Department of Mathematics and Systems Analysis

Model-based decision processes for agenda building and project funding

Eeva Vilkkumaa

Aalto University

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Abstract

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Abstract

Essentially all organizations need to recognize relevant future developments in their operational environment as a backdrop for building strategic priorities which are typically implemented by choosing corresponding actions (such as R&D projects). These interlinked processes – most notably horizon scanning, strategic priority-setting and project selection – can all be framed as decision problems in which a subset or portfolio of alternatives is to be selected subject to limited resources and other relevant constraints. They can therefore be approached with methods of portfolio decision analysis (PDA) in order to maximize the value that the selected portfolio can be expected to yield and also to improve the transparency and quality of decision processes.

This Dissertation develops PDA methods to support the above decision processes, particularly in contexts where there are significant uncertainties. These methods capture uncertainties through set inclusion of feasible parameters and probability distributions. The methods accommodate the possibly conflicting preferences of multiple decision-makers, and they help identify portfolios that are resilient across a range of scenarios about the future. They also help mitigate so-called post-decision disappointment, which results from the fact that those projects whose values have been overestimated are more likely to be selected.

The methods in this Dissertation can also be used to develop optimal project funding policies which maximize the average value of the selected project portfolio or the number of those projects whose values are exceptionally high. They also guide the reduction of uncertainties by indicating about which projects it is optimal to acquire additional value estimates such that the resulting increase in the value of the portfolio exceeds the costs of acquiring such estimates.

Keywords Portfolio decision analysis, project selection, multi-attribute value theory, group decision making, incomplete information, robustness, scenarios, Bayesian modeling, value of information

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Tiivistelmä

Organisaatiot pyrkivät ennakoimaan toimintaympäristönsä olennaisia kehityskulkuja ja linjaamaan näiden pohjalta strategisia prioriteetteja, joita tyypillisesti toteutetaan vastaavilla toimenpiteillä (esim. t&k-hankkeilla). Nämä toisiinsa kytkeytyvät prosessit – erityisesti ennakointi, strateginen priorisointi ja hankevalinta – voidaan kuvata päätöstehtävinä, joissa osajoukko tai portfolio vaihtoehtoja valitaan rajallisten resurssien ja muiden rajoitusten puitteissa. Portfoliopäätösanalyysin soveltaminen voi parantaa sekä valitun portfolio arvoa että päätösprosessien laatua ja läpinäkyvyyttä.

Väitöskirjassa kehitetyt portfoliopäätösanalyyttiset menetelmät tukevat yllä kuvattuja päätösprosesseja erityisesti tilanteissa, joihin liittyy merkittäviä epävarmuuksia. Epävarmuutta mallinnetaan käypien parametrien joukoilla tai todennäköisyysjakaumilla. Menetelmät ottavat huomioon usean päätöksentekijän mahdollisesti ristiriitaiset mielipiteet; ne auttavat myös tunnistamaan sellaiset portfoliot, joilla organisaatiot voivat sopeutua erilaisiin tulevaisuuden näkymiin. Lisäksi menetelmät auttavat pienentämään niin kutsuttua päätöksen jälkeistä pettymystä, joka aiheutuu siitä, että sellaiset vaihtoehdot, joiden arvo on yliarvioitu, tulevat todennäköisemmin valituiksi.

Väitöskirjan menetelmiä voidaan käyttää myös linjattaessa hankerahoitusmenettelytapoja, jotka maksimoivat valitun hankeportfolion keskimääräisen arvon tai poikkeuksellisen hyvien hankkeiden määrän. Menettelytavat auttavat lisäksi tunnistamaan, mistä hankkeista on optimaalista hankkia lisäarvioita epävarmuuksien vähentämiseksi siten, että paremmasta arviointitiedosta aiheutuva portfolion arvon nousu kattaa lisäarvioinnin kustannukset.

Avainsanat Portfoliopäätösanalyysi, hankevalinta, monitavoitteinen arvoteoria, ryhmäpäätöksenteko, epätäydellinen informaatio, robustisuus, skenaariot, bayesilainen mallinnus, informaation arvo

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Publications

This Dissertation consists of a summary article and the following papers:

- [I] Vilkkumaa, E., A. Salo, J. Liesiö. 2014. Multicriteria portfolio modeling for the development of shared action agendas. *Group Decision and Negotiation* **23** 49–70.
- [II] Könnölä T., A. Salo, C. Cagnin, V. Carabias, E. Vilkkumaa. 2012. Facing the future: Scanning, synthesizing and sense-making in horizon scanning. *Science and Public Policy* **39** 222–231.
- [III] Vilkkumaa, E., J. Liesiö, A. Salo. 2014. Selecting a portfolio of actions with incomplete and action-dependent scenario probabilities. *Submitted manuscript*, 28 pages.
- [IV] Vilkkumaa, E., J. Liesiö, A. Salo. 2014. Optimal strategies for selecting project portfolios using uncertain value estimates. *European Journal of Operational Research* **233** 772–783.
- [V] Vilkkumaa, E., A. Salo, J. Liesiö, A. Siddiqui. 2014. Funding breakthrough technologies – balancing between experimentation and commitment. *Submitted manuscript*, 30 pages.

Author's contribution

Paper [I]: Vilkkumaa is the primary author. Salo proposed the research topic. Vilkkumaa established the theorems, carried out the computations for the case study, and wrote the paper under the guidance of Salo and Liesiö.

Paper [II]: Könnölä and Salo are the primary authors. Vilkkumaa carried out the computations for the numerical analyses and took the lead in writing section 3.3.

Paper [III]: Vilkkumaa is the primary author. She proposed the research topic. She established the theorems under the guidance of Liesiö, and designed and carried out the numerical analyses. Vilkkumaa wrote the paper under the guidance of Liesiö and Salo.

Paper [IV]: Vilkkumaa is the primary author. Salo proposed the initial research topic, which was later extended by Vilkkumaa and Liesiö to cover the analysis of value of information. Vilkkumaa established the theorems under the guidance of Liesiö, and designed and carried out the numerical analyses. Vilkkumaa wrote the paper under the guidance of Liesiö and Salo.

Paper [V]: Vilkkumaa is the primary author. She took the lead role in establishing the research topic with inputs from Salo. She formulated the model, established the theorems under the guidance of Liesiö, and carried out the numerical analyses. Salo commented on the positioning, structure, and scope of the text, together with Liesiö and Siddiqui.

Preface

This Thesis would not have been possible without the help, commitment and support of several people.

First of all, I wish to express my gratitude to my supervisor and instructor, Professor Ahti Salo, who has provided invaluable support throughout the years. His expertise, broad understanding of what constitutes high-quality research, and uncompromising attitude towards scientific writing have made it possible for me to produce articles that I can be proud of. It has truly been a privilege to work under the guidance of an internationally celebrated scholar in decision analysis.

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Helsinki, May 2014

Eeva Vilkkumaa

Contents

1 Introduction

Essentially all organizations pursue their goals by selecting and implementing courses of action that consume resources (Golabi *et al.* 1981, Stummer and Heidenberger 2003, Ewing *et al.* 2006, Kleinmuntz 2007, Phillips and Bana e Costa 2007). For instance, public research funding agencies define focal areas towards which funding is directed to promote scientific, economic, and social advancement. Companies evaluate and select R&D projects in the hope of increasing revenues and gaining a larger market share. Processes such as these can be framed as decision problems in which the decision-maker (DM) selects an agenda or *portfolio* of actions (referred to as *projects* in what follows), subject to the availability of scarce resources and other relevant constraints.

Regardless of the decision context, the impacts of the selected projects are typically uncertain (e.g., Grushka-Cockayne *et al.* 2008, Lindstedt *et al.* 2008). Moreover, these impacts may need to be evaluated with regard to multiple criteria. The key stakeholders in the decision-making process may have different, even conflicting preferences about the relative importance of these criteria, and about the desirability of the performance of the projects on these criteria (Salo 1995, Rios and Rios Insua 2008). Furthermore, the projects are often interdependent, whereby it may not suffice to analyze them separately, but rather as portfolios, whose number increases exponentially with the number of alternative projects.

The quality and transparency of such complex project portfolio selection decisions can be improved by methods of *portfolio decision analysis*. Indeed, formal methods to support such decisions have been developed since the 1950s (Mottley and Newton 1959) and, at present, there is a rich variety of such methods (see Kleinmuntz 2007 or Salo *et al.* 2011 for an overview). Advances in optimization models and increased computational power have made it possible to solve large mixed integer optimization problems that account for multiple resources, project interactions, and multiple time periods (Lockett and Gear 1975, Heidenberger 1996). Also, methods of multicriteria decision analysis (MCDA) have been developed for situations in which projects are evaluated on multiple criteria (Golabi *et al.* 1981, Ewing *et al.* 2006, Liesiö *et al.* 2007, Kleinmuntz 2007, Phillips and Bana e Costa 2007).

Uncertainty about the projects' impacts can be captured in different ways. For instance, some MCDA methods use set inclusion of feasible parameters to model uncertainty about the relative importance weights of the evaluation criteria and the projects' performances on these criteria (Salo 1995, Kim and Ahn 1999, Liesiö *et al.* 2007, 2008). Such models can be particularly useful in group decision settings, in which the group members may find it difficult to agree on precise weight and performance estimates. Also, scenario-based models have been presented to support project portfolio selection decisions in situations where the uncertainty about the projects' impacts is best captured by a set of alternative futures, called scenarios (Poland 1999, Gustafsson and Salo 2005, Toppila *et al.* 2011, Liesiö and Salo 2012).

From the perspective of modeling uncertainties, earlier methods for project portfolio selection are not entirely aligned with decision support needs. First, most group decision support methodologies based on MCDA – even those that accommodate incomplete information about criterion weights and the projects' criterion-specific performances – either (i) assume that the group can agree on a joint preference model, or (ii) consider the group members' preference models separately. In the first case, the group members may be less inclined to commit themselves to the decision recommendation if they feel that it is based on a forced consensus, whereas in the second case it may be difficult to identify compromise solutions on which the group could agree. Second, most scenario-based portfolio models assume that either (i) precise estimates can be obtained for the scenario probabilities, or (ii) the selected projects have no impact on these probabilities. The elicitation of precise probability estimates may be difficult or even impossible, and failing to account for the impacts that the selected projects have on the scenario probabilities may lead to suboptimal decisions.

Finally, the use of Bayesian analysis for modeling uncertainties has received hardly any attention in the context of project portfolio selection. Bayesian models, which help synthesize the prior belief about the projects' values with uncertain estimates about these values, have a long tradition in financial portfolio selection (Winkler and Barry 1975, Aguilar and West 2000, Polson and Tew 2000, Brandt *et al.* 2005, Soyer and Tanyeri 2006) and simulation modeling (Chick 1997, Cheng 1999, Merrick *et al.* 2005, Poropudas and Virtanen 2011). Moreover, the application of Bayesian methods to the selection of a single decision alternative has given important insights (Harrison and March 1984, Smith and Winkler 2006), suggesting that this thinking approach can be useful in portfolio selection problems as well.

1.1 Objectives and scope

This Dissertation develops methods for managing uncertainty in agenda building and project portfolio selection. These methods capture uncertainties about the model parameters through (i) set inclusion or (ii) probability distributions. In particular, this Dissertation discusses the following research themes, which are linked to Papers [I]-[V] as shown in Table 1:

RT1: The accommodation of the possibly conflicting views of multiple stakeholders about both the outcomes of the selected projects and the desirability of these outcomes,

RT2: The development of recommendations for project portfolios that are resilient towards wide variations in the future operational environment and help the DM steer the course towards the desirable future,

RT3: Ways to synthesize the prior belief about the projects' values with uncertain estimates about these values,

RT4: Optimal division of the total resources between project funding and costs of obtaining more accurate value estimates for the projects,

RT5: Optimal policies for project funding, evaluation, and abandonment, when the aim is to ensure that good projects are funded on the one hand, and to enable a rapid reaction to new emerging opportunities on the other hand.

Table 1: Scope of Papers [I]-[V].

	[I]	[II]	[III]	[IV]	[V]
RT1	X	X			
RT2			X		
RT3				X	X
RT4				X	X
RT5					X

1.2 Research methods and dissertation structure

Mathematical models are central in portfolio decision analysis. The modeling approaches in Papers [I] and [II] are multiattribute value theory (MAVT; Keeney and Raiffa 1976, von Winterfedt and Edwards 1986, French 1986, Belton and Stewart 2001), MCDA and, in particular, Robust Portfolio Modeling (RPM; Liesiö *et al.* 2007, 2008). Paper [III] uses decision trees to model uncertainties about the projects' impacts (see, e.g., Clemen 1996), and the Conditional Value-at-Risk measure to model risk preferences (Rockafellar and Uryasev 2000). Moreover, Papers [I]-[III] use set inclusion to accommodate incomplete information about the model parameters (e.g., Kirkwood and Sarin 1985, Hazen 1986, White *et al.* 1981) and multi-objective zero-one linear programming (MOZOLP; see Kiziltan and Yucaoğlu 1983) to compute the non-dominated portfolios.

Papers [IV] and [V] use Bayesian analysis to model uncertainties about the projects' values (see, e.g., Gelman *et al.* 2004 for an overview). Moreover, information value theory (Howard 1966) and statistical decision theory (Raiffa and Schlaifer 2000) are used to analyze the value of acquiring additional value estimates for the projects. Paper [V] formulates two-stage stochastic programming problems (Shapiro *et al.* 2009), which are solved by numerical simulation.

The rest of this summary article is structured as follows. Section 2 discusses the theoretical foundations of the main topics in this Dissertation. Section 3 presents the key contributions of Papers [I]-[V]. Section 4 summarizes the implications of these contributions and suggests avenues for future research.

2 Theoretical Foundations

Salo *et al.* (2011) define portfolio decision analysis as 'a body of theory, methods, and practice which seeks to help DMs make informed multiple selections from a discrete set of alternatives through mathematical modeling that accounts for relevant constraints, preferences, and uncertainties'. Early examples in this field include the work of Mottley and Newton (1959) in the context of selecting projects for industrial research, and that of Friend and Jessop (1969) in the context of coordinating planning decisions within local government. Over the years, methods of portfolio decision analysis have been applied in various decision-making contexts, including the selection of a portfolio of solar energy projects (Golabi *et al.* 1981), capital allocation in healthcare organizations (Kleinmuntz and Kleinmuntz 1999), the development of strategic plans for air traffic management (Grushka-Cockayne *et al.* 2008), and the dynamic adjustment of resources among project classes in a research and innovation center (Gutjahr 2011).

2.1 Multicriteria decision analysis in group decision support

From the 1990s onwards there has been an expansion of MCDA approaches to portfolio problems (e.g., Heidenberger and Stummer 1999, Phillips and Bana e Costa 2007, Stummer *et al.* 2009). Most of these approaches utilize multi-attribute value theory (MAVT; Keeney and Raiffa 1976) to model the DM's preferences about the projects. Under reasonable assumptions, these preferences can be captured with an additive value function in which

(i) the projects' criterion-specific performances are mapped to scores v_{ij} using the (possibly non-linear) criterion-specific value function, and (ii) the overall value of project x_j is the weighted sum $V(x_j) = \sum_i w_i v_{ij}$ of its criterion-specific scores (Keeney and Raiffa 1976). Here, the weights w_i reflect the relative importance of the criteria, i.e., the value gained from changing the criterion-specific performance of a project from the worst performance level to the best. The overall value of portfolio p can, then, be modeled as the sum of the projects' values included in it (Golabi *et al.* 1981, Golabi 1987)

$$V(p) = \sum_{x_j \in p} \sum_{i=1}^{n} w_i v_{ij}. \tag{1}$$

Keeney and Kirkwood (1975) show that, under reasonable assumptions, additive value functions can also be used to aggregate individual preference models $V_k(x_j) = \sum_j \sum_i w_{ik} v_{ij}$, $k = 1, \ldots, K$ of K DMs into cardinal group representations $V(x_j) = \sum_k g_k \sum_i w_{ik} v_{ijk}$, where g_k is the *group weight* of the k-th DM or *group member*. Using this representation, the overall value of portfolio p for the group becomes

$$V(p) = \sum_{x_j \in p} \sum_{k} g_k \sum_{i} w_{ik} v_{ijk}. \tag{2}$$

The group weights g_k in the above representation reflect the relative importance of the group members' preferences in determining the value of a portfolio. The assessment of such weights calls for interpersonal comparisons of value, which raises nontrivial questions about how or by whom such comparisons can be made (Keeney and Kirkwood 1975). To avoid making such comparisons, the entire range of the group members' possibly different views and preferences can be captured by methods that accommodate incomplete information about the weights w_i and scores v_{ij} in value representation (1) (White *et al.* 1981, Hazen 1986). Such methods have, indeed, proven useful in group decision settings (Salo 1995, Kim and Ahn 1999, Clìmaco and Dias 2006, Mateos *et al.* 2006, Salo and Hämäläinen 2010).

The RPM methodology, for instance, models uncertainty about the weights w_i and scores v_{ij} in value representation (1) through sets of feasible parameters such that these sets (i) include the 'true' values and (ii) are consistent with the DMs' preferences and beliefs about the projects' outcomes (Liesiö *et al.* 2007, 2008). For instance, rather than assessing precisely *how much* more important criterion 1 is than criterion 2, the DMs may simply agree that criterion 1 is more important than criterion 2. Similarly, scores may be assessed as intervals instead of precise numbers, allowing subjective statements such as 'the societal impact of this project has a score between 70 and 90', or 'the net present value of this project is between 200 and 240 thousand euros'. Although such statements do not generally result in a single 'best' portfolio, they can be used to generate robust recommendations about which projects should be selected or discarded, and which ones should be subject to closer analysis.

MCDA methods that admit incomplete information about weights and scores have been applied to a variety of group decision processes, such as screening of innovation ideas (Könnölä *et al.* 2007), participatory budget elaboration (Rios and Rios Insua 2008), and development of air traffic management plans (Grushka-Cockayne *et al.* 2008). These applications, however, assume either that there is a joint value representation all group members agree on, or that the DMs are able to provide complete preference information. Such assumptions can be problematic in decision settings where the DMs have uncertain but yet conflicting preferences about the relative importance of the evaluation criteria.

2.2 Scenario models for project portfolio selection

In some decision contexts, uncertainty about the projects' impacts is best described by a set of alternative futures, called *scenarios* (Meristö 1989, Mobasheri *et al.* 1989, Bunn and Salo 1993, Schoemaker 1995, Peterson *et al.* 2003). This is particularly the case when the projects' impacts are influenced by exogenous uncertainties through depending, for instance, on whether a major legislative change takes place or not. By drawing attention to uncertainties, scenarios can help select project portfolios that perform relatively well across alternative futures (Wilson 2000).

A conventional approach to scenario-based project portfolio selection is to assess the probability of the scenarios, to evaluate the impacts of the projects in each scenario, and, finally, to select the project portfolio that has the highest expected performance (e.g., Poland 1999). It may, however, be difficult to obtain precise estimates for the scenario probabilities due to psychological biases associated with subjective probability estimation, for instance (Tversky and Kahneman 1974, Hogarth and Makridakis 1981, Goodwin and Wright 2001). Therefore, methods have been developed to generate decision recommendations in settings where the information about these probabilities is incomplete (Walley 1991, Moskowitz *et al.* 1993). Liesiö and Salo (2012), for instance, use set inclusion to model uncertainty about the scenario probabilities. For instance, rather than saying that the probability of a major legislative change is exactly 65%, the DM may state that this change is more likely to happen than not (i.e., has a probability higher than 50%).

Just like the incomplete weights and scores in the MCDA framework, incomplete scenario probabilities may not result in a single best portfolio. Nevertheless, dominance relations can be used to identify portfolios that are not outperformed by any other portfolio for any feasible scenario probabilities. However, although such decision recommendations are robust across the scenarios, they do not account for the influence that the selected projects may have on scenario probabilities and, in particular, on the probability of reaching the more desirable scenarios (Schoemaker 1995, Peterson *et al.* 2003, Robinson 2003, Porter *et al.* 2004). Failing to account for the possibility of influencing these probabilities may, therefore, lead to suboptimal decisions.

2.3 Bayesian models in decision analysis

Besides set inclusion, uncertainty about the decision parameters can be modeled through probability distributions. Such models can benefit from Bayesian analysis, where prior belief about the projects' values is updated according to the evaluation information (e.g., Gelman *et al.* 2004). Bayesian modeling of uncertainties has received hardly any attention in portfolio decision analytical methodologies. Yet, the application of Bayesian methods to the selection of a single decision alternative has made it possible to increase the expected value of the selected alternative (Bielza *et al.* 1999) and to uncover and mitigate the problem of post-decision disappointment (Brown 1974, Harrison and March 1984, Smith and Winkler 2006), suggesting that this approach can be useful in portfolio selection problems as well.

The Bayesian framework also facilitates the analysis of value of information. In particular, the framework helps study how much the acquisition of additional value estimates for some projects is expected to increase the value of the selected portfolio *prior to actually acquiring these estimates* (Howard 1966, Raiffa and Schlaifer 2000). Such analysis helps organize the evaluation process cost-efficiently in that additional estimates are acquired only for those projects for which the increase in the value of the selected portfolio can be expected to offset the costs of acquiring the estimates.

Delquié (2008) shows that under quite general assumptions, the value of information in choosing between two alternatives is highest when the DM is indifferent between the two, and lower when there is strong initial preference for choosing one alternative over another. In the context of choosing one of many alternatives with normal prior and likelihood distributions, Frazier and Powell (2010) conclude that it pays off to obtain additional estimates about a subset of alternatives only, and that this subset is smaller when the estimation accuracy is better. In portfolio decision analysis, the value of information has been studied primarily through simulation studies (Keisler 2004, 2009).

3 Contributions of the papers

Table 2 summarizes the contributions of papers [I]-[V]. Specifically, Paper [I] extends the RPM methodology to account for the possibly conflicting views of multiple DMs. In paper [II], the RPM methodology is used in a foresight project to synthesize the assessments of multiple experts about emerging policy issues. Paper [III] develops a scenario-based portfolio model that accounts for incomplete and project-dependent scenario probability information. Paper [IV] develops a Bayesian framework for modeling uncertainties in project portfolio selection problems. Extending this framework to a multi-period setting, paper [V] studies optimal policies for funding so-called breakthrough technology projects.

Specifically, the group model presented in Paper [I] uses value representation (2) – i.e., $V(p) = \sum_{x_j \in p} \sum_k g_k \sum_i w_{ik} v_{ijk}$ – such that the information about the criterion weights w_{ik} and value scores v_{ijk} can be incomplete. No precise group weights g_k need to be specified either; instead, it is possible to introduce statements such as 'the weight of DM 1 is larger than that of DM 2' without stating exactly how much larger it is. Importantly, no information about the relative importance of the group members is needed. Decision recommendations that reflect the full range of the group members' viewpoints may foster stronger commitment to the implementation of the decision. Often, however, a consensus can be reached over assigning a minimum weight to each group member, and the group model presented in Paper [I] supports the transparent modeling of such constraints.

Because of the incompletely defined value scores v, criterion weights w and group weights g, no single portfolio usually maximizes the overall value for the group within the feasibility constraints. Instead, decision recommendations are based on the concept of *dominance*. In particular, portfolio p is said to dominate portfolio p', if the value of p is higher than or equal to that of p' for all feasible values of (v, w, g), and strictly higher for some combination of them. It would be irrational for the group to choose portfolio p', because portfolio p is certain to be at least as valuable and possibly more valuable. Thus, the analysis makes it possible to recommend *non-dominated* portfolios, i.e., those that are not dominated by any other feasible portfolio (RT1).

Based on the computation of non-dominated portfolios, the projects can be categorized into three groups: core projects are included in all, exterior projects in none and borderline

Table 2: Contributions of the papers

Paper	Research objectives	Methodology / Approach	Main results
[I]	Extend the RPM methodology to group decision settings	RPM methodology and multi-objective zero-one linear programming	Methodology to identify jointly non-dominated project portfolios and project-specific points of agreement / disagreement
[II]	Validate the viability of the RPM methodology in foresight processes	Case study: RPM methodology applied to supporting a foresight project by the Bureau for European Policy Advisors	RPM methodology is useful in highlighting those issues that merit attention from different perspectives (relevance, different views, rare events)
[III]	Develop a scenario-based project portfolio selection model that accounts for incomplete and project-dependent information about scenario probabilities	Decision trees and multi-objective zero-one linear programming	Methodology to generate decision recommendations for resilient and proactive project portfolios
[IV]	Develop a Bayesian framework for modeling uncertainties in project portfolio selection problems	Bayesian analysis, information value theory / statistical decision theory	Bayesian modeling helps increase portfolio value, mitigate post-decision disappointment, and obtain additional information cost-efficiently
[V]	Develop a multi-period project portfolio selection model to study optimal policies for funding breakthrough technology projects	Bayesian analysis, stochastic programming, numerical simulation	One should experiment by starting a large number of projects but commit resources only to those projects which, based on experimentation, have the potential to result in breakthroughs

projects in some but not all non-dominated portfolios. Core projects should thus be selected because they are supported by the whole group for any feasible choice of decision parameters. Likewise, exterior projects should be discarded. Further discussion and efforts towards obtaining additional score information should be focused on the remaining borderline projects, because narrower score intervals on core or exterior projects do not reduce the set of non-dominated portfolios. To support the selection of the final portfolio, an *acceptability index* is developed to help analyze how the non-dominated portfolios resulting from the group model perform in terms of the group members' own value models.

Paper [II] presents a foresight exercise carried out by the Joint Research Centre - Institute for Prospective Studies (JRC-IPTS) for the Bureau of European Policy Advisors. The aim of this exercise was to identify future trends and disruptive events that could have major implications on EU policy-making by 2025. For this purpose, 129 forward-looking reports were analyzed by JRC-IPTS experts to identify emerging policy issues. These issues (381 in total) were then assessed on a 1-7 Likert scale in an online survey by 270 external experts with regard to three criteria: (i) relevance to EU policy-making, (ii) novelty in comparison with earlier policy debates, and (iii) probability of occurence by 2025.

The expert assessments were synthesized using the RPM framework (RT1). In particular, the sets of non-dominated issue portfolios were computed for (i) mean-oriented analysis, (ii) variance-oriented analysis, and (iii) rare event -oriented analysis. In the mean-oriented analysis, the aim was to identify those issues which most of the respondents found relevant, novel, and probable. Thus, the criterion-specific scores for the issues were obtained by taking the means of the respondents' assessments. In the variance-oriented analysis, the aim was to identify those issues on which the respondents had different views. For this purpose, the scores were defined by the variances of the respondents' assessments. The rare event -oriented analysis was carried out to identify those issues that the respondents considered improbable but still novel and relevant. Here, the scores of the issues on relevance and novelty were obtained as in the mean-oriented analysis, but those issues with the lowest probability assessment 1 received the highest probability score 7 and vice versa, i.e., *Probability score = 8 - average of the probability assessments*.

In each of the three analyses (mean-, variance-, and rare event -oriented), ordinal information about the relative importance of the three evaluation criteria was used to generate the sets of non-dominated portfolios consisting of the top ten policy issues. Information about those issues which were included in more than 50% of the non-dominated portfolios in at least one of the three analyses were presented to the participants of a two-day workshop, the purpose of which was to prepare proposals for cross-cutting challenges that combined at least three of such issues. In this way, the RPM analysis helped focus on the most pertinent issues based on which the workshop participants formulated cross-cutting challenges and, moreover, developed visions as to how the EU could respond to these challenges through policy making.

Paper [III] develops a scenario-based model to generate decision recommendations for project portfolios when (i) the information about scenario probabilities is incomplete, and (ii) the selected projects may affect these probabilities (RT2). Technically, the incomplete probability information is modeled by bounding the set of feasible probabilities through constraints that may depend on which projects are selected. Decision recommendations are then based on dominance relations between the portfolios. The recommended portfolios are (i) resilient across the range of future scenarios in light of the incomplete scenario probability information, and (ii) proactive in that they help steer the course towards the desired scenario by influencing these probabilities. As in RPM, these recommended portfolios help prioritize the individual projects by dividing them into three categories: (i) core projects that should be selected, (ii) exterior projects that should not be selected, and (iii) borderline projects.

Paper [IV] develops a Bayesian model framework to tackle with uncertainties attached to the estimation of the projects' values (RT3). Due to estimation uncertainties, it is difficult to identify the truly best projects, whereby the selected portfolio is typically suboptimal. Furthermore, it can be shown that the value of the selected portfolio is systematically overestimated, causing the DM to experience *post-decision disappointment* (Harrison and March 1984, Smith and Winkler 2006). The phenomenon underlying post-decision disappointment is, in short, that the more the value of a project has been overestimated, the more probable it is that this project will be selected. Thus, even if the value estimates are unbiased *a priori*, the optimization-based selection process implies that the estimates for the recommended projects are likely to be higher than the actual values of these projects.

The model framework in Paper [IV] helps alleviate problems of suboptimality and post-decision disappointment by explicitly modeling the underlying uncertainties through Bayesian methods (Gelman *et al.* 2004). That is, by associating a prior probability distribution with the projects' true values and a conditional distribution with the estimates, a posterior distribution for the true values given the observed estimates can be obtained by using Bayes' rule. With the help of the posterior distribution, the decision problem can be formulated as that of maximizing the expected portfolio value given the projects' value estimates, instead of maximizing the estimated portfolio value. This approach is shown to increase the expected portfolio value and to eliminate the expected post-decision disappointment.

The posterior distribution can also be used to compute the probability P_i of project i being included in the truly optimal portfolio. This probability can serve as a measure for analyzing the performance of individual projects with respect to the portfolio. Such a project performance measure can be more suitable in portfolio selection than, for instance, the benefit-to-cost ratio, because it takes into account factors such as the project's cost relative to the budget or interdependencies with other projects.

Finally, the Bayesian model framework provides tools for analyzing the value of additional project evaluations. Because the evaluation process can be expensive and time-consuming, the DM should re-evaluate only those projects about which the additional information can be expected to lead to a higher portfolio value that offsets the cost of the re-evaluation. With the help of the Bayesian model framework, the expected value of re-evaluating any subset of projects can be computed explicitly. As a rule of thumb, it pays off to obtain additional evaluations of only those projects that can be re-evaluated relatively accurately and that have particularly uncertain initial value estimates close to the selection threshold (RT4).

Building on the Bayesian uncertainty model of Paper [IV], Paper [V] develops a multi-period project selection model to study optimal funding policies for promoting so-called breakthrough technology projects that offer exceptionally high value to society. In particular, the model helps examine how to optimally allocate resources between (i) committing to completing some technology projects based on initial project evaluation and (ii) experimenting by starting a large number of projects about which additional information is obtained through interim evaluations before deciding which projects will be completed.

In the model, new project proposals become available in each period. Out of these proposals, the DM grants full funding to some projects and conditional funding to others based on an initial evaluation. Those projects that obtain conditional funding are re-evaluated after some time at a cost and, based on the more accurate value information, some of these projects can be abandoned to release resources for new opportunities. In each period, there is a fixed budget to be allocated to project funding and evaluation costs. The *funding policy* is determined by how many projects are launched, re-evaluated and abandoned in each period, and by the number of periods the projects are funded prior to re-evaluation.

The model is used to determine the optimal static funding policy that would, on average, yield (i) the highest expected portfolio value or (ii) the highest number of funded breakthrough technology projects over time. Technically, the optimal funding policies for these two objectives are determined by solving two-stage stochastic optimization problems with discrete decision variables. Because no analytical solutions can be derived for these problems, guidelines for optimal funding policies are obtained by numerical simulation.

The numerical results suggest that in order to promote breakthrough technologies, more resources should be allocated to experimentation; in particular, one should first launch a large number of projects, re-evaluate most projects after some time and, based on the resulting information, abandon a high proportion of on-going projects (RT4). The more uncertain the initial estimates, the longer one should wait before abandoning projects (RT5). This policy differs from the optimal policy for maximizing the expected portfolio value, which is to fully commit to those projects that appear to be the best based on the initial evaluation. These differences are important in that a policy which serves to maximize the expected portfolio value may fail to promote breakthrough technologies, and vice versa.

4 Discussion

4.1 Theoretical and practical implications

This Dissertation develops new models to capture uncertainties in project portfolio selection. Papers [I] and [III] extend the RPM methodology which, in addition to the case study presented in Paper [II], has been used in several applications: screening innovation ideas for the Finnish Ministry of Trade and Industry (Könnölä *et al.* 2007), supporting the development of research agendas for the Finnish Forestry Industry (Brummer *et al.* 2008), and optimizing bridge maintenance programs for the Finnish Road Administration (Mild 2006). The Bayesian modeling framework studied in Papers [IV] and [V], on the other hand, represents a novel approach to modeling uncertainties in portfolio decision analysis.

The group decision support model developed in Paper [I] is the first to accommodate incomplete information about criterion weights, the projects' criterion-specific performances, and the group members' relative importance weights. This model offers several benefits. First, the points of agreement and disagreement are explicitly revealed, so that negotiation efforts can be focused on the most pertinent issues. Second, the developed performance measures provide systematic tools for analyzing the acceptability of the recommended portfolios and the projects included in them from the points of view of both the group and the group members. Finally, the methodology helps generate compromise solutions outside the group members' individually preferred portfolios, thus possibly alleviating the 'zero-sum game' nature of the negotiation process.

In Paper [II], RPM is used in a novel way to support the identification of emerging EU policy issues in a foresight exercise. One might argue against the use of an additive value model in this setting, for instance because one of the criteria on which the issues are evaluated is 'probability'. From a practical point of view, however, the aim of the RPM analysis in this exercise was not to support the selection of an issue portfolio but, rather, to screen out those issues out of many that were seen as most interesting from different perspectives. With a large number of issues, such screening processes may benefit from the use of quantitative methodologies such as RPM. At best, such methodologies complement other, qualitative approaches used for generating issues for the foresight exercise and synthesizing the results of the quantitative analysis (Könnölä *et al.* 2007, Brummer *et al.* 2008).

The scenario model developed in Paper [III] is the first to accommodate both incomplete and project-dependent information about scenario probabilities. This model generates project-specific recommendations even with fairly loose constraints on scenario probabilities, which is likely to increase trust in these recommendations among DMs who find it difficult to provide precise probability estimates. The focus of the model on both resilience and proactivity resonates well with many practical applications. For instance, the current approaches to addressing risks of climate change are (i) adaption, i.e., building resilience towards changes in the climate conditions, and (ii) mitigation, i.e., taking proactive measures to reduce net CO_2 emissions (Hamin and Gurran 2009, Moss *et al.* 2010).

Paper [IV] proposes a novel approach for modeling uncertainties in portfolio decision analysis. While providing computational tools for developing an optimal project evaluation and selection process, it also gives important qualitative insights into portfolio selection problems. First, because the value estimates are uncertain, the DM should expect to be disappointed in the value of the selected portfolio. Second, the more uncertain the value estimates, the more they should be adjusted towards average project values to increase the value of the selected portfolio and to yield more realistic expectations about this value. Finally, it often suffices to re-evaluate only a small subset of the projects on condition that these are appropriately selected. Because the available time and monetary resources for project evaluation are often limited, this result is of considerable practical interest.

Paper [V] is the first to develop an analytic model to support the shaping of funding policies for promoting breakthrough technologies. This model serves to highlight that breakthrough technologies can be best fostered by (i) experimenting by initiating a large number of technology projects, and (ii) committing resources only to those projects that, based on the experimentation, seem to have the potential to result in breakthroughs. The model makes explicit the important trade-off between allocating scarce resources to experimentation on the one hand, and completing projects on the other hand. Making such trade-offs is crucial in practical applications, such as public funding of breakthrough research: empirical findings suggest that high impact research is connected with long-term funding (Bourke and Butler 1999, Heinze 2008) but, on the other hand, committing resources for a long period of time to some projects increases the risk of failing to fund some other projects that could have resulted in breakthroughs (Melin and Danell 2006, Kanniainen 2011).

4.2 Avenues for future research

This Dissertation opens up several avenues for future research. First, empirical case studies are needed to test the methodological developments of Papers [I], [III] and [IV]. For instance, it would be interesting to apply the Bayesian methodology of Paper [IV] to adjusting the cost estimates of public works projects, whose realized costs are typically much higher than estimated (28% on average; Flyvbjerg *et al.* 2002). To do this, methods are needed to estimate the prior and likelihood distributions based on (i) the estimated costs of *all* project candidates, but (ii) the realized costs of only those projects that have been implemented.

Second, behavioral studies could be carried out to examine how subjects allocate resources between project funding and the acquisition of additional value information without recourse to formal decision support methods. In particular, it would be interesting to examine whether and to what extent these resource allocation strategies differ from the optimal strategies suggested by Papers [IV] and [V]. These kinds of studies benefit from simulation software tools, such as the one presented by Ylilammi (2014). Such simulation tools could also be useful in demonstrating the effects of estimation uncertainties in project portfolio selection, including post-decision disappointment.

Finally, several methodological extensions could be introduced. For instance, the scenario model developed in Paper [III] could be integrated with a game-theoretic framework to support project portfolio selection when both the projects' impacts and the scenario probabilities are possibly affected by the projects selected by other DMs. This model could also be extended to support multi-period portfolio selection processes in which the DM has the opportunity to revisit the initial selection decision in a later period. Also, the analysis of the value of information in Paper [IV] could be extended to a multicriteria setting. Furthermore, by developing a different kind of modeling approach, the policy guidelines for promoting breakthrough technologies in Paper [V] could be supported by analytic results.

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Errata

Paper [II] contains the following errors:

(i) The inequalities in section 3.3.2 should be '$w_2 > w_1 > w_3$'.

(ii) The sentence following these inequalities should read 'This analysis helped identify issues that the respondents did not see similarly...'.

(iii) The end of the second sentence in section 3.3.3. should read '...but v_3^j was defined so that the issues with the lowest occurence probabilities received the highest scores, i.e., $v_3^j = 8 -$ *the average of the probability assessments*'.

(iv) The inequalities in section 3.3.3. should be '$w_3 > w_1 > w_2$'.

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