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PORTFOLIO DECISION ANALYSIS FOR ROBUST PROJECT SELECTION AND RESOURCE ALLOCATION

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Title: Portfolio Decision Analysis for Robust Project Selection and Resource Allocation

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Abstract: Organizations must take decisions on how to allocate resources to 'go/no-go' projects to maximize the value of their project portfolio. Often these decisions are complicated by several value criteria, multiple resource types and exogenous uncertainties that influence the projects' values. Especially when the number of projects is large, the efficiency of the resource allocation and the quality of the decision making process are likely to benefit from systematic use of portfolio decision analysis.

This Dissertation develops and applies novel methods to manage uncertainty in decision analytic models for project portfolio selection. These methods capture incomplete information through sets of feasible model parameter values and use dominance relations to compare portfolios. Based on the computation of all non-dominated portfolios, these methods identify i) robust portfolios that perform well across the range of feasible parameter values and ii) projects that should surely be selected or rejected in the light of the incomplete information.

These methods have several implications for project portfolio decision support. Explicit consideration of incomplete information contributes to the reliability of analysis, which is likely to increase the use of portfolio decision analysis in new contexts. Furthermore, cost and time savings in data elicitation may be achieved, because these methods can give robust decision recommendations based on incomplete data and identify projects for which additional information is beneficial. Finally, these methods support consensus building within organizations as different views about projects' quality or exogenous uncertainties can be considered simultaneously to identify projects on which further negotiations should be focused.

Keywords: Decision analysis, project portfolio selection, multi-objective optimization, multi-attribute value theory, utility theory, incomplete information, scenarios, risk measures, robustness.

Otsikko: Portfoliopäätösanalyysi robustissa projektivalinnassa ja resurssiallokoinnissa

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Tiivistelmä: Organisaatiot joutuvat tekemään päätöksiä siitä, miten jakaa resurssit projektiehdokkaille pyrkiessään maksimoimaan projektiportfolionsa arvoa. Näitä päätöksiä vaikeuttaa useiden arvokriteerien ja resurssityyppien huomioiminen sekä projektien arvoon vaikuttavat ulkoiset epävarmuudet. Erityisesti projektiehdokkaiden määrän kasvaessa portfoliopäätösanalyysimenetelmien soveltaminen auttaa saavuttamaan tehokkaampia resurssiallokaatioita ja parantaa päätösprosessin laatua.

Tässä väitöskirjassa kehitetään ja sovelletaan uusia menetelmiä epävarmuuden hallitsemiseen päätösanalyyttisissä projektiportfoliovalintamalleissa. Nämä menetelmät mallintavat epätäydellisen informaation käypien malliparametrien joukkoina ja käyttävät dominanssirelaatioita portfolioiden vertailuun. Kaikkien ei-dominoitujen portfolioiden ratkaisuun perustuen voidaan tunnistaa i) robustit portfoliot, jotka ovat hyviä kaikilla sallituilla malliparametrien arvoilla ja ii) projektit, jotka tulisi hyväksyä tai hylätä huolimatta informaation epätäydellisyydestä.

Nämä menetelmät hyödyttävät projektiportfoliopäätöstukea useassa suhteessa. Epätäydellisen informaation mallintaminen lisää analyysin ja sen tulosten luotettavuutta, mikä avaa uusia sovellusmahdollisuuksia portfoliopäätösanalyysille. Menetelmät mahdollistavat rahallisten ja ajallisten säästöjen saavuttamisen datan keruussa, koska robustien päätössuositusten antaminen on mahdollista epätäydellisellä datalla ja ne projektit, joista lisäinformaation hankkiminen on hyödyllistä, voidaan tunnistaa. Lisäksi menetelmät tukevat yhteisymmärryksen rakentamista organisaatioissa mahdollistamalla useiden näkemyksien huomioimisen projektien hyvyydestä tai ulkoisista epävarmuuksista ja tunnistamalla projektit, joihin jatkoneuvottelut tulisi kohdistaa.

Avainsanat: Päätösanalyysi, projektiportfoliovalinta, monitavoiteoptimointi, monitavoitteinen arvoteoria, hyötyteoria, epätäydellinen informaation, skenaariot, riskimitat, robustisuus.

Academic Dissertation
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Portfolio Decision Analysis for Robust Project Selection and Resource Allocation

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Official opponent:	Research Professor Don N. Kleinmuntz, University of Southern California, USA

Publications

The Dissertation consists of the present summary article and the following papers:

[I] Liesiö, J., Mild, P., Salo, A. (2007). Preference Programming for Robust Portfolio Modeling and Project Selection, *European Journal of Operational Research*, Vol. 181, pp. 1488–1505.

[II] Liesiö, J., Mild, P., Salo, A. (2008). Robust Portfolio Modeling with Incomplete Cost Information and Project Interdependencies, *European Journal of Operational Research*, Vol. 190, pp. 679–695.

[III] Lindstedt, M., Liesiö, J., Salo, A. (2008). Participatory Development of a Strategic Product Portfolio in a Telecommunication Company, *International Journal of Technology Management*, Vol. 42, pp. 250–266.

[IV] Salo, A., Liesiö, J. (2006). A Case Study in Participatory Priority Setting For A Scandinavian Research Program, *International Journal of Information Technology & Decision Making*, Vol. 5, pp. 65–88.

[V] Liesiö, J., Salo, A. (2008). Scenario-Based Portfolio Selection of Investment Projects with Incomplete Probability and Utility Information, Systems Analysis Laboratory Research Report E23, Helsinki University of Technology.

Contributions of the author

Liesiö is the main contributor to Papers [II] and [V]. Liesiö, Mild and Salo contributed equally to Paper [I], for which Salo proposed the model framework and Liesiö developed the proofs and algorithms. In Paper [III], Lindstedt, Liesiö and Salo contributed equally to model development and scientific reporting. Liesiö is the secondary author of Paper [IV].

Preface

This Dissertation has been made possible by several people in my life, who I have the privilege to acknowledge here.

First of all I wish to thank my supervisor Professor Ahti Salo for his guidance and feedback, and for having the courage to let me work on novel ideas, even when favorable outcomes seemed highly uncertain. My research has benefitted enormously from fruitful collaboration with my colleagues, and friends, Pekka Mild and Antti Punkka. I am deeply grateful for those hundreds of hours we have spent brainstorming in front of the blackboard. I also wish to thank the preliminary examiners Professor David Ríos Insua and Professor James E. Smith for instructive comments that will indeed benefit my future research.

Throughout the preparation of this Dissertation, I have had the privilege to work in the the Systems Analysis Laboratory. I want to thank each member of the personnel, especially the head of the laboratory Professor Raimo P. Hämäläinen, for the laboratory's innovative work environment.

I will always be indebt to by parents Liisa and Jaakko for their encouragement and support throughout my studies. Finally, I wish to thank my family, Linda and Eeva, for your patience and the strength you have given me simply by being there.

Espoo, October 2008

Juuso Liesiö

Contents

1 Introduction

The allocation of resources to 'go/no-go' projects (e.g., products, infrastructure investments, research themes, policy options) is an important decision problem in public administration and companies. Achieving maximal project portfolio value for the resources used is often complicated by multiple value criteria, several resource types (e.g., budget, human-resources) and project interdependencies caused by synergy/cannibalization effects or logical dependencies (Kleinmuntz, 2007; Stummer and Heidenberger, 2003). Presence of exogenous uncertainties that influence the projects' future values motivates consideration of portfolio risks (Gustafsson and Salo, 2005).

Because the number of alternative portfolios grows exponentially with the number of projects, the use of decision analytic modeling to address these issues is likely to increase the quality of portfolio decisions by improving the efficiency of the resource allocation and management of risks. Systematic use of these models may also contribute to the quality of the decision making process by increasing its transparency and by supporting equatable treatment of project proposals.

Indeed, it is not surprising that plenty of research has been done to develop models for project portfolio selection. Earliest contributions were published under capital budgeting (Lorie and Savage, 1955; Bernhard, 1969) using strictly financial measures to value projects and portfolios. Later advances in optimization algorithms and increase in computational power have made it possible to solve large (mixed integer) optimization models that account for multiple resources, project interactions and multiple time periods (e.g., Lockett and Gear, 1975; Heidenberger, 1996). In these models, approaches for capturing uncertain project values vary from assumption of normally distributed project values (e.g., Weingartner, 1966) to scenario trees that make it possible to model risk-preferences and mutually dependent project values (Gustafsson and Salo, 2005).

Yet, simple scoring methods that prioritize projects based on aggregate value derived from their performance on several evaluation criteria (see, e.g., Archer and Ghasemdazeh, 1999) are widely used in practice (Cooper *et al.*, 1999). This may partly be explained by their applicability, transparency and use of multiple value criteria. Financial measures do not alone capture the value of projects in not-for-profit-organizations wherefore multi-criteria approaches are called for. Even in for-profit-organizations difficulties in obtaining reliable estimates for financial measures are addressed by using supplementary criteria (such as alignment with business strategy) as indicators of probable long term financial performance.

Project scoring methods do not necessarily ensure the quality of portfolio selection, because they do not explicitly take into account portfolio level considerations, such as multiple resource constraints, portfolio balance requirements and other project interactions. Multi-criteria project portfolio models, on the other hand, seek to combine project portfolio optimization with explicit consideration multiple value criteria (Golabi *et al.*, 1981; Golabi, 1987). These models build on the well established multi-attribute value theory (MAVT; see, e.g., Keeney and Raiffa, 1976) to aggregate the multi-criteria project values into a portfolio overall value and use integer linear programming to determine the optimal composition of the project portfolio subject to resource and other constraints. Several high impact applications of multi-criteria portfolio models have been reported in the fields of military resource allocation (Ewing *et al.*, 2006), R&D portfolio selection (Golabi *et al.*, 1981), product release planning (Ruhe and Saliu, 2005) and healthcare capital allocation (Kleinmuntz, 2007), among others.

In terms of managing uncertainty, earlier project portfolio models are not entirely aligned with decision support needs. First, optimization models stemming from the capital budgeting literature assume known probability distributions for project values in the form of decision or scenario trees, for instance (Heidenberger, 1996; Salo and Gustafsson, 2005). While these methods are well-suited for dealing with concrete projects with clear sources of uncertainties, obtaining the needed parameter estimates may be impossible within the time and resources available when dealing with less concrete projects such as research themes or policy options. Second, multi-criteria portfolio models rely solely on ex-post analysis of the optimal portfolio's sensitivity to uncertainties in the model parameter values (see, e.g., Beaujon *et al.*, 2001).

This Dissertation develops methods for managing uncertainty in project portfolio models. These methods i) explicitly capture incomplete information about model parameter values through set inclusion and ii) identify the implications of such incomplete information for project and portfolio decisions. More specifically, Papers [I] and [II] develop the Robust Portfolio Modeling (RPM) methodology, which extends multi-criteria project portfolio models to address incomplete information about the decision maker's (DM's) preferences, projects' values, available resources and projects' costs. RPM is applied to support the formation of a strategic product portfolio in a telecommunications company in Paper [III]. Paper [IV] presents a case study in which multi-criteria methods that capture incomplete information are used in forming priorities for research projects. Paper [V] extends scenario based modeling of exogenous uncertainties in project portfolio selection to account for incomplete information about the scenario probabilities and risk preferences.

The rest of this summary article is structured as follows. Section 2 discusses some key methodological foundations in decision analysis and project portfolio selection. Section 3 summarizes the contributions of the Papers. Section 4 discusses the implications of the methodological developments for project portfolio decision support and Section 5 concludes.

2 Methodological Foundations

2.1 Multi-Criteria Value of Project Portfolios

Multi-attribute value theory (MAVT; see, e.g., Keeney and Raiffa, 1976; French, 1986; Belton and Stewart, 2001) offers a normative model for decision making in view of multiple (conflicting) objectives. The mutually exclusive decision alternatives are described by their performance on several attributes (or criteria) that measure the alternatives' achievement of the objectives. Under reasonable assumptions the DM's preferences can be captured with an additive value function in which i) the alternatives' criterion-specific performances are mapped to scores using the (possibly non-linear) criterion-specific value functions and ii) the overall value of an alternative is the weighted sum of its scores. The weights reflect the relative importance of the criteria, i.e., the value gained when the criterion-specific performance of an alternative is changed from the worst performance level to the best. Although the validity of the assumptions behind the additive value function are not always thoroughly tested in applications, it is often accepted as a reasonable approximation, because more complex value functions would undermine the transparency of the decision support model (for applications of MAVT see, e.g., Keefer *et al.*, 2004; Hämäläinen, 2004).

Many project prioritization methods aggregate projects' performances on several criteria into overall project priorities (cf. overall value), often using approaches that fall into the

MAVT framework. These priorities are then used to form an optimal portfolio by selecting projects in descending order of the priority-cost ratios until the budget constraint is met (Hendriksen and Traynor, 1999; Kleinmuntz and Kleinmuntz, 1999; Phillips and Bana e Costa, 2007). However, such heuristics do not extend to settings with multiple resources or project interactions. Indeed, overall values for the portfolios need to be captured to strictly comply with MAVT framework, since portfolios correspond to the decision alternatives.

Golabi *et al.* (1981) model the portfolio overall value as a sum of projects' values included in the portfolio. Optimizing the portfolio overall value subject to multiple resources constraints leads to a zero-one linear programming problem (ZOLP), for which several solution algorithms exist (see, e.g., Bertsimas and Tsitsiklis, 1997). The ZOLP formulation can accommodate various project interactions through use of linear constraints and dummy variables (see, e.g., Stummer and Heidenberger, 2003). The additive portfolio value model captures non-linear criterion-specific value functions at the project level, but does not allow decreasing marginal portfolio value. However, the ZOLP-formulation can be used to restrict the criterion-specific performances of the portfolios to levels where the constant marginal value assumption serves as a feasible approximation (Kleinmuntz, 2007).

2.2 Scenario-Based Project Portfolio Selection

The values of projects may be influenced by exogenous uncertainties, such as market growth, wherefore the projects' values become mutually dependent. Exogenous uncertainties are a considerable source of portfolio risk as they may realize as low values for several projects in the portfolio simultaneously, thus significantly declining the overall portfolio value, too. In contrast, large deviations from the expected portfolio value are not likely, if the projects' values are uncertain but mutually independent due to project-specific uncertainties.

Managing risks caused by project-specific uncertainties should be addressed at the project level. For instance, decision tree analysis of each project's implementation plan can be used to identify these risks and optimal mitigation actions (see, e.g., Poland, 1999). Exogenous uncertainties, on the other hand, should be addressed at the portfolio level because dependencies between projects' values can be exploited to structure the portfolio so that it hedges against these uncertainties (see, e.g., Kouvelis and Yu, 1997).

Scenarios offer a practical tool for capturing exogenous uncertainties for two reasons. First, an extensive literature exists on processes and methods to structure scenarios (for a survey see Bunn and Salo, 1993). Second, modeling of risk preferences in scenario based portfolio models generally results in computationally manageable optimization problems (Rockafellar and Uryasev, 2000; Gustafsson and Salo, 2005).

The expected utility theory (EUT; von Neumann and Morgenstern, 1947) is the standard normative theory for modeling decision under risk. If a DM complies with the rationality axioms of EUT then i) her risk preferences can be captured by a utility function that maps outcomes of decision alternatives (portfolio values) onto a utility scale and ii) the most preferred alternative (portfolio) is the one that maximizes expected utility. Risk aversion, i.e., preferring a certain outcome to a uncertain one with equal expectation, corresponds to a concave utility function, wherefore optimizing expected utility of a portfolio generally leads to a non-linear optimization problem.

Another approach to model risks stems from the context of optimizing a portfolio of market traded financial instruments (Markowitz, 1952; Artzner *et al.*, 1999), where risk measures that map each random variable (portfolio value) to a real-valued measure for risk are widely used in practice. For instance, Value-at-Risk (VaR; Jorion, 1996) measures the greatest loss with a certain confidence interval. However, VaR does not comply with the requirements for coherent risk measures (Artzner *et al.*, 1999), because in some cases diversification can increase VaR. Therefore, Conditional Value-at-Risk (CVaR), the expectation of losses exceeding VaR, has recently become increasingly popular measure for risk in financial portfolio models (see, e.g., Rockafellar and Uryasev, 2000).

Portfolio optimization models use risk measures by i) maximizing portfolio expected value subject to constraints on the portfolio risk (e.g., Dentcheva and Ruszczynski, 2006), ii) minimizing the portfolio risk subject to constraints on the portfolio expected value (Markowitz, 1952) or iii) aggregating risk and expected value into a single objective function (e.g., Gustafsson and Salo, 2005).

2.3 Modeling Incomplete Information

In project portfolio selection and decision analysis, the model parameters often describe preferences or subjective beliefs. Hence, obtaining complete information about these parameters may be time-consuming and costly. Relying on point estimates may result in decision recommendations that are sensitive to errors in these estimates, caused by misinterpretation of parameters describing preferences, for instance. Ex-post sensitivity analysis is not readily applicable for producing robust decision recommendation in problems with dozens of parameters.

Motivated by these considerations, methods for incorporating *incomplete information* (also partial or imprecise information) about the model parameters have been developed in context of choosing one of few mutually exclusive, explicitly defined, decision alternatives. For instance, *Preference Programming* methods build on MAVT and model incomplete information about the criterion weights and scores (e.g, Kirkwood and Sarin 1985; Hazen, 1986; Weber, 1987; Arbel, 1989; Rios Insua and French, 1991; Salo and Hämäläinen, 1992, 1995, 2001; Salo and Punkka, 2005; Mustajoki and Hämäläinen, 2005). Several approaches also consider incomplete information about the probability distributions and utility functions (e.g, Fishburn, 1965; White *et al.*, 1981; Rios Insua, 1992; Moskowitz *et al.*, 1993; Smith, 1994).

These methods model incomplete information though set inclusion, i.e., by considering sets of feasible parameter values that i) are consistent with the given preference statements or evaluations and ii) are assumed to include the 'correct' parameter values. Decision recommendations are often based on dominance relations: An alternative dominates another, if it has greater overall value (expected utility) for all feasible weights and scores (probability distributions and utility functions) and strictly greater for some. Hence, dominated alternatives can be discarded from further analysis and efforts of eliciting more complete information can be focused on the remaining non-dominated alternatives. Decision rules can be used to identify robust alternatives that perform reasonably well across the set of feasible parameter values.

Incorporating incomplete information in the project portfolio context is not straightforward. Establishing dominance relations is based on pairwise comparisons of all alternatives with suitable linear programming formulations. However, in the project portfolio context the decision alternatives are defined implicitly through resource and other constraints, wherefore use of pairwise comparisons would require enumeration of all feasible portfolios. Since the number of portfolios grows exponentially with the number of projects, this approach is applicable only up to some 30 projects and may take several hours (Stummer and Heidenberger, 2003). More efficient algorithms have been developed in the field of multi-objective zero-one linear programming (MOZOLP; Bitran, 1977; Villareal and Karwan, 1981; Kiziltan and Yucaoglu, 1983), which, however, are applicable for solving non-dominated portfolios only for some special forms of incomplete information.

3 Contributions

The contributions of Papers [I]–[V] are summarized in Table 1. Papers [I], [II] and [V] extend the methods of multi-criteria and scenario based project portfolio selection to handle incomplete information. Papers [III] and [IV] present case studies where multi-criteria methods that account for incomplete information were applied to support project portfolio selection and priority setting processes.

Specifically, Paper [I] develops the Robust Portfolio Modeling methodology (RPM) that builds on the additive project portfolio value optimization model of Golabi *et al.* (1981), but following Preferences Programming methods, captures incomplete information about the projects' scores and criterion weights by means of set inclusion. For instance, instead of giving precise criterion weights, ordinal statements of the form 'a unit increase in project net present value is more valuable than a unit increase in market share' can be used without quantifying the exact value difference. Similarly, projects can be evaluated by assessing intervals on the criterion-specific performances, which can be interpreted as preferential uncertainty (e.g. 'the project's strategic fit -score is between 50 and 60') or uncertainty about future outcomes (e.g. 'the project will generate cash-flows between 100 and 120 thousand euros').

As in Preference Programming, the focus on portfolios that are non-dominated is well justified: For any feasible dominated portfolio it is possible to identify a non-dominated portfolio with greater overall value for all feasible criterion weights and project scores. Decision rules are applicable in project portfolio context as well to identify robust non-dominated portfolios whose worst-case overall value across feasible parameters is maximal, for instance.

Table 1: Contributions of the Papers

Paper	Research objectives	Methodology / Approach	Main results
[I]	Extend the use of incomplete information to multi-criteria project portfolio problems	Multi-attribute value theory and multi-objective zero-one linear programming	RPM methodology that produces robust project and portfolio decision recommendations based on the computation of all non-dominated portfolios
[II]	Extend the RPM methodology to account for project interdependencies and incomplete information on project costs and budget	RPM methodology and multi-objective zero-one linear programming	Budget level dependent decision recommendations and cost-to-benefit analyses based on computation of all (cost)efficient portfolios
[III]	Study the benefits of RPM methodology to project portfolio decision support in practice	A case study in supporting strategic product portfolio formation in a telecommunication company	RPM methodology is especially useful in organizational portfolio decision contexts to account for different views and support consensus building
[IV]	Study the applicability of Preference Programming methods in participatory formation of priorities	A case study in a Scandinavian research program	Systematic use of multicriteria methods contributes to the transparency and equitability of a priority setting process
[V]	Develop a scenario-based project portfolio selection model that accounts for incomplete information on scenario probabilities and risk preferences.	Expected utility theory, coherent risk measures and multi-objective zero-one linear programming	Methodology to identify portfolios that have desired levels of expected value and risk in view of incomplete information

The composition of non-dominated portfolios can be used to analyze the quality of individual projects. For this purpose RPM defines project's *core index* as the share of non-dominated portfolios that include the project. Based on the core indexes projects are classified into three groups: *core projects* are included in all, *exterior projects* in none and *borderline projects* in some but not all non-dominated portfolios. Therefore, core projects are certain choices, since the optimal portfolio would contain all core projects for any weights and scores within the feasible sets. Similarly, exterior projects can be discarded from further consideration as they are not included in any of the non-dominated portfolios. Efforts of obtaining additional information, i.e., narrower project score intervals, should be focused on the borderline projects: Additional information on core or exterior projects does not reduce the set of non-dominated portfolios and therefore will not result in more core or exterior projects.

Paper [II] extends the RPM methodology to account for i) variable resource levels (e.g. budget), ii) incomplete information on projects' resource consumption (e.g. costs) and iii) project interactions such as project synergies and logical dependencies. Following the usual practice, project interactions are modeled with additional linear feasibility constraints and dummy projects whose criterion scores and costs represent the synergy/cannibalization effects (see, e.g., Stummer and Heidenberger, 2003). However, the novel feature in the RPM methodology is that these effects can be modeled as intervals and analyzed with the help of their core indexes. If a synergy is not active in any non-dominated portfolio, the positive effects of the synergy are not strong enough to justify selection of a portfolio that utilizes this synergy.

For cases where the resource constraints (e.g. budget) are not fixed, Paper [II] builds on the concept of (cost) efficient portfolios: A feasible portfolio is efficient if any feasible portfolio that dominates it is also more expensive. Since the set of efficient portfolios includes non-dominated portfolios for all budget levels, overall values of the non-dominated portfolios and the core indexes can be visualized as a function of the budget level. This gives insights into what marginal value could be achieved with additional resources or at which budget levels a certain project is a core project. Such information can be used for cost-benefit analyses of projects and portfolios, and to support determination of the optimal budget level.

The computation of non-dominated portfolios leads to a MOZOLP problem with interval-valued objective function coefficients (interval-MOZOLP). Paper [I] develops a dynamic programming algorithm for this problem, but assumes non-negative coefficients in the objective functions and constraints. This assumption is relaxed in Paper [II], which makes it possible to solve efficient portfolios and to handle project interactions. Indeed, the algorithm of Paper [II] may be of boarder interest outside project portfolio modeling as it is the first algorithm for solving an interval-MOZOLP problem.

Paper [III] studies the challenges in applying RPM methodology through a case study in strategic product portfolio formation in a telecommunication company. The value of each product was evaluated with regard to expected profits, market risk and technology risk. Adding a product into the portfolio required human resources in terms of marketing and technical support personnel. Product evaluation was carried out by e-mail and based on these evaluations non-dominated product portfolios and products' core indexes were computed. These results were then used in a decision workshop, in which the company personnel responsible for the product lines selected the final portfolio. Some key factors that contributed to the applicability of RPM in this case study can be identified. First, the model was readily understood by the workshop participants without strong mathematical background. Second, criterion-specific interval values allowed the consideration of the different views on products' values. Finally, use of core indexes as a primary way of giving decision recommendations left room for holistic judgement in the workshop.

Paper [IV] presents a case study where Preference Programming methods were applied to support priority setting in a Scandinavian research program. The focus is on the formation of priorities, which were later used in the 'call for proposals' -mechanism that would produce the research project proposals. The case study is of interest from the viewpoint of portfolio selection as well, because the implementation of the priorities through the selection of a project portfolio can succeed only if suitable project proposals are available. A similar priority setting process can also be used in other contexts as a preparatory process for project portfolio selection.

Paper [V] considers scenario-based project portfolio selection under incomplete information. The exogenous uncertainties are captured through scenarios and projects' values are evaluated in each scenario. EUT is used to model risk preferences in view of sets of feasible scenario probabilities and utility functions. This makes it possible to consider ordinal probability statements such as 'scenario 1 is more probable that scenario 2' without defining how much more probable. Also risk preferences can be incompletely defined; allowing all concave or linear utility functions avoids defining the precise level of risk aversion, but still implies that a certain value is preferred to an uncertain one with equal expectation.

The non-dominated portfolios (no other feasible portfolio has a greater expected utility for all feasible scenario probabilities and utility functions) are computed by solving a MOZOLP problem, whereafter linear programming is used to discard portfolios that are dominated in view of the given information on scenario probabilities and risk preferences. As in RPM methodology, the MOZOLP formulation makes it possible to account for portfolio balance requirements, synergy effects and logical project dependencies.

The composition of non-dominated portfolios can be used to identify projects that should be selected/rejected in view of the incomplete information and projects whose selection is contingent on the level of acceptable portfolio risk. Paper [V] also develops methods to use CVaR with incomplete scenario probabilities, wherefore the selection from the set of non-dominated portfolios can be done by interactively constraining the level of acceptable portfolio risk.

4 Implications for Project Portfolio Decision Support

In addition to the case study in Paper [III], the RPM methodology has been used in several other applications, such as the screening of innovation ideas for the Finnish Ministry of Trade and Industry (Könnölä *et al.*, 2007), supporting development of research agendas for the Finnish Forestry Industry (Könnölä *et al.*, 2008) and for the International Research Program on Wood Material Science (Brummer *et al.*, 2008a/b), ex-post portfolio evaluation in context of an innovation programme (Salo *et al.*, 2006) and optimization of bridge maintenance programs for the Finnish Road Administration (Mild, 2006).

The experiences from these applications suggest that the modeling of incomplete information contributes to the applicability of portfolio decision analysis methods. Decision support processes that do not require precise parameter estimates seem to be more readily accepted in practice, but when building such processes, overly complex models to produce decision recommendations have to be avoided to ensure transparency. The methods of this Dissertation help avoid these pitfalls by using a relatively simple model for incomplete information (i.e., set inclusion) and by producing the entire set of defensible decision recommendations (i.e., non-dominated portfolios).

Another novelty that has been well received by the DMs is that while the portfolio optimization is performed at the portfolio level – enabling explicit modeling of (multiple) resources and project interactions – the focus is on analyzing the implications for project-specific decisions. Portfolios are more readily interpreted through the projects they contain, rather than the numerical portfolio overall values. Also the effects of incomplete information are often best understood by explicitly showing which project decisions are contingent on the exact parameter values, rather than the range in which portfolio overall values vary.

In many of these applications, elicitation of precise preferences or project value estimates would have been impossible or at least required time-consuming interviews with the DMs. Therefore, the timely implementation of these decision support processes has benefited from the use of RPM methodology, as it i) produces decision recommendations based on incomplete information and ii) identifies parameters for which more precise information would possibly result in more conclusive portfolio and project decision recommendations. Especially, if the number of projects is large, focusing the efforts of eliciting additional information only on the borderline projects may lead to cost savings.

The methods of this Dissertation show promise in organizational contexts, where one key function of decision support is to help reach a consensus decision such that the whole organization is motivated to implement it. Rather than force agreement on the model parameters, these methods consider different opinions simultaneously and identify which projects can be agreed upon and on which further negotiations should be focused. Such negotiations are likely to catalyze discussion on arguments that support the different views, enhance distribution of knowledge and thus increase the quality of the decision making process.

5 Conclusions and Future Research Directions

The methods of this Dissertation introduce a novel approach to capture uncertainty in project portfolio models; they build on relatively simple project portfolio models, but recognize that the parameter values are not precise. This incomplete information is modeled through sets of feasible parameter values and decision recommendations are given based on the computation of non-dominated portfolios.

The developed methods benefit decision support in that preferential uncertainties, uncertain evaluations and different opinions of DMs in group contexts can be readily used to produce robust portfolio and project decision recommendations and to identify projects for which additional information is beneficial. This reduces requirements for evaluation data which may enable time and resource savings in decision support processes. In organizational contexts these methods support building consensus by identifying projects on which further negotiations should be focused on.

Apart from project portfolio selection, the methods can be applied in continuous portfolio management, where project decisions have to be made in view of the current portfolio and resources that can be freed through the termination of ongoing projects. Based on the computation of non-dominated portfolios that can be structured from all new proposals and ongoing projects (with updated value estimates), it is possible to give decision recommendations on which ongoing projects should be terminated and which new proposals accepted. If needed, linear constraints can be used to ensure the continuation of ongoing projects that are not in a suitable stage for termination. Even if no new proposals exist, identification of cost efficient portfolios that can be formed from the ongoing projects provides insights into which projects should be terminated if the resources are cut down by one third, for instance.

This Dissertation suggests several avenues for future research. Empirical case studies are needed to test the methodological developments of Papers [II] and [V] in practice. Extending the scenario-based model of Paper [V] to account for scenario probabilities that are contingent on the project decisions may open up new application areas for such case studies. For instance, if scenarios represent risk events, the selection of risk mitigation actions that reduce the probability of these events can be modeled as a project portfolio problem.

The extended RPM methodology of Paper [II] could be applied in supporting hierarchial resource allocation in organizations, where the top management defines the strategic objectives and allocates resources to business units to pursue these objectives. However, more research is needed on methods and processes that ensure consistent measurement of projects' values across the organization.

In settings where several DMs have formal power to accept or reject projects that produce different benefits for each DM, game theoretic aspects have to be taken into account. Here RPM methodology offers an appealing platform for group negotiation support, because modeling of incomplete preference information may help to identify projects that are core projects from the view point of each DM.

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