probability distributions, new cost distributions as well as new belief distributions) are activated. This yields no modifications of the structure or the consequences of any risk, but carrying out a mitigation incurs a cost and the risk descriptors are then replaced by new ones. All trees are of (usually) no more than three levels of depth (although there is no theoretical limit). They are all binary since each tree models a situation where a risk occurs or not. The expected cost of a risk is then calculated by a procedure in which the branching probabilities are multiplied for each branch and then the expectation is computed on the leaves of the tree (final consequence outcomes). The uncertainty is handled by the distribution of belief over the probabilities and costs. The expected portfolio cost is finally computed as the sum of the expected costs of the individual risks.

We have here assumed a principle of going concern, i.e. all assets and expectations are valued under the assumption that the business will operate for an indefinite time, and thus the large number of portfolio events can be approximated with skew-normal distributions having truncated tails. We can then use the distribution calculus (addition and multiplication operators) from [7] that enables the aggregation of risks in multi-level risk trees.

3. Probability Input Data Considerations

The purpose of the method is to support real-life applications of portfolio risk management, where the probabilities and costs are entered by domain experts (in this case sales personnel) with often very limited knowledge of probability theory. The data elicitation is then of course critical. In the application module, the users are asked for upper and lower bounds of the probabilities and costs involved. In addition, they are also asked for a third data point, the modal point. If the modal outcome is unknown, we use uniform or trapezoid distributions over the intervals for reasons elaborated upon in [7]. But if it can be reasonably estimated, then the (second-order) belief in probability distributions can be estimated by a three-point approach using the triangle distribution (cf. [11]) in [4] as well as the Dirichlet distribution in [6]. Distributions such as Beta and Erlang generally give similar triangular distributions and, e.g., [9] considers some frequently employed such. However, we assume that we only have limited sample data in the sense of the minima, maxima, and modal values.

A practical concern with employing Dirichlet distributions is that it is determined by the mean value rather than the modal value. In fact, for some parameter values, there exists no modal value at all. The goal of the method is to support real-life applications of portfolio risk management, where the probabilities and values are entered by domain experts (in this case sales personnel) with often very limited knowledge of probability theory. Since has turned out to be easier for laymen to visualise the top of a triangle rather than where the mean (centroid) is, it follows that the modal value in this sense is a more reliable input requirement than

Risks	Probabilities (%)			Costs (MEUR)		
	Min.	Mid.	Max.	Min.	Mid.	Max.
A	30	45	65	1.2	1.8	3.0
B	25	40	55	1.6	2.2	2.8
C	20	30	60	1.0	1.3	1.8
D	2	3	5	2.0	2.5	5.0
E	5	10	20	2.2	3.0	4.4
F	5	10	15	0.8	1.2	2.2

Figure 1: Portfolio entry with six risks

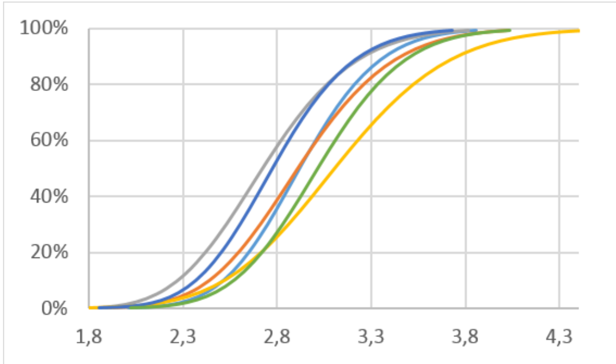

Figure 2: Cdf curves of the six distributions

the mean. To find out how much this issue influences the results of the method, we carried out a set of simulations, where the probability input to the model was given in six ways. Either as uniform or trapezoid two-point distributions, or as triangular or Dirichlet three-point distributions. The latter two with two different interpretations of the focal point (midpoint), either as a modal value or as a mean value.

As an example, consider the (unmitigated) portfolio entry with six risks, A-F, in Fig. 1. The expected value of this portfolio entry (see the previous section for a definition) gives rise to a cumulative density function (cdf) ranging approximately from 1.8 to 4 MEUR. In Fig. 2, the cdf for the six probability input distributions uniform (yellow), trapezoid (green), triangle/modal (light blue), triangle/mean (dark blue), Dirichlet/modal (red/orange), and Dirichlet/mean (grey) are shown. The cost input distribution was kept at the same triangular one for all cases.

The selection of which belief distributions to use was based on the reliability and validity of the input given the fact that it emanates from non-mathematically trained employees in the organisation we discuss. The distribution used most often in reality became the light blue triangle/modal. It can be seen (in Fig. 2 - from the example in Fig. 1 - and from simulations) that the results from that distribution are often very similar to Dirichlet/modal, so the latter option has not been incorporated in the released method. Due to the problems of project managers and sales personnel correctly estimating the mean (and oftentimes mixing the concept up with the modal, sometimes even not understanding the difference), the decision was made not to allow for mean input but only for modal. It is much more important for the organisation to achieve high data quality in terms of reliability, consistency, and transparency than offering a variety of input methods. The plausibility of that choice has been reinforced in subsequent discussions with the organisation, where they underline the importance of a few but clear-cut ways of making input and in a common understanding of the concepts involved. In these discussions, the concept of modal ("most likely") has a much higher understanding than mean ("mass point"). Finally, the trapezoid can be seen as the best two-point input alternative, getting closer to the three-point distributions in cases where there is considered to be no way available to estimate a modal value.

4. Concluding Remarks

In risk management considerations, the efficiency of mitigation measures must be taken into account, without violating a tolerable level of effectiveness. In this article, we have informally presented a novel method for risk analysis of business project portfolios under strong uncertainty, representing and evaluating such risks using intervals and belief distribution assessments, augmented with an evaluation method based on a belief mass interpretation of the output intervals. The method adheres to the principle of keeping the cognitive demand of its users to a practical minimum in order to keep up transparency and internal reliability in the sense that different users should obtain as similar results as possible in the same modelling situation by being able to give the same input. This requirement has made us use triangular input distributions using modal values rather than means for both probabilities and costs. Using simulations, we have also demonstrated to what extent such an approach affect the results and found that using a centroid-based method for probabilities might yield a smaller gain in theoretical precision. This would, however, probably come with the price of a larger loss in practical precision due to misunderstandings and input errors, rendering it less useful for practical purposes. This is not a restriction of the method as such, and a centroid-based approach could be used instead, but the choice is a practical consideration after having utilised the method in large-scale real-life portfolio risk management.

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References

[1] Rafik Aliev, Witold Pedrycz, Lala Zeinalova, and Oleg Huseynov. Decision making with second-order imprecise probabilities. *International Journal of Intelligent Systems*, 29(2):137–160, 2013. doi: 10.1002/int.21630.

[2] Thomas Augustin and Rudolf Seising. Kurt weichselbergers contribution to imprecise probabilities and statistical inference. *International Journal of Approximate Reasoning*, 98:132–145, 2018. doi: 10.1016/j.ijar.2018.04.009.

[3] Gustave Choquet. *Theory of capacities*. University of Kansas, Department of Mathematics, 1954.

[4] Mats Danielson and Love Ekenberg. Efficient and sustainable risk management in large project portfolios. In Jelena Zdravkovic, Janis Grabis, Selmin Nurcan, and Janis Stirna, editors, *Perspectives in Business Informatics Research - 17th International Conference, BIR 2018, Stockholm, Sweden, September 24-26, 2018, Proceedings*, volume 330 of *Lecture Notes in Business Information Processing*, pages 143–157. Springer, 2018. doi: 10.1007/978-3-319-99951-7_10. URL https://doi.org/10.1007/978-3-319-99951-7_10.

[5] Mats Danielson, Love Ekenberg, and Ying He. Augmenting ordinal methods of attribute weight approximation. *Decision Analysis*, 11(1):21–26, 2014. doi: 10.1287/deca.2013.0289.

[6] Mats Danielson, Love Ekenberg, and Aron Larsson. Decideit 3.0: Software for second-order based decision evaluations. In Jasper De Bock, Cassio P. de Campos, Gert de Cooman, Erik Quaeghebeur, and Gregory Wheeler, editors, *Proceedings of the Eleventh International Symposium on Imprecise Probabilities: Theories and Applications*, volume 103 of *Proceedings of Machine Learning Research*, pages 121–124, Thagaste, Ghent, Belgium, 03–06 Jul 2019. PMLR. URL http://proceedings.mlr.press/v103/danielson19a.html.

[7] Mats Danielson, Love Ekenberg, and Aron Larsson. A second-order-based decision tool for evaluating decisions under conditions of severe uncertainty. *Knowledge-Based Systems*, 191:105219, 2020. ISSN 0950-7051. doi: https://doi.org/10.1016/j.knosys.2019.105219. URL http://www.sciencedirect.com/science/article/pii/S0950705119305477.

[8] Didier Dubois and Henry Prade. Possibility theory and its applications: Where do we stand? *Springer Handbook of Computational Intelligence*, page 31–60, 2015. doi: 10.1007/978-3-662-43505-2_3.

[9] Dmitri Golenko-Ginzburg. Controlled alternative activity networks for project management. *European Journal of Operational Research*, 37(3):336–346, 1988. doi: 10.1016/0377-2217(88)90196-8.

[10] Cristoph Jansen, Georg Schollmeyer, and Thomas Augustin. Concepts for decision making under severe uncertainty with partial ordinal and partial cardinal preferences. *International Journal of Approximate Reasoning*, 98:112–131, 2018. doi: 10.1016/j.ijar.2018.04.011.

[11] Samuel Kotz and Johan René Van Dorp. Beyond beta - other continuous families of distributions with bounded support and applications. *World Scientific Press*, 2004. doi: 10.1142/9789812701282.

[12] Isaac Levi. *The enterprise of knowledge: an essay on knowledge, credal probability and chance*. MIT Press, 1983.

[13] Matthias C. M. Troffaes and Ullrika Sahlin. Imprecise swing weighting for multi-attribute utility elicitation based on partial preferences. In A. Antonucci, G. Corani, I. Couso, and S. Destercke, editors, *Proceedings of the Tenth International Symposium on Imprecise Probability : Theories and Applications, 10-14 July 2017, Lugano (Switzerland).*, Proceedings of Machine Learning Research, pages 333–345. PMLR, June 2017.