Tuomas J. Lahtinen Improving the practice of model based problem solving with a systemic behavioral perspective

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Department of Mathematics and Systems Analysis

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Improving the practice of model based problem solving with a systemic behavioral perspective

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Abstract

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Abstract
In practice, behavioral phenomena and procedural aspects are often the most important factors determining the overall success in model based problem solving. Earlier literature has discussed procedural practices and behavioral phenomena such as cognitive biases. However, little attention has been paid to the interdependence between behavioral phenomena and the problem solving process. This Dissertation introduces the idea of path dependence in model based problem solving and in decision analysis, which is a branch of model based problem solving. This idea offers a systemic perspective for capturing the overall impact of cognitive biases and other behavioral phenomena. The term path refers to the sequence of steps taken in the problem solving process. There are usually alternative paths to be followed and the choice of the path can matter. The factors affecting the path include the behavior of the problem solving team, as well as the processes followed, the modeling techniques used, and the problem solving environment, for instance. The idea of paths draws attention to the dynamic interaction of these factors. This Dissertation includes considerations of the effect of the starting point, the accumulation of behavioral effects, and difficulties in changing the path.

Taking the path perspective can support the management of model based problem solving projects. This Dissertation provides a checklist to help the problem solving team to reflect on their path and to be aware of its drivers. Procedures are described to help reduce the risk that the problem solving project gets stuck on a poor path. In decision analysis, the path perspective can help in mitigating the effects of cognitive biases. Biases are a concern especially when their effects build up along the path followed in the decision analysis process. This Dissertation shows that it is sometimes possible to find paths along which the effects of biases cancel out each other. In general, one should try to avoid paths where the effects of biases build up in favor of certain alternatives. This Dissertation introduces new bias mitigation techniques. These techniques are shown to be effective in a decision analysis process.

Portfolio decision analysis is another systemic perspective discussed in this Dissertation. Environmental decisions are often portfolio problems where the task is to find a combination of actions, i.e. a portfolio, to meet the overall objectives. In these decision problems, the traditional approach has been to follow a standard decision analysis process to evaluate alternative portfolios generated manually by experts. This Dissertation describes how biases and path dependence create risks in such processes. The portfolio approach helps avoid these risks and creates new possibilities for stakeholder engagement. This Dissertation presents a review and a synthesis of alternative portfolio modeling approaches. A framework is developed to help environmental modelers use portfolio decision analysis.

Keywords Behavioral operational research, multi-criteria decision making, environmental modelling, portfolio decision making, path dependence, systems perspective, cognitive biases, debiasing

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Tekijä
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Väitöskirjan nimi
Malliperusteisen ongelmanratkaisun käytänteiden parantaminen systeemisen käyttäytymisnäkökulman avulla

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Tiivistelmä

Malliperusteisessa ongelmanratkaisussa keskeisiä tekijöitä ovat osallistujien toiminta ja heidän seuraamansa prosessit. Aiemmassa kirjallisuudessa on käsitelty prosesseihin liittyviä käytänteitä ja ihmisten käyttäytymiseen liittyviä ilmiöitä kuten kognitiivisia vinoumia. Näiden vuorovaikutukseen ei kuitenkaan ole kiinnitetty juurikaan huomiota. Tässä väitöskirjassa esitellään polkuriippuvuuden käsite malliperusteisen ongelmanratkaisun ja monitavoitteisen päätösanalyysin kentille. Tämä käsite luo systeemisen näkökulman, joka auttaa hahmottamaan kognitiivisten vinoumien ja muiden käyttäytymiseen liittyvien ilmiöiden kokonaisvaikutusta. Polku muodostuu ongelmanratkaisuprosessin vaiheiden tai askelten ketjusta. Vaihtoehtoisia polkuja on yleensä tarjolla, ja polun valinnalla on merkitystä. Mallinnusprojektissa voidaan päätyä eri poluille riippuen muun muassa osallistujien toiminnasta, ongelmanratkaisuympäristöstä, seuratuista prosesseista ja käytetyistä mallinnustekniikoista. Ajatus polusta nostaa esiin dynaamisia ilmiöitä. Tässä työssä pohditaan projektin alussa tehtävien valintojen merkitystä, ihmisen toiminnan vaikutusten kasautumista ja polun vaihtamisen vaikeutta.

Käytännössä polkunäkökulma voi tukea malliperusteista ongelmanratkaisua hyödyntävien projektien hallintaa. Tässä väitöskirjassa esitetään tarkistuslista, joka auttaa polun hahmottamisessa ja polkuun vaikuttavien tekijöiden tunnistamisessa. Lisäksi tässä väitöskirjassa kuvataan tapoja vähentää kehnolle polulle jumiutumisen riskiä. Päätösanalyysissä polkunäkökulma auttaa lieventämään kognitiivisten vinoumien vaikutusta. Vinoumat ovat ongelma erityisesti, jos niiden vaikutukset kasaantuvat. Tässä väitöskirjassa näytetään, että joskus on mahdollista löytää polkuja, joita pitkin kuljettaessa eri vaiheissa syntyvien vinoumien vaikutukset kumoavat toisensa. Yleisesti ottaen tulisi välttää polkuja, joilla vinoumien vaikutukset kasaantuvat joidenkin päätösvaihtoehtojen eduksi. Tässä työssä esitellään uusia tekniikoita vinoumien vaikutusten lieventämiseksi. Nämä osoitetaan toimiviksi eräässä päätösanalyysiprosessissa.

Portfoliopäätösanalyysi on toinen tässä väitöskirjassa käsiteltävä systeeminen näkökulma. Ympäristöä koskevassa päätöksenteossa on usein haasteena muodostaa sopiva toimenpidekokonaisuus, eli portfolio. Perinteistä monitavoitemenetelmää sovellettaessa asiantuntijat luovat vaihtoehtoisia portfolioita ilman portfoliomallien apua. Tässä on riskinä, että ajattelun vinoumat ja polkuriippuvuus muodostuvat ongelmaksi. Tässä väitöskirjassa esitetään kuinka portfoliopäätösanalyysi voi auttaa välttämään nämä riskit, ja kuvataan vaihtoehtoisia tapoja mallintaa portfoliopäätöksiä. Portfoliopäätösanalyysin soveltamisen vaiheista luodaan viitekehys ympäristökysymyksiin erikoistuneiden mallintajien tueksi.

Avainsanat Käyttäytymistutkimuksellinen operaatioanalyysi, monikriteerinen päätöksenteko, ympäristömallinnus, portfoliopäätöksenteko, polkuriippuvuus, systeeminäkökulma, kognitiiviset vinoumat, vinoumien lieventäminen

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Publications

This dissertation consists of a summary and of the following papers.

I. Hämäläinen, R.P., Lahtinen, T.J. 2016. Path Dependence in Operational Research - How the Modeling Process Can Influence the Results. *Operations Research Perspectives,* 3: 14-20.

II. Lahtinen, T.J., Guillaume, J.H.A., Hämäläinen, R.P. 2017. Why Pay Attention to Paths in the Practice of Environmental Modeling? *Environmental Modeling & Software,* 92: 74-81.

III. Lahtinen, T.J., Hämäläinen, R.P. 2016. Path Dependence and Biases in the Even Swaps Decision Analysis Method. *European Journal of Operational Research,* 249(3): 890-898.

IV. Lahtinen, T.J., Hämäläinen, R.P., Jenytin, C. 2017. A Systemic Perspective on Bias Mitigation in Decision Analysis. *Submitted manuscript, 22 pages.*

V. Lahtinen, T.J., Hämäläinen, R.P., Liesiö, J. 2017. Portfolio Decision Analysis Methods in Environmental Decision Making. *Environmental Modeling & Software,* 94: 73-86.

Contributions of the author in the papers

Paper I: Lahtinen and Hämäläinen wrote the text together. Lahtinen assisted Hämäläinen in developing the ideas in the paper. Paper II: Lahtinen was responsible for the main part in writing the text. Lahtinen, Guillaume, and Hämäläinen jointly developed the ideas in the paper. Paper III: Lahtinen was responsible for the main part in writing the text. Lahtinen designed the experiments and analyzed the data. Lahtinen and Hämäläinen collaborated in developing the ideas in the paper. Paper IV: Lahtinen initiated the paper and wrote the text. Hämäläinen provided comments. Lahtinen was the principal designer of the computational analysis. Jenytin did the programming and helped Lahtinen analyze the results. Paper V: Lahtinen was responsible for the main part in writing the text. Hämäläinen initiated the paper. Lahtinen, Hämäläinen, and Liesiö collaborated in developing the ideas in the paper.

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Going through doctoral studies has been great. I have had the opportunity to read, think, discuss, and write in an intellectually stimulating environment. I have begun to see the breadth, the depth, and the value of the knowledge and wisdom that humanity has accumulated over time. This makes me feel both humbled and empowered.

Espoo, 4 December 2017
Tuomas Lahtinen

Contents of the summary

1. Introduction

Model based problem solving and decision analysis projects are frequently carried out in government agencies, companies, and other organizations around the world. The application areas range from high stakes environmental decision making to business analytics. Today, advanced software support makes it easier than ever to produce analyses that look convincing and scientific to most people. Yet, success in model based problem solving requires more than just technical and mathematical competence. It is important to understand and be able to manage procedural and behavioral issues as well (Hämäläinen et al. 2013).

Behavioral Operational Research is a new scientific area that aims to improve the practice of model based problem solving by taking into account the behavioral aspects involved (Hämäläinen et al. 2013, Franco and Hämäläinen 2016). So far, these aspects have been studied mainly in decision analysis and in system dynamics (for overviews, see, e.g. French et al. 2009, Sterman 2000), which are subdisciplines of model based problem solving. In decision analysis modelers work directly with preferences and other subjective inputs provided by decision makers and stakeholders. Therefore, natural research questions have been, e.g. how cognitive biases affect these inputs (see, e.g. Clemen 2008), and how to work interactively with stakeholders (see, e.g. Franco and Montibeller 2010). In the general literature on model based problem solving, the importance of behavioral and procedural aspects was acknowledged early (see, e.g. Churchman and Schainblatt 1965, Hildebrandt 1981), but the subsequent interest has been sporadic (Meredith 2001, Franco and Hämäläinen 2016).

This Dissertation takes a systemic perspective to improve the understanding and management of behavioral phenomena in model based problem solving. It is important to pay attention to the overall effects of cognitive biases and other behavioral phenomena. These overall effects result from the interaction of all the factors in the socio-technical system that emerges in the problem solving situation. This system consists of the members of the problem solving team, the processes followed, the techniques used, the problem context, and the external environment, for instance. In the earlier literature, little attention has been paid to the interdependence between behavioral phenomena and the problem solving process.

This Dissertation aims to i) improve the planning and management of model based problem solving projects (Papers I and II), ii) help mitigate biases in decision analysis processes (Papers III and IV), and iii) support environmental decision makers in utilizing portfolio methods (Paper V).

Paper I introduces the concept of path dependence in model based problem solving. In practice, the results of a modeling process can depend on the path followed. Alternative paths are almost always available. This paper studies the drivers and implications of path dependence on different scales.

Paper II describes how the path perspective can help to improve the planning and management of model based problem solving projects. This paper draws examples from environmental modeling, where a typical problem is participatory and includes multiple sources of uncertainties. These factors increase the need to reflect on the path taken.

Paper III presents a behavioral experiment that demonstrates the existence of biases and path dependence in a decision analysis process. This paper also describes how biases can create path dependence in decision analysis in general.

Paper IV is focused on ways to mitigate cognitive biases in decision analysis. This paper presents four bias mitigation techniques and evaluates them computationally.

Paper V describes how environmental modelers can benefit from using portfolio decision analysis methods. This paper presents a synthesis and a review of portfolio modeling approaches and a framework for using portfolio decision analysis.

2. Background

2.1 On Model Based Problem Solving

"A model is an abstract description of the real world; it is a simple representation of more complex forms, processes, and functions of physical phenomena or ideas" (Rubinstein 1975). Modeling can support problem solving in various ways. For instance, models can help to generate alternatives or solution candidates, to evaluate alternative policies or systems, and to automate routine decision making (see, e.g. Brill et al. 1982, Pidd 1999). In general, developing and using models can help to organize one's thinking and to increase understanding of the situation under study (see, e.g. Rubinstein 1975).

Traditionally, a model based problem solving process is seen to consist of stages (see, e.g. Churchman et al. 1957). Typical stages include: 1. Defining the situation under study, e.g. identifying objectives and the scope of the problem. 2. Developing models, e.g. specifying the assumptions used and the key variables. 3. Data collection, estimation of the magnitudes of parameter values, and the elicitation of preferences. 4. Solving the models. 5. Evaluating and using the models, e.g. comparing results against data or expert judgment, performing sensitivity and what-if analyses. 6. Using results of the models to inform the decision makers and communicating the insights to stakeholders. These stages are not always carried out in the same order and one can iterate between them.

In practice, there are almost always many plausible and justifiable ways to carry out each stage in the modeling process. Choices made by the problem solving team drive the progression through the stages (Hämäläinen et al. 2013). Therefore, it is not surprising that different problem solving teams can obtain different results when the same problem is given to them (see, e.g. Mulvey 1979, Richels 1981, Linkov and Burmistrov 2003). Members of the problem solving team typically include modelers, subject matter experts, problem owners, and stakeholders.

2.2 On Decision Analysis

Decision analysis is a subdiscipline of model based problem solving. Technically, decision analysis aims to help decision makers evaluate alternatives in the face of multiple conflicting objectives and uncertainties (see, e.g. Keeney and Raiffa 1976). In practice, increased insight is often the overall goal in decision analysis processes (see, e.g. Howard 1980, Keeney 1982). The benefits may also include, for instance, improved communication, greater transparency, and the identification of the conflicting views among the stakeholders.

The decision analysis process aims to comprehensively identify, explicate, and analyze the facts and values that are relevant to the decision problem at hand. A typical process includes the following stages (see, e.g. Keeney 1982). 1. Identifying the objectives of the decision makers and stakeholders. 2. Developing alternative courses of action. 3. Determining attributes for measuring the achievement of the objectives. 4. Estimating the consequences of the alternatives in the attributes. 5. Eliciting the decision maker's preferences and developing value models for evaluating the alternatives. 6. Analyzing the performances of the alternatives and conducting sensitivity analyses. There are usually different ways to carry out each of these stages. Revisiting earlier stages is also possible. In portfolio decision making, the problem is to find a combination of actions with desirable overall consequences (see, e.g. Salo et al. 2011). Then additional stages are needed in the decision process in order to identify and model interactions across the set of action candidates, to develop models to calculate the overall consequences of alternative portfolios, to to specify the problem constraints, and to identify non-dominated portfolios by using optimization techniques.

The Even Swaps process (Hammond et al. 1998) is one approach to help the decision maker identify her most preferred alternative. This process can be carried out after the decision alternatives have been specified and their consequences have been estimated in the attributes. In the Even Swaps process the decision maker's preferences are not captured with a value model as in a typical decision analysis process. Instead, the decision maker performs a sequence of even swap tasks. In these tasks, the decision maker modifies an alternative in two attributes in order to create a preferentially equivalent hypothetical alternative. The goal is to create situations where a modified alternative either dominates, or is dominated by, another alternative. Even swap tasks are carried out until only one alternative remains non-dominated.

An important practical issue in decision analysis is coping with cognitive biases when preferences and other subjective inputs are elicited from decision makers and stakeholders. There have been many suggestions on how to mitigate the effects of biases (see, e.g. Montibeller and von Winterfeldt 2015). However, the number of studies analyzing the effectiveness of these suggestions remains very limited.

3. Contributions of the papers

3.1 Path perspective

Papers I and III introduce the concept of path dependence in model based problem solving and in decision analysis, respectively. Paper II describes how taking the path perspective can support the management of model based problem solving and decision making projects. Paper IV uses the path perspective in the mitigation of biases in decision analysis. Paper V describes how path dependence can create risks in a decision making approach used traditionally in environmental portfolio problems.

The term path refers to the sequence of steps taken in the problem solving process, or alternatively to the trajectory describing how a problem solving project develops over time. In the practice of model based problem solving, there are usually alternative paths to be followed and the choice of the path can matter. Path dependence is an integrative concept because it draws attention to all the factors that shape the path. These factors can relate to the behavior of the problem solving team, as well as the processes followed, the modeling techniques used, and the problem solving environment, for instance. The path perspective emphasizes the sequential nature and dynamics of modeling processes. Examples include the effect of the starting point (see, e.g. Papers I, II and V), the accumulation of behavioral effects along the path (see, e.g. Papers III and IV), and that changing the path at an intermediate step can be difficult (see, e.g. Paper II).

Path dependence is not a risk as such. In most cases, there are likely to be different paths that can lead to useful outcomes. However, a risk emerges from the possibility that a modeling process may follow and get stuck on a poor path. Optimistically, one may think that mistakes along the path are usually easy to notice and correct. Papers I and II explain why this might not be the case. A modeling process can get stuck on a certain path, for example, due to budget and time constraints, hidden motives, cognitive biases such as anchoring (Tversky and Kahneman 1974) and confirmation bias (Nickerson 1998), and also due to a social environment that causes people to hold back critical opinions on the path taken (see, e.g. Janis 1982).

Paths discussed in this Dissertation:

- Paths in modeling and decision analysis projects in general. A starting point of such a path can be the initial meeting between modelers and problem owners. The end of the path can be, e.g., the point when a final report is delivered, or when problem owners have decided on a course of action. However, clear starting and ending points do not necessarily exist.
- Paths in preference elicitation processes. A path consists of the sequence of preference elicitation tasks carried out by the decision maker.
- Paths in the Even Swaps process. A path consists of a sequence of even swap tasks carried out by the decision maker.

- Paths in the generation of portfolios without modeling support. A path is the order in which different actions are considered and added into the portfolio.
- “Historical” paths in the development of research communities, organizations, etc. These paths relate to general trends such as the popularity of methods, ideas and research topics.

The last item relates closely to the concept of path dependence discussed in economics (David 1985, Arthur 1989) and organizational decision making (Sydow et al. 2009), for instance.

3.2 Contributions by paper

A summary of the contributions of each paper is provided in Table 1.

Paper I describes how path dependence can emerge in model based problem solving processes in general. In modeling, the path is driven by systemic phenomena, learning, the procedures used, behavioral and motivational phenomena, uncertainties, and the external environment. The awareness and understanding of these drivers can help modelers to manage their problem solving processes better. This paper describes several mechanisms, which may cause a problem solving team to become anchored to their initial approach. Procedures to cope with path dependence are identified and discussed. These include starting the modeling process by carefully exploring the goals and objectives of the stakeholders, openness to multiple approaches, creating multiple parallel modeling processes, and adaptive problem solving.

Paper II clarifies why and how to pay attention to paths in model based problem solving projects. This paper draws examples from environmental modeling, but the conclusions are applicable to model based problem solving in general. This paper elucidates how the path perspective can i) help plan and manage modeling projects, ii) help communicate about the practice of modeling, and iii) provide a lens for understanding the role of behavioral effects in modeling. This paper develops a framework, which is intended to help modelers reflect on their paths. The framework classifies path related phenomena based on their origins and their possible effect. These phenomena may affect choices at the forks on the path, give a reason to redirect the path, and make it difficult to change the path taken. This paper also develops a checklist for the practitioner. This checklist supports detecting forks, evaluating alternative paths, and recognizing situations where changing the path may be desirable.

Paper III shows that decision analysis processes can be path dependent. A major reason is that the impact of cognitive biases can depend on the path followed. On some paths, the effects of biases may accumulate or build up such that one alternative becomes favored in the decision process. It is also possible that the effects of biases cancel out each other. This paper presents a behavioral experiment that shows the existence of path dependence in the Even Swaps process (Hammond et al. 1998). This is explained by the accumulated effect of two well known cognitive biases. These are the loss aversion bias (Tversky and Kahneman 1991) and the measuring stick bias, which is also called the scale compatibility bias (Tversky et al. 1988, Delquié 1993). This paper suggests ways to mitigate the effects of these biases.

Paper IV develops and evaluates techniques for bias mitigation in decision analysis. These techniques are based on the ideas introduced in Paper III. The basic idea is to look for paths where the overall effect of biases is minimal. The first new technique is to introduce a virtual reference alternative in the decision problem. The second one is to introduce a virtual measuring stick attribute. The third approach is to rotate the reference point used. The fourth one is the intermediate restarting of the process in order to eliminate the impacts of biases that have accumulated during the earlier steps. A computational analysis demonstrates that these techniques help to mitigate biases in the Even Swaps decision analysis process. It is described how these techniques could be used with other decision analysis processes as well. This paper demonstrates that a computational approach helps to take a systemic perspective on debiasing. In particular, this approach enables assessing the overall effect of multiple biases that occur on different steps along the decision making process. Earlier literature has mostly considered the effects of biases in isolated steps of the decision analysis process.

Paper V reviews portfolio modeling approaches and provides a framework to help environmental modelers use portfolio decision analysis in practice. An illustrative case dealing with an environmental decision is presented. This case is analyzed using a portfolio decision analysis method called Robust Portfolio Modeling (Liesiö et al. 2007). In environmental portfolio problems, the traditional approach has been to follow a standard decision analysis process to evaluate alternative portfolios generated by experts without modeling or optimization support. This paper describes how biases and path dependence create risks in such an approach. Furthermore, when the traditional approach is used, it can be impossible to consider all combinations of actions even in moderate sized problems (e.g. 10 action candidates), because the number of combinations is too high. Portfolio modeling alleviates these concerns because all action candidates can be included simultaneously in the same analysis. Use of portfolio decision analysis also creates new possibilities for stakeholder engagement. The participants of the process can easily suggest actions to be included in the same analysis together with all the other action candidates. This can help create a sense of shared ownership of the process.

Table 1: Summary of the papers.

	Contexts	Main objectives	Main results
I	Model based problem solving in general.	To demonstrate the existence of path dependence and to describe its origins.	Path dependence can originate from systemic phenomena, learning, procedure, behavior, motivation, uncertainty, and external environment. There are procedures for coping with path dependence.
II	Model based problem solving projects. Environmental modeling.	To describe how the path perspective can help to improve the practice of model based problem solving.	Taking the path perspective can help modelers to navigate their paths in a reflective mode. A checklist for planning and managing modeling projects.
III	Decision analysis processes. The Even Swaps process.	To study path dependence experimentally in a decision analysis process.	Path dependence exists in the Even Swaps process. This can be explained by the accumulated effect of the loss aversion and the measuring stick biases.
IV	Decision analysis processes. The Even Swaps process.	To develop bias mitigation techniques and to evaluate them computationally.	New bias mitigation techniques are effective. The computational approach helps assess the overall impact of biases.
V	Portfolio decision analysis processes. Environmental decision making.	To help environmental modelers to use portfolio decision analysis.	Portfolio decision analysis offers new possibilities for environmental decision making. A framework for using portfolio decision analysis.

4. Discussion

4.1 Practical implications

This Dissertation helps to understand the impact of behavioral phenomena in model based problem solving. In practice, behavioral phenomena and procedural aspects are often the most important factors determining the overall success in model based problem solving. Participatory environmental problem solving is one application area where these factors are particularly important.

The notion of path dependence helps to acknowledge that alternative paths are usually available in model based problem solving and that the choice of path can matter. Increased understanding of path related phenomena can improve one's ability to identify and evaluate alternative paths. The path perspective can be useful for anyone working with model based problem solving. In modeling projects, reflecting on the path and its drivers can help to notice forks on the path and to redirect the path if needed. Practitioners may find interest in the procedures to cope with path dependence described in Paper I, and in the framework and in the checklist developed in Paper II.

In decision analysis, an important practical issue is to mitigate biases in the subjective inputs elicited from stakeholders. Papers III and IV show that in the mitigation of biases it can be useful to consider the entire path followed in the decision analysis process. It may be possible to find paths along which the effects of biases cancel out each other. In general, one should at least try avoid situations where the effects of biases build up in favor of a certain alternative. Paper IV describes techniques, which are shown to be effective at mitigating cognitive biases in the Even Swaps process. These techniques are likely to be applicable also with other decision analysis methods, such as swing and trade-off methods for the elicitation of attribute weights.

Environmental decisions are often portfolio problems, where a combination of actions is needed to create a successful management policy. Paper V describes tools and provides a framework to help environmental managers and modelers address such problems. The framework includes the most important steps and tasks needed to analyze a portfolio decision problem.

4.2 Avenues for future research

The idea of path dependence can be seen as an integrative perspective in Behavioral Operational Research. When studying cognitive biases and other behavioral phenomena in model based problem solving, it is important to pay attention to their overall effects. The overall effects result from the interaction of all the factors in the problem solving process.

This Dissertation provides several directions for future research on the management of modeling projects. It could be evaluated how to best take the path perspective into account already when commissioning a modelling project. Moreover, the idea of parallel modeling teams should be tested in practice and developed further. One question that is likely to arise in practice is how to compare the results obtained by different teams. Another interesting topic would be to study how the principles of systems intelligent leadership (Saarinen and Hämäläinen 2004) might help to manage modeling projects and to work interactively with stakeholders. The path perspective relates closely to five dimensions of systems intelligence (Törmänen et al. 2016). These are systems perception, reflection, spirited discovery, wise action, and effective responsiveness.

In decision analysis, a systemic perspective is needed when assessing the effects of cognitive biases and evaluating bias mitigation methods. Earlier literature has identified a number of biases. However, these have been analyzed mostly in isolated steps of the decision analysis process. This Dissertation shows that one should also consider the possibility that the effects of biases build up or accumulate. The effects of biases may also interact with each other. A computational approach could be more generally used for supporting the design and evaluation of new bias mitigation methods.

In environmental decision making, the portfolio approach should be tested in practice. This is likely to evoke a number of interesting research questions. For example, procedures for creating the portfolio model interactively with stakeholders are likely to be needed. It might also be useful to develop better tools for supporting situations with strong non-linearities or a high number of interactions across the set of actions.

This Dissertation identifies a number of behavioral phenomena that can influence the problem solving path, as well as phenomena that can emerge due to the path followed. A natural theme for future research is to consider these phenomena in more detail and in different contexts. Paying attention to behavioral effects is important particularly when using models to support high stakes policy decision making, such as the development of climate policies. Greater understanding of behavioral phenomena is likely to increase transparency of model based problem solving and to help run modeling projects more successfully.

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Path dependence in Operational Research—How the modeling process can influence the results

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HIGHLIGHTS

- The results of modeling process can depend on the problem solving path.
- Awareness of the possibility of path dependence is important in OR.
- The drivers are: system, learning, procedure, behavior, motivation, uncertainty and context.
- Sociopsychological dynamics create a system in participative problem solving.
- Ways to cope with path dependence are discussed.

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ABSTRACT

In Operational Research practice there are almost always alternative paths that can be followed in the modeling and problem solving process. Path dependence refers to the impact of the path on the outcome of the process. The steps of the path include, e.g. forming the problem solving team, the framing and structuring of the problem, the choice of model, the order in which the different parts of the model are specified and solved, and the way in which data or preferences are collected. We identify and discuss seven possibly interacting origins or drivers of path dependence: systemic origins, learning, procedure, behavior, motivation, uncertainty, and external environment. We provide several ideas on how to cope with path dependence.

1. Introduction

Path dependence is a concept which has been widely used in different areas including economics [1–3], policy studies [4,5], ecology [6,7], complex adaptive systems [8,9], sociology [10–12], political science [13], and organizational decision making [14]. The general idea is that 'history matters', i.e. the current state of the world depends on the path taken to reach it. The concept also often refers to the lock-in phenomenon: the development of strong anchor points from which it is not easy to move forward. The most famous example is the QWERTY layout which has become the worldwide standard for keyboards [1].

We have earlier discussed path dependence in decision analysis [15] and in this paper we want to bring path dependence into focus also in modeling and Operational Research (OR) in general. We see that the topic is of both theoretical and practical interest in model supported problem solving and decision making. A path is the sequence of steps that is taken in the modeling or problem solving process. The steps can include, for example, the initial meeting between the problem owners and modelers, formation of the problem solving team, the framing and structuring of the problem, the choice of model, the order in which different parts of the model are specified and solved, the way in which data or information about preferences are collected, communication with the model, as well as the implementation of the results in policy and practice. Earlier research on path dependence in other disciplines has focused on exposing and describing it. In OR we also want to find ways to mitigate the risks related to it. Behavioral and social effects are likely to be the most important drivers of path dependence in OR. We see path dependence as an important topic in the emerging area of Behavioral Operational Research (BOR) [16]. Although the focus of this paper is mainly in OR, we believe that the ideas and the phenomena described in this paper are relevant in policy analysis, systems analysis, and generally in all model supported problem solving approaches.

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Table 1
Summary of origins and drivers of path dependence.

Origin or driver	Relates to	Brief explanation
System	Interactions between participants of the problem solving team, related organizations, stakeholders, and the system under study.	Social dynamics influence the modeling process. Technical properties related to the problem or the system under study can also result in path dependence.
Learning	Learning during the OR process.	Increased understanding about the problem and methods used can direct the modeling and problem solving process.
Procedure	Structure and properties of the models, algorithms and problem solving procedures used.	Different procedures can lead the OR process to different outcomes. Structures and properties of the methods used interact with the other drivers of path dependence.
Behavior	Cognitive biases and behavioral phenomena related to individuals.	These phenomena can occur in different steps and their overall effect depends on the path followed.
Motivation	Exposed and hidden goals.	People can promote their own interest and behave strategically in the OR process.
Uncertainty	Uncertainty about structural assumptions and correct parameter values.	Different structural assumptions can lead us to consider different models. Results usually depend on the parameter values chosen.
External environment	Context and external environment.	The problem environment can change so that the chosen modeling process becomes invalid or it can lead to a different outcome.

There are usually alternative ways of using models to support problem solving. The possibility that different 'valid' modeling paths lead to different outcomes was acknowledged already early by Landry et al. [17] but the topic has received little interest later in the OR literature. Path dependence is implicitly recognized in the papers on best practices in OR as this literature recognizes the possibility of following different practices (see, e.g. [18–21]). Little [22] and Walker et al. [23] have suggested that models should be adaptively adjusted as the process evolves and intermediate results are obtained. This naturally results in one form of path dependence as the model outcomes change in response to changes in the model. Also the literature on the ethics of modeling discusses how the modeling process matters [24,25]. These papers clearly acknowledge that the process can influence the results in model supported problem solving. Still, research on the drivers and consequences of path dependence in different modeling contexts remains scattered and very limited. We see that the term path dependence is useful as an integrative term referring to the different phenomena that originate from the modeling and problem solving process and influence its outcome.

The ideal situation in OR is that we have a model and a solution procedure which produces one optimal solution. In OR practice, the risk of path dependence still exists. Awareness of path dependence and its possible consequences is important especially in major policy problems in areas such as environmental management [26] and in long term policy analyses involving deep uncertainties [27]. Yet, when the main goals of the process are related to learning and creation of a common view about the problem situation, then path dependence might not only be a negative phenomenon. Working through the process along different paths with different outcomes can sometimes be useful. It can show the sensitivity of the solution and that a model can give rise to different conclusions.

This paper studies the origins and drivers of path dependence in model supported problem solving. We also discuss possible ways to cope with path dependence in practice. We identify seven types of origins for path dependence: systemic, learning, procedure, behavior, motivation, uncertainty and external origins. These possibly interacting drivers and origins relate to humans, technical systems, as well as the problem context. In practice, the listing or categorization of the drivers and origins is not a goal in itself but it is important to try to consider all possible causes of path dependence.

2. Origins and drivers of path dependence

In the following, we describe the seven drivers and origins of path dependence. These can interact and occur together. A summary is provided in Table 1.

2.1. Systemic origins

Systemic origins of path dependence relate to the social system formed by the interaction of people involved in the problem solving process, the organizations related to the process, the stakeholders, and the system under study.

Groupthink, studied by Janis [28], is a social phenomenon which can occur in cohesive modeling communities of practice. Members of a problem solving team can convince each other of the correctness of the approach designed by the team without critical thinking or consideration of alternative approaches. According to Janis [28] groupthink is more likely to occur if the group is insulated, the background of the group members is homogeneous, and also if there is high stress due to external threats. In the OR context the team members can all have their background in the same modeling community dedicated to the use of a particular approach. External threat could be created for example by competing modeling teams or result from time constraints to complete the project.

A related human trait is the need for closure, which has been studied in model based group decision making by Franco et al. [29]. A group with high need for closure wants the problem solving process to end up in an unambiguous uncontested outcome. Once the first clear solution candidate has been obtained, the group members can start to endorse this solution and refrain from further deliberation.

The way in which the modelers initially interact with the participants in the social setting can greatly influence the results in participatory modeling processes [30]. Mehrotra and Grossman [31] provide an example where trust earned from the frontline workers of the client organization was essential for successful communication and problem identification. Social phenomena which occur in groups also include the contagion of emotions. This phenomenon can naturally play a role when the people engaged in the modeling process meet and communicate with each other. Contagion of positive mood has been found to increase cooperation and decrease conflicts in group problem solving [32]. Yet, contagion of positive mood does not necessarily improve the modeling process as elevated positivity can reduce critical thinking and cause groupthink [32].

In practice it can often be impossible to undo the steps taken and restart the modeling process again once one path is initiated. A lock-in to one approach and one software can emerge when the problem solving team and the organization become more and more involved and have invested time and resources in the process. This is a problematic situation if there are new, better, approaches available but the organization keeps on using the old one. The sunk cost effect can sometimes explain the lock-in situation but it can also be due to the fact that old (modeling) habits die hard [33]. Another perspective is that users of models can be 'lazy' [34]. When faced with new requirements for the model, the user may prefer the option that takes the least initial effort. This often means incremental adjustments to the old approach.

Sydow et al. [14] discuss organizational reasons that could prevent restarting modeling processes. These include overcommitment due to the social pressures faced by the managers in charge and due to structural inertia in large organizations. Restarting can be impossible also due to practical reasons such as lack of personnel, budget or time. It is important to consider the risk of lock-in and irreversibilities in decision making and policy processes when working with large complex issues such as climate policies [4]. Lock-in situations do not necessarily occur only due to systemic origins but can result also from, e.g., behavioral and motivational phenomena.

In today's academic world disciplinary silos can become a significant source of systemic path dependence. It is often the case that researchers in different communities do not follow what is happening outside of their own specialty.

The possibility of lock-in emphasizes the starting point of the problem solving process. The mental models and preconceptions of the people who participate in the process can matter a lot. They have an influence on the initial problem framing and choice of tools and procedures. If the same problem solving process would be replicated with different participants, they might not follow the same path. Cultural background is one factor that also can influence the mental models and the process (see, e.g. [35]).

Systemic origins of path dependence can also be technical. The dynamics of nonlinear systems can create path dependence due to increasing returns, bifurcation points, and feedback loops. It is also well known that complex nonlinear systems can be very sensitive to initial conditions.

Increasing returns is identified as the cause of path dependence in the seminal paper on technological development by Arthur [2]. The dynamics of a technology can be such that the technology becomes increasingly valuable as it becomes more widely adopted and the number of other technologies based on it grows. Consequently, it may become increasingly costly to change the technology that was initially adopted. Development of regional economies and organizational decision making are other examples where path dependence can occur due to increasing returns resulting, e.g., from learning, coordination benefits, or synergies [3, 14]. Today spreadsheets are widely used and the number of Excel based OR models including, e.g. optimization and Monte Carlo simulation has grown rapidly [36]. This represents the increasing returns phenomenon as it has become increasingly easy to develop new applications on this platform.

Bifurcation points are typical, for example, in fishery models [6] where the collapse of a fishery can represent such a point. If overfishing causes the collapse of a fishery, then it can be impossible to restore it in the short run by regular fishery management policies. Thus, optimizing the policy is dependent on the history. The modeling of feedback loops is the focus in systems dynamics (see, e.g. [37]) where the models typically include behavioral dynamics. Sterman and Wittenberg [10] demonstrate that feedback loops can drive path dependence in the development of science. In their model, higher confidence in a scientific paradigm increases the rate at which the paradigm is used to solve puzzles and vice versa. The same argument could also apply to problem solving with models.

2.2. Learning

During the modeling process the OR expert as well as the problem owners and stakeholders learn and their understanding increases about the problem which is being modeled. The interests of the modeling team can be directed to different aspects and perspectives as they learn different characteristics of the problem (see, e.g. [38]). The fact that learning takes place in the modeling process has been recognized especially in systems dynamics [39,40] and problem structuring [41] as well as in the literature on participatory decision analysis [42,43]. Studies on management simulators and games explicitly aim at supporting managerial learning (see, e.g. [44]). Learning can affect the outcome of the OR intervention because the learning process is likely to depend on the people involved and on the properties and structure of the problem solving process.

Modeling tools used by the problem solving team can naturally shape the learning process. Lane [38] notes that when systems dynamics models are considered, then the attention often quickly turns into the dynamic aspects of the problem. This observation relates to the priming effect discussed in the psychological literature (see, e.g. [45,46]). When one is first exposed to systems dynamics tools, one can become primed to be most sensitive to issues related to the dynamic phenomena within the problem.

In participatory processes, the time of formal engagement with the problem owners and representatives of the stakeholders is important. The participants can have started a heuristic problem solving process before the OR process and the facilitator are introduced. This can have already fixed the participants' expectations of the results. Then it can be difficult to launch an open model based problem solving process and unlearn the early expectations.

2.3. Procedure

Procedural origins of path dependence relate to the properties and structures of the algorithms, the models and the procedures used in the interactive problem solving process.

Procedural path dependence can be due to the technical properties of the mathematical methods used. For example, it is well known that the choice of stepsize can influence which solution is obtained by the algorithm. In numerical optimization we can end up in a local or the global optimum depending on the iteration scheme used. The solution that is found can also depend on the initial starting point. Technical path dependence has been shown to exist also in the construction of regression models in statistical analysis where the forward selection and backward elimination methods for variable selection can produce different models (see, e.g. [47]).

In multi-method processes (see, e.g. [48,49]) the order in which the methods are used can affect the outcome. In problem structuring the choice of the initial perspective can be important. For example, in environmental modeling the process can be started, e.g. with a socioeconomic or an environmental perspective and this can have an effect on which issues will be given the most attention. These order effects can interplay with behavioral phenomena such as scope insensitivity bias and splitting bias which we discuss in the following section.

In large modeling problems it can be impractical or difficult to build an overall aggregate model. Rather, the problem needs to be decomposed into sub-problems which are solved separately. The decomposition method and the order in which different subsystems are modeled can affect the solution. Such problems can be found in industries with large and complicated systems, e.g. the healthcare and airline industries [50,51], and today in particular in climate modeling (see, e.g. [52]).

Effects related to the order in which problem solving steps are taken can occur in sequential decision processes and lead to path dependence even without any behavioral causes. For example, when multiple decision makers are involved in strategic decision making the order of choices often has an impact on the outcome. A well-known effect in strategic decision making, or games, is the so-called first mover advantage which has been discussed in different economic settings and management decisions (see, e.g. [53,54]). Also the OR problem solving process can create a strategic situation with its participants as the players. The order in which group members voice their concerns and preferences can influence the subsequent behavior of the other group members.

2.4. Behavior

Path dependence can be caused by cognitive biases and other behavioral phenomena related to individuals (see, e.g. [16,26]). The occurrence and effects of these phenomena depend on the path followed, and thus their overall impact can be path dependent.

Multi-criteria decision analysis (MCDA) is an area of OR which explicitly relies on the use of subjective data elicited from stakeholders and experts. This data can relate to preferences, as well as subjective estimates of probabilities and magnitudes of effects. Thus biases such as loss aversion [55] are likely to be important drivers of path dependence in MCDA. Lahtinen and Hämäläinen [15] demonstrate how path dependence can emerge from the accumulation of biases along a sequential comparison process in a decision analysis method. In general, there are many different paths available in the MCDA process and the overall effect of biases can depend on the path. There exists a number of biases related to problem framing, preference elicitation, and how information is presented. A recent review of biases in decision and risk analysis is provided by Montibeller and Winterfeldt [56]. Naturally, biases in preference elicitation can play a role also in optimization problems where the objective function is often a multiple criteria value or utility function.

One phenomenon studied in the decision analysis literature is the splitting bias [57–59]. It refers to the situation where an attribute receives a higher weight if it is split into more detailed lower level attributes. This phenomenon can create path dependence in value tree analysis. The number of detailed lower level attributes included in each branch of the value tree can depend on the modeling process. Therefore, different processes could lead to different weights.

Insensitivity to scope [60] refers to the phenomenon where the subjective value given to a consequence is insensitive to the magnitude of this consequence. A similar effect is the range insensitivity phenomenon studied in the weighting of multiple criteria [61]. These phenomena can interplay with the order effects mentioned in the previous section. For example, the modeling team may give too much attention to non-essential issues that were considered early in the modeling process.

Anchoring [62] is a behavioral phenomenon which can influence the outcome of the OR process in general. Information displayed in the initial steps can direct the OR process to a certain path due to anchoring. This type of path dependence has been found to exist in interactive multi-criteria optimization [63,64]. Anchoring effects have also been observed in decision support systems [65], preference elicitation [66,67], negotiation [68], as well as in valuation, probability estimation, and forecasting (for a review, see [69]).

The idea of constructed preferences is discussed in the psychological literature (see, e.g. [70,71]). According to this idea, people do not have stable pre-existing preferences. Instead, preferences are constructed during the elicitation process. The way information is displayed and processed during the elicitation has an impact on the preferences that are formed. Payne et al. [72] have noted that preference construction is likely to be path dependent. Also in model based problem solving, different paths for solving the same problem could lead the decision makers and stakeholders to construct their preferences in different ways.

It is widely known that preference statements given in the analytic hierarchy process (AHP) can be inconsistent (see, e.g. [73]). Yet, we are unaware of studies that would discuss the connection between human inconsistencies and path dependence in AHP. For example, it would be interesting to find out if a certain order of preference elicitation tasks would systematically favor one alternative. However, due to the normalization procedure used in AHP, including a new alternative in the analysis can change the preference order of pre-existing alternatives (see, e.g. [74]). This can be thought of as procedural path dependence.

Behavioral reasons and biases can also lead to lock-in type situations in modeling. The status quo bias [75] refers to the tendency to prefer the current solution or approach over possible new ones. The sunk cost effect [76] refers to the phenomenon where people want to keep on committing resources to a project in which they have previously invested. This happens regardless of whether the earlier investments have been successful or not. For example, an organization can have initially adopted a certain modeling tool, such as a spreadsheet model, to support its operations. Over time this tool can have grown excessively and become unwieldy and nontransparent. Still the organization can keep on using the old model. The reason can be the sunk costs and effort put in developing the original model.

2.5. Motivation

Motivational origins of path dependence are related to situations where people's goals affect the problem solving process. This risk is high when the problem is messy and controversial with alternative modeling approaches being possible.

An unethical modeler may intentionally try to find an approach which leads to results that she finds desirable. It is possible that a modeler is hired to build a model that supports a position that is beneficial to the client [25]. Motivated reasoning and confirmation bias [77,78] can lead the modeler to unintentionally construct a model that support his prior beliefs about the 'right' solution to the problem. When a model concurring with the initial expectations is found, then the modeler may become satisfied and stop looking for alternative models.

Strategic behavior is likely to be found in group processes. The stakeholders in participatory modeling projects can try to influence the outcome by strategic behavior, for example, by intentionally emphasizing some features of the problem [26]. Hajkowicz [79] finds evidence of strategic behavior in weighting. Winterfeldt and Fasolo [80] observe that stakeholders in participatory decision analysis often suggest to include or enrich those dimensions that are familiar to them. In negotiation, the starting point can have a strong impact on the process. The participants may strategically select the initial offer or even misrepresent their preferences to set the process on a favorable path [81]. Lehtinen [82] studies how strategic behavior can influence the degree of path dependence in voting.

2.6. Uncertainty and changes in the external environment

Uncertainty can exist in the model assumptions as well as in the external environment. If the same modeling process is repeated, it can lead to different outcomes due to changes in the external environment.

The basic assumptions of the model are not always clear and fixed. Different estimates of the model parameters naturally can lead to different results. A high level of uncertainty about the model assumptions increases the risk of path dependence. Even in the face of uncertainty one has to select some initial approach. The risk exists that later the modeling team or community can become fixed to only looking for refinements in the initial approach and fail to consider other approaches.

Large structural uncertainties are faced, for example, in climate models (see, e.g. [83]) which include many important subsystems, such as socioeconomic, weather, solar, oceanic, and industrial systems. In the comprehensive aggregate model there can remain uncertainties related to the interaction of the different subsystems. Borison [84] discusses uncertainties in the modeling of real options. These relate to structural assumptions of the model and whether parameter values should be obtained with market data or subjective estimates.

Sensitivity analysis is traditionally performed when there exists uncertainty about the parameter values. Scenario analysis can be used to account for future uncertainties in policy modeling (see, e.g. [85]). To identify and mitigate the effects of structural uncertainty, one possibility is the use of multi-modeling and averaging out the errors in different model-based predictions [86]. However, the question of how to weight the outputs from different models creates new behavioral challenges in multi-modeling.

Changes in the external environment can relate, for example, to the market situation. In many political and economic decisions the timing of the start of the decision making process can be very crucial. The environment may change while the start is delayed which again can make some paths unavailable and some outcomes unreachable. Sometimes it can be beneficial to postpone early decisions and wait for more accurate information to become available before choosing the path [87]. Model based maintenance strategies (see, e.g. [88]) provide an example where wearing is an external driver of the process.

3. Coping with path dependence

Increased awareness is the natural first step to reduce the risk of path dependence. Acknowledging the possibility of path dependence challenges one to be open to new possibilities and to critically evaluate and improve one's practices. The possibility of path dependence and its origins should be openly discussed with the problem solving team. Thinking of the perspectives provided here the problem solving team should be better able to identify path dependence and to find ways to analyze whether there is possibility and need to avoid it. Furthermore, being open about the possibility of path dependence can increase the problem owners' trust towards the modeling process. In problem situations with multiple decision makers and stakeholders holding different preferences and views about the problem it can be useful to analyze the problem following different paths based on different perspectives and learn from the results.

The use of multiple models is a natural way to detect path dependence and to increase confidence in the solutions obtained. We can be more confident about a solution if a similar solution is obtained with another model. Moreover, one should also consider using more than one parallel problem solving process with different modeling teams. This might help consider a larger variety of alternative problem formulations and model structures. Linkov and Burmistrov [89] demonstrate that differences among models built by alternative teams can be very large. Detecting and discussing these differences can help to understand the problem better and to build better models. Use of multiple models should not be confused with multi-method approaches where methods are used in sequence to cover different aspects of the problem. These are discussed in the problem structuring literature (see, e.g. [49]).

Furthermore, in important policy problems we could have peer reviews or a parallel modeling team assigned to the role of Devil's advocate. This team would be encouraged to find and challenge crucial assumptions in the model created by the primary team and to perform worst case analyses. The use of a Devil's advocate within a modeling team has been previously suggested to be beneficial in problem formulation and also in systems dynamics model building [90,91]. Janis [28] suggested that assigning the role of Devil's advocate to one of the group members can reduce the risk of groupthink. A policy which is seldom used in practice is to have a portion of the budget of the modeling process set aside for the purpose of later having another team critically evaluate the model. The possibility of running a parallel modeling process or intentionally including a team working as the Devil's advocate should be considered and possibly announced already at the start of the modeling process. If these ideas are brought up only after results have been obtained, there can exist resistance to such procedures.

Following an adaptive problem solving approach (see, e.g. [22,23]) is a possible way to cope with changes and uncertainty in the modeling environment. In this approach the modeling process is revised at checkpoints, where intermediate results are obtained, learning has occurred, and possibly new data has become available. In this way one avoids committing to one approach or solution too early. The possibility to revise the process at certain checkpoints gives the team members a chance to challenge the approaches taken and propose new directions.

One can try to use debiasing methods to reduce the effects of cognitive biases in preference elicitation and in estimation tasks involving expert judgment. Ideas for debiasing have been suggested in the decision analysis literature. These ideas relate to problem framing, design of elicitation questions, better training, and calibration of judgments (see, e.g. [56]). Lahtinen and Hämäläinen [15] propose that besides reducing biases in single preference elicitation tasks one can also attempt to design the elicitation procedure so that the effects of biases cancel each other out. So far, research on the effectiveness of debiasing methods remains very limited.

The risk of path dependence and lock-in makes it important to be careful in the framing and in the early steps in the problem solving process. In our view, the existence of path dependence stresses the importance of the advice by the OR pioneers Churchman, Ackoff and Arnoff [92] to approach OR problem solving with "an openness of mind about techniques, together with a broad knowledge of their usefulness and an appreciation of the over-all problem". Following the idea of value-focused thinking by Keeney [93,94], in OR problem solving it might be beneficial to start the process by carefully exploring the goals and objectives of the decision makers and stakeholders. Only then should one choose the actual model or problem solving procedure to be used. Keeney [94] argues that thinking first about alternatives, and not values, reduces our creativity. For example, we may spend too much time on thinking about incremental changes in the status quo solution. Experimental research suggests that the use of value-focused thinking helps to identify relevant objectives and to develop good alternatives [95–98]. Evans [99] discusses the role of creativity in OR problem solving in general, as well as several approaches for structuring creative processes. One may also find interest in the TRIZ framework developed to aid in creative problem solving [100].

The fact that the modeling process matters calls for attention to all its elements including the whole design of the process and the way communication takes place. These issues are reflected in many papers on the practice of OR. For example, the transformation competence perspective discussed by Ormerod [101] emphasizes the modeler's attention to context in OR interventions. Franco and Montibeller [21] discuss the modeler as a facilitator and the social processes including the subjectivity of the participants. Social dynamics are emphasized by Slotte and Hämäläinen [30] in their paper on decision structuring dialogue. Our general conclusion is that the systems perspective is needed in problem solving. We should be able to observe, understand and manage the system created by the modeling process. The concept of Systems Intelligence by Saarinen and Hämäläinen [102] refers to these abilities. Systems intelligence is defined as "our ability to behave intelligently in the context of complex systems involving interaction, dynamics and feedback". The eight dimensions of systems intelligence include systems perception, attunement, reflection, positive engagement, spirited discovery, effective responsiveness, wise action, and positive attitude [103]. These are also competences that we find to be valuable in practical interactive model based problem solving [104].

4. Conclusions

Acknowledging the possibility of path dependence challenges us to critically evaluate our approaches and improve our modeling practices. In the practice of model based problem solving, path dependence can originate from systemic causes, learning, procedure, behavior, motivation, uncertainty, and external origins. These interacting origins and drivers are related to human behavior and social interaction and also to the technical properties of the procedure used and the problem context. By considering these origins, the practitioner should be better able to identify path dependence and find ways to analyze whether it could or should be avoided. We should take seriously the risk that the modeling team is fixed to one approach and only looks for refinements in the model that was initially chosen. Such lock-in can leave better approaches unnoticed.

Increased awareness is the natural first step to reduce the risk of path dependence. The existence of path dependence emphasizes the importance of early reflection in the beginning of the OR process. We should be open to multiple approaches. In important policy problems such as climate policy we should consider the use of more than one parallel independent problem solving process. One modeling team can be assigned to the role of Devil's advocate. This can help us to detect path dependence and possibly to improve our confidence in the results which are obtained. Adaptive modeling is another natural way to mitigate the effects of path dependence. In this approach the modeling process is revised at checkpoints, where intermediate results are obtained, learning has occurred, and possibly new data has become available.

Path dependence is an important theme in Behavioral Operational Research where the essential question is to understand the human impact on the whole OR process. This naturally leads us to consider the path that is followed in the process. We do not claim that our analysis is comprehensive. Path dependence can well originate also due to other causes than those discussed in this paper. Future research should consider especially the human related drivers of path dependence in more detail in different contexts and in different modeling processes.

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Paper II

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Why pay attention to paths in the practice of environmental modelling?

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ABSTRACT

Taking the 'path perspective' helps to understand and improve the practice of environmental modelling and decision making. A path is the sequence of steps taken in a modelling project. The problem solving team faces several forks where alternative choices can be made. These choices determine the path, together with the impact of uncertainties and exogenous effects. This paper discusses phenomena that influence the problem solvers' choices at the forks. Situations are described where it can be desirable to re-direct the path or backtrack on it. Phenomena are identified that can cause the modelling project to get stuck on a poor path. The concept of a path draws attention to the interplay of behavioral phenomena and the sequential nature of modelling processes. This helps understand the overall effect of the behavioral phenomena. A path checklist is developed to help practitioners detect forks and reflect on the path of the modelling project.

1. Introduction

This paper aims to show that the idea of paths in modelling is an important perspective for people working with model supported problem solving, planning, policy development, management, and decision making. The literature on environmental modelling has discussed *processes* and *best practices*. There is, however, a key difference compared to a *path*, which is defined as the sequence of steps taken in a problem solving case (Hämäläinen and Lahtinen, 2016). Process descriptions and best practices describe what is intended to be done, whereas a path describes what consequently actually occurs. When the term *process* is used, it does not necessarily become clear that a given process might manifest itself in different ways, which generate different paths that can lead to different outcomes (Hämäläinen et al., 2013). That is, there can be *path dependence* in modelling (Hämäläinen and Lahtinen, 2016; Lahtinen and Hämäläinen, 2016).

Reflecting on paths is particularly important in environmental modelling (Hämäläinen, 2015), where the problems are often complex, participatory, and include multiple sources of uncertainties. In such contexts we can easily end up following different paths. Taking the path perspective means awareness of the fact that the choice of the modelling path can matter. Even if we cannot assume that there is a perfect path or that we could find it, a poor path or possibilities to improve a planned path can often be identified.

The concept of path discussed here differs from the pathway concepts considered in the environmental literature. The term *adaptive policy pathway* relates to policy processes under deep uncertainties regarding the system under study (see, e.g. Haasnoot et al., 2013). Gregory et al. (1997) use the term *decision pathway* to describe possible chains of reasoning when people construct their opinions regarding an environmental policy problem.

The message and the conclusions in this paper resonate with the recently proposed socio-environmental modelling agenda by Voinov et al. (2014) that emphasizes subjectivity in the practice of modelling. Our starting point is different but consonant. It is a fact that modelers, like all people, are social, can be biased, make mistakes, and may sometimes act in self-interest.

What does a path look like? During a modelling project, the problem solving team faces several *forks* with alternative plausible and justifiable next steps or directions to be pursued. The choices and omissions made at these forks can have a strong influence on the path (see, e.g. Linkov and Burmistrov, 2003). Forks cover the

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breadth of the project; ranging from the choice of people invited to the problem solving team, to the choice of software and methods used, as well as to transferring the modelling results into practice. Sometimes the problem solvers are not aware they have passed a fork, e.g. when collecting data, or when they adopt a particular problem framing because they have always done so. Forks in the statistical analysis of data are notably discussed by Gelman and Loken (2014).

The following narratives characterize ‘ideal’ and ‘worst-case’ paths:

Ideal path: The path is formed by well-justified choices by the problem solving team with consideration given to the well-understood preferences of the stakeholders. The approaches used and procedures followed are suitable for taking into account the essential characteristics of the problem at hand. The path is navigated in a reflective mode, which can benefit from the modelers' experience in different situations. The path is reconsidered and redirected if needed, for example, due to changes in the problem environment.

Worst-case path: The path is determined by narrow-sighted problem framing and affected by hidden strategic motives. Inadequate judgment and procedures drive the analysis. Biased reasoning dominates thinking. The steps which are already taken are never reconsidered or backtracked. The problem and its environment are assumed to stay unchanged over time.

In systems terminology, a path can be described as the trajectory of the system of problem solving. Franco and Hämäläinen (2016) describe the system of modelling that consists of *actors, methods,* and *context* whose interaction forms the *praxis* leading to *modelling outcomes*. The path perspective encourages and helps consider the dynamics present in this system. For instance, sometimes backtracking is not an option so the choices made in the first steps can make certain outcomes unreachable in the sequential modelling process.

To be specific, we believe the path perspective holds promise in at least three ways:

1) The perspective helps practitioners plan and manage modelling projects more successfully. It challenges modelers to identify critical forks in their projects, and consider the options more widely at these forks. Awareness of path dependence encourages modelers to follow adaptive modelling practices (Hämäläinen and Lahtinen, 2016).
2) The term path is useful when communicating about models. It evokes the importance of modelers' choices at forks. It is useful to acknowledge that behavioral aspects and subjectivity are inherent in model-supported problem solving (see, e.g. Hämäläinen et al., 2013; Voinov et al., 2014). When interpreting modelling outcomes, the path metaphor is a reminder that other paths could also have been followed. The implementation of a set of best practice procedures depends on the people involved – the best possible result is not necessarily guaranteed.
3) The concept of a path offers a systemic and integrative perspective, which helps to understand the overall effect of behavioral phenomena as well as cognitive and motivational biases in modelling. These phenomena do not occur only at isolated steps – they take place within the sequence of interrelated steps over the whole modelling project.

Fig. 1 introduces the path framework used in this paper with a mountain hiking related metaphor. It highlights phenomena and recommendations discussed in the following sections, regarding choices at forks (Sections 2 and 3), redirecting the path (Sections 4 and 5), getting stuck on a poor path (Sections 6 and 7), along with the factors involved in each case. In Section 8, the path related phenomena are placed within the framework (Table 1) and a checklist is provided (Table 2).

2. Phenomena that influence choices at forks

The choices at forks together with exogenous impacts determine the path followed in a modelling project. This section discusses phenomena influencing these choices. These phenomena can: affect the evaluation of alternative courses of action, cause the problem solving team to find or overlook an alternative, or cause the team to miss the opportunity to make a choice altogether.

Focused thinking refers to deliberately directing one's thinking, e.g. by the choice of focal issues, or by intentionally taking a certain perspective. A broad scope is needed in policy problems, where the goal is to provide transparent policy recommendations. Ideally, such recommendations are based on a comprehensive analysis of the problem, but in turn depend on focused tasks concerning, for example, stakeholder engagement, technical feasibility, or analysis of risks. Framing can also reveal synergies. For instance, McCollum et al. (2013) show that it is less expensive to address global problems related to energy, air-pollution, and global warming as a whole rather than separately solving each of the problems. Following a path determined by a narrow scope can be justified in other circumstances, such as when the goal is to generate specific new insights to advance basic science. The choice of focus matters especially in the early stages of the modelling project, for example when the problem solvers define the scope of the project and set the objectives.

Narrow thinking can limit the number of alternative paths perceived to be available at a fork. Ignorance or unintentional disregard of important aspects related to the overall problem can lead to a *myopic problem representation* with missing policy alternatives, objectives, or scenarios (Montibeller and von Winterfeldt, 2015). The problem solving team may omit an important perspective, for example, if they are not familiar with the relevant information, concepts, or models. Sometimes a person's ignorance of facts, perspectives, or possible paths to be followed can be, *deliberate ignorance* (Hertwig and Engel, 2016), i.e. a self-interested and possibly strategic choice.

The approaches used influence mental models and thinking. This can naturally happen as models are often used as tools for thinking. The mental models, i.e. internal representations of the world, held by the problem solvers are likely to be influenced by the approaches they have adopted in the past. For example, a cost-benefit analysis can lead to the view that all environmental impacts can be quantified in monetary terms. The mental models held by the problem solvers and the way they think naturally have an effect on their choices at forks (see, e.g. Jones et al., 2011). In preference elicitation, the results can depend on the elicitation technique (see, e.g. Pöyhönen and Hämäläinen, 2001). The choice of results to be used creates a fork in the path. The problem context and the availability of data impact the choice of approaches, and the approaches used influence the data requirements (see, e.g. French and Geldermann, 2005; Kelly et al., 2013).

Expressed preferences and hidden motives influence choices at forks. Preferences and motives determine the desired destination of the path. It is common that stakeholder preferences are assessed in a problem solving project. Ideally, clearly stated objectives would guide the choices at forks. However, all motives rarely become explicit and the problem solvers can strategically or unintentionally bring in their own interests (see, e.g. Kunda, 1990; Huesemann, 2002). Such interests can include minimizing one's workload and career advancement related risks. For example, an important decision may be postponed to escape responsibility (Gregory et al., 2006). This may cause some desirable paths to become unavailable.

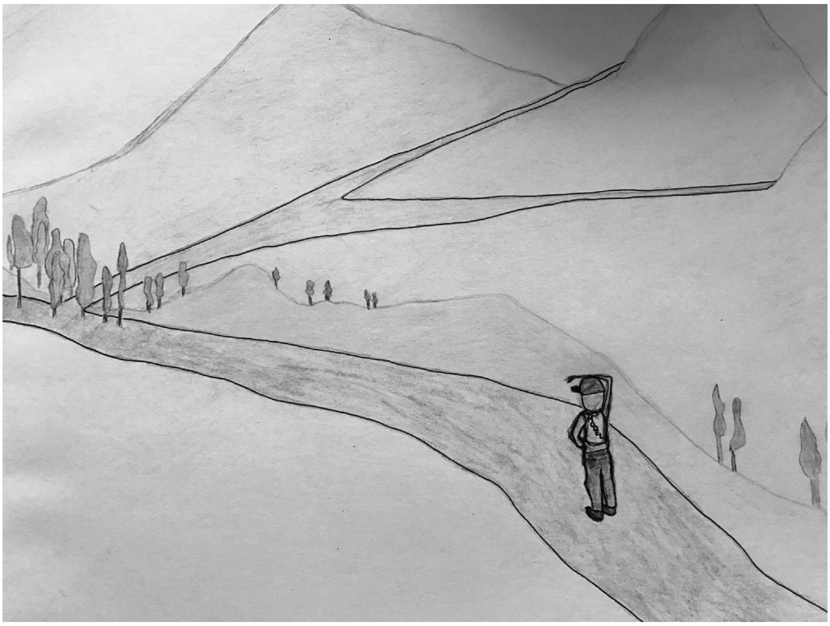

Fig. 1. A visual introduction to the path theme and framework (also see Table 1). A hiker looks back to the path she has taken in the landscape. She realizes that she has made a wrong *choice* (Section 2) in the previous fork and is now on a poor path for reaching her goal of climbing up the mountain. The best option is to double back, *backtracking* to the fork (Section 4). In this way, she *avoids getting stuck* on the poor path (Section 6), which is long and requires passing a stream. Still many forks remain on the way up the mountain. The path to be taken depends on *deliberate reasoning* (e.g. planning the route on a map), the *approaches* to be used (e.g. following a beaten path or taking a straight course), *preferences* (e.g. desire to avoid risks on the path), *intuition* (e.g. how did she walk earlier in similar terrain), and the *structure* of the area (e.g. impassable obstacles).

Table 1
A summarizing framework of path related phenomena in model based problem solving.

Origins	Phenomena that influence choices at forks	Phenomena that give reasons to redirect the path	Phenomena that make it difficult to change the path taken
Deliberate thinking (or lack thereof)	Focused thinking, Narrow thinking	Learning more about the problem or how to address it	Lack of critical evaluation of the path taken
Processes, methods and approaches used	The approaches used influence mental models and thinking	Problems arise with the approaches used	Lack of resources prevents changing the path
Preferences and motives	Expressed preferences and hidden motives influence choices	Preferences change	Preferences evolve to align with the path taken, Hidden motives to stick with the initial path
Intuitive reasoning	Heuristics and cognitive biases affect choices	Realizing an undesired effect of biases or heuristics	Sunk cost fallacy
System of problem solving and system under study	Strong impact of the starting point, Structures generate behavior	Changes in the system under study	Emergence of lock-in to the initial path due to the structure and dynamics of a system
Possible effect:	**The choices determine the path**	**Problem solving team realizes the need to change the path**	**Project stuck on a poor path**

Heuristics and cognitive biases affect choices at forks. In complex problems one may need to adhere to heuristics, i.e. mental shortcuts or practical rules of thumb. The preferred heuristics are likely to vary across modelers. Heuristics can be appropriate and useful when applied in the right context (see, e.g. Gigerenzer and Todd, 1999; Keller and Katsikopoulos, 2016). Cognitive biases can affect the problem solvers' judgments. For example, the problem solving team may become *anchored* to the modelling approaches that are suggested first. Biases can also impact the preference statements given by stakeholders and estimates obtained by expert judgment (see, e.g. Hämäläinen, 2015; Lahtinen and Hämäläinen, 2016). The effects of biases can accumulate along a sequential preference elicitation process (Lahtinen and Hämäläinen, 2016).

Strong impact of the starting point. The number of paths available is the highest at the start of the problem solving process. Then a single choice, such as the choice of members to the modelling team, can rule out many modelling approaches and paths. A modelling project can start from different perspectives. A value-focused process starts with the identification of the values and goals of the stakeholders (Keeney, 1992; Gregory and Keeney, 1994). Alternatively, the starting point could be, e.g. the identification of decision alternatives, or the analysis of pre-existing data. Linkov et al. (2014) describe how starting with data analysis and starting with the identification of values typically result in very different paths in environmental risk management. The impacts of early choices can last throughout the project.

Structures generate behavior. This is a key finding in the systems literature (see, e.g. Senge, 1992). Examples of concrete structures are the project schedule, the communication platforms used, and the physical arrangement of the venue at a stakeholder workshop. These naturally influence the modelers' and stakeholders' incentives, possibilities, and the consequences of their actions. The path followed in the project is likely to also depend on the personal characteristics of the individuals in the problem solving team and the social system prevailing in the team. The interactions among people can generate trust and openness but also an environment of fear in which people are not positively engaged (Hämäläinen and Saarinen, 2007). In complex environmental problems we need an understanding of the system under study and the problem solving system, as well as the ability to act intelligently in the social system generated by the problem solving process. Here the Systems Intelligence perspective (Hämäläinen and Saarinen, 2007; Törmänen et al., 2016) and facilitation skills (see, e.g Franco and Montibeller, 2010) will help to manage the overall situation and successfully engage people in the process.

3. Recommendations to improve decision making at forks

The literature on the practice of environmental modelling provides several ideas on how to improve decision making in modelling projects. The examples listed in this paper demonstrate that many path related phenomena have already been at least implicitly recognized. The references are only illustrative and similar recommendations can be found in other papers as well.

- Invite a diverse group of stakeholders and experts to take part in problem framing and scoping (see, e.g. Voinov 2008, Gregory et al., 2012). This reduces the risk of narrow thinking and helps find a successful path.
- Create a project steering group to ensure project objectives drive the process (see, e.g. Caminiti, 2004). The steering group helps keep in mind the desired destination when choices are made at critical forks.
- Do not let a few stakeholders dominate group meetings (see, e.g. Blackstock et al., 2012). Otherwise the path can be influenced too much by the perspectives offered by few stakeholder groups with possible hidden motives.
- Apply debiasing techniques where possible (see, e.g. Voinov et al., 2016). This can reduce the risk that biases lead the project to a poor path.
- Document the reasons behind choices throughout the modelling project (see, e.g. Jakeman et al., 2006). This increases transparency and can reduce the impact of strategic self-interested behavior on the choices made in the problem solving project.
- Put strong effort into defining the problem and objectives of the project (see, e.g. Nicolson et al., 2002). This recognizes the impact of the starting point on the path followed.

4. Phenomena giving reasons to redirect a path

Backtracking and taking a different path is sometimes desirable. This can involve restarting the project, restarting parts of it, or even abandoning the project altogether. While previous steps cannot always be completely undone, it may be possible to return to a previous fork and reconsider the decisions made.

Learning more about the problem or how to address it. New information or data can become available along the path after the modelling project has started. New perspectives or solution approaches can suggest better paths, which enable addressing the problem more effectively than before. For example, in an environmental portfolio decision analysis case, stakeholders may bring up new criteria or invent new action candidates when analyzing the results of the initial model (Lahtinen et al., 2016). As a result of learning, the best option is sometimes to backtrack steps and take another path, e.g. revise the model. Learning is an essential element in adaptive environmental management (see, e.g. Walters and Holling, 1990).

Problems arise with the approaches used. Even if an approach is the most suitable one when it is first selected, the situation can change, especially in extensive projects that go on for many years. For example, the transparency of the analysis can be lost if the models and software become increasingly complicated over time. Then modelers may need to take another path, e.g. to develop a simplified model (see, e.g. Voinov et al., 2014).

Preferences change. Individuals rarely hold fixed preferences regarding complicated questions they have not faced before. Instead, they *construct preferences* (Slovic, 1995) as they reflect on the problem and learn more about it (see, e.g. Hayashi et al., 2016). This can be the reason why stakeholders sometimes give different statements when the same preference assessment questions are asked from them at different phases of the modelling project (see, e.g. Lienert et al., 2016). Major changes in preferences may require revising the objectives related to the project and redirecting the path.

Realizing an undesired effect of biases or heuristics. Critical reflection on the path followed can reveal that biases or heuristics have led the project in an undesired direction, which should be corrected. For example, the initial perception of risks can be influenced by the *availability heuristic* (Tversky and Kahneman, 1973), whereby people may overestimate the frequency and importance of events that are easily imaginable or recalled. The risk perception can change when the stakeholders become more familiar with the problem.

Changes in the system under study can make it necessary to revise the model assumptions or scope of the problem solving project, i.e. take a new path. The initial model may have been built under the assumption that the environmental system is stable over time (see, e.g. Glynn, 2015). However, for example climate change can alter the frequency of extreme weather events such as severe floods. If this happens, the role of such events naturally needs to be reconsidered. Time spans in scientific work can be long, so changes in the socio-economic setting of the problem can occur even during the modelling project.

5. Procedures to help redirect a path if needed

The idea underlying these recommendations is to follow a problem solving process with intermediate evaluation points where the path can be redirected if needed.

- Follow an iterative problem solving approach (see, e.g. Jakeman et al., 2006). An iterative process allows the path to be adjusted when the problem solvers learn more about the problem.
- Consider an adaptive modelling project with checkpoints where the model and data are re-evaluated and there is a possibility to abandon the project (see, e.g. Caminiti, 2004). A checkpoint provides an explicit opportunity to think critically and to change the path if needed.
- Expert elicitation methods like Delphi build in feedback to allow for changes in preferences (see, e.g. Krueger et al., 2012; Fu and Guillaume, 2014)
- Use multiple elicitation metrics to reveal hidden biases (see, e.g. Arvai et al., 2006). Repeating a preference elicitation with another method can yield different results and give a reason to reconsider the path.
- Do active adaptive management to build learning into the management process (see, e.g. Walters and Holling, 1990).

- Develop adaptive policy pathways which anticipate future changes in the system under study (see, e.g. Haasnoot et al., 2013).

6. Getting stuck on a poor path

A problem solving project can get stuck on a poor path, which is misleading or an inferior route to find solutions to the problem at hand. In the midst of a project, it is easy to miss the possible need to change the path. Sometimes the project develops so that taking another path becomes very difficult.

Lack of critical evaluation of the path taken. Individuals sometimes refrain from voicing critical opinions about the modelling process. *Overconfidence*, negligence, and laziness, are possible causes of this. The reason can also be a socio-psychological phenomenon, such as *groupthink* (Janis, 1982), whereby individuals try to minimize conflict within a group and conform to the prevailing ideas. The risk of groupthink is higher in cohesive groups where people have similar backgrounds. Time pressure can further discourage critical reflection of the path taken.

Lack of resources prevents changing the path. The budget or time available can sometimes be insufficient to backtrack steps and restart the path followed. The risk of resources running out can form an ‘external threat’, which may lead to groupthink (Janis, 1982). The problem solving team may uncritically accept the path followed rather than obtain new resources to change the path. Workshops with stakeholders, preference assessment, and expert judgment exercises are steps that require significant commitment from multiple participants. There is often only one chance to get these right.

Preferences evolve to align with the path. The perspectives considered along the path can have an impact on the preferences that modelers and stakeholders construct during the modelling project (see, e.g. Slovic, 1995). Participants in the problem solving process can experience *cognitive dissonance* (Festinger, 1957) if the path followed is in conflict with their preferences. This can lead to pressures to either adjust their preferences or the path. A modeler can feel uneasy if her preferred method is not used.

Hidden motives to stick with the path. The subjective attractiveness of a certain outcome can become a hidden motive to stay on a path leading to the outcome. The desired outcome can be, for example, one's favorite project or policy. The fear of *losing face* can also be the reason why modelers get stuck on the initial path. Need to restart or abandon a project can be perceived as a failure which damages one's reputation (see, e.g. Guler, 2007). When the success of the path taken is evaluated, the modelers may selectively bring up only those facts which speak in favor of the choices made. This can be strategic or happen unintentionally due to *confirmation bias*, which is a tendency to gather and use evidence in a way that supports one's initial beliefs and assumptions (see, e.g. Nickerson, 1998).

Sunk cost fallacy refers to the phenomenon that people are often unwilling to give up a project when they have invested time or money to it even if sticking with the project is irrational (Arkes and Blumer, 1985). This phenomenon can create an erroneous perception of the desirability to continue on a path instead of changing it. As a result, the problem solving team may stick with a poor path that is based on the wrong or inferior modelling approach when lots of resources have been invested in the project. Such situations may also exhibit the *escalation of commitment*, which refers to continuously increasing one's effort to try make a failing approach work (Staw, 1981).

Emergence of lock-in due to the structure and dynamics of a system is another reason why a project can get stuck with the initial path. Such lock-in can easily occur in major problem solving efforts with many participants and large organizations involved (see, e.g. Sydow et al., 2009). For instance, it can be very difficult to change the basic frameworks selected at the start of a large project because so many people would need to re-adjust their thinking about the framework.

7. Ideas to reduce the risk of getting stuck on a poor path

These recommendations follow two basic concepts. One is to directly address the reasons why projects can get stuck on a path. The other is to follow multiple paths to reduce the risk that the results are determined by a single, possibly poor, path.

- Appoint a Devil's advocate or a parallel modelling team to challenge the approaches of the main team (see, e.g. Glynn, 2015). This can help avoid groupthink and reduces the risk of getting stuck on a poor path.
- Create an atmosphere of trust so that open reflection of the methods chosen is easier. Fear of mistakes can prevent learning, lead to anchoring to standard methods, and cause avoidance of creative thinking (see, e.g. Gregory et al., 2012).
- Set up more than one problem solving team with different foci or approaches to be used (see, e.g. Nicolson et al., 2002). This enables the evaluation of different paths and reduces the risk that a single focus or approach determines the overall conclusions.
- Consider the possibility of using multiple models (see, e.g. Refsgaard et al., 2006). Comparing results from different models can create insights and possibly increase confidence on the results.
- Do rapid prototyping with models (see, e.g. Nicolson et al., 2002). Developing prototype models can be a resource-efficient way to consider multiple approaches.
- Conduct a peer review of the modelling process (see, e.g. Hämäläinen, 2015). Peer review provides a second opinion on the path followed. It reduces the risk that one biased project is given too much weight in policy making.
- Do not allocate all funds up front (see, e.g. Nicolson et al., 2002). This reduces the risk that lack of resources prevents redirecting the path.
- Establish performance criteria for model evaluation (see, e.g. Refsgaard and Henriksen, 2004). This can reduce the risk that strategic behavior or confirmation bias causes modelers to settle for an inferior model.
- Manage expectations of stakeholders from the start of the modelling project (see, e.g. Caminiti, 2004). Publicly announced commitments, e.g. to a certain technique or time schedule, can create expectations which make it difficult to change the path taken if needed.

8. Summary and path checklist

Table 1 presents a framework, which summarizes the path related phenomena discussed in this paper. It is hoped to help understand what drives the behavior and choices of people associated with a modelling project and how this can influence the problem solving path. Awareness of the phenomena in general helps the problem solving team navigate their path in a reflective mode. The team can have checkpoints where they evaluate if there is a good reason to change the path. The team can prepare for, and possibly try avoid, the phenomena that can make it difficult to change the path.

The phenomena are categorized by the type of their origin.

Deliberate thinking and *intuitive reasoning* are different ways by which people process information and make judgments or choices along the path. The problem solving team applies *processes, methods, and approaches*. The goals of the project depend on the *preferences and motives* of stakeholders and members of the problem solving team. The interaction of people and other elements

Table 2
Path checklist for reflecting on forks and paths in modelling projects.

Tasks and decision forks at different stages	Risks to be mitigated	Comment
Stage: Initial meeting between the problem owners and modelers		
Describe the problem addressed by modelling and specify an initial list of the main objectives.	Anchoring to insignificant objectives, lack of reflection	The problem definition sets the initial direction of the path. Redirecting the path later can be difficult.
Determine whether the goal of the project is to provide prescriptive recommendations or to improve learning.	Narrow thinking	The path perspective is particularly relevant in prescriptive use of modelling, which requires completeness and strong justifications for the choices made.
Consider the possibility of setting up an independent parallel problem solving process.	Problem solving may follow a poor path	The parallel process can follow an alternative path. This supports learning and can build confidence in the results.
Describe how to notice if an unsatisfactory path is followed.	Problem solving can get stuck on a poor path	If the path is unsatisfactory, predetermined criteria to notice the situation can be useful. Such criteria can help cope with hidden motives and biases causing resistance to the change of path.
Ensure that resources are reserved for possible backtracking, redirecting, or restarting of the project. If not, give reason why.	Lack of resources prevent backtracking steps or restarting	If the path is unsatisfactory, redirecting or restarting the project can be the right choice.
Stage: Forming the problem solving team		
Form a modelling team with balanced composition. If not, give reason why.	Narrow thinking	When faced with a fork in the path, a team with diverse backgrounds can more easily notice alternatives and consider multiple perspectives.
Ensure appropriate stakeholder representation.	Marginal interests dominate choices	The choices that determine the path should be informed by the preferences and concerns of the relevant stakeholders. Marginal interests should not dominate the choices made.
Identify motivational goals of modelers and stakeholders. Plan how to ensure they do not cause a poor path to be followed.	Hidden motives affect choices	A poor path can result if choices are driven by hidden motives and self-interest.
Ensure that the role of Devil's advocate is filled in the upcoming stages. If not, give reason why.	Lack of critical evaluation of the path taken	A Devil's advocate helps ensure that a successful path is followed. He or she questions the assumptions made by the team and introduces perspectives that have not been considered.
Stage: Defining the problem		
Search broadly for background information and prior work providing possible starting points for the project.	Setting off from a wrong starting point	To provide new insight, the path should start from the point where others have left off. Awareness of the background information helps ensure that effort is not spent redoing what has already been done.
List different perspectives that can be taken in the problem solving. Justify the perspective selected.	Narrow thinking	The choice of perspectives is a fork in the path. Explicitly considering the alternative perspectives helps ensure the team is thinking broadly enough.
List the most significant sources of uncertainty within the problem.	Lack of critical evaluation of the path taken	More information about the problem can reveal better paths to be followed. Awareness of the sources of uncertainty helps when searching new data and information.
Stage: Planning the modelling process		
Specify the objectives and requirements for the model.	Ill-defined goals drive the process	Clearly stated objectives and requirements help make choices at forks faced in model development. They reduce the risk that the choices are based on hidden motives or convenience.
Specify the criteria used to evaluate the success of the model.	Sunk cost fallacy	Predetermined criteria help notice if a poor path is followed. Explicit criteria can reduce cognitive and motivational biases when evaluating the model.
Plan mid-process checkpoints where the model and data are evaluated. If not, give reason why.	Project stuck on a poor path	The mid-process evaluation creates a fork where the path can be re-directed.
Use multiple modelling approaches in parallel.	The approaches used dominate thinking	More than one path can be followed. Using multiple approaches reduces the risk that important perspectives are missed.
Consider developing multiple prototype models.	The approaches used dominate thinking	Developing prototype models can be a resource-efficient way to use multiple modelling approaches.
Stage: Data collection and elicitation of preferences		
Identify data requirements that have not been adequately met.	Incomplete data drives thinking	How to deal with lack of data creates a fork in the path. One possibility is to collect expert judgments.
Identify biases that can affect preference assessment and expert judgment. Assess the possible impacts of these biases.	Biased judgments and choices	Effects of the biases can accumulate along the path. Reducing the overall bias can be possible. This possibility creates a fork in the path.
Use multiple techniques to assess preferences and obtain expert judgments. If not, give reason why.	Biased judgments and choices	Use of multiple elicitation techniques can reveal the effect of biases and generate additional insights compared to using one technique only.
Stage: Checkpoints for the evaluation of the path followed		
Evaluate the progress of the project in relation to its overall objectives.	Problem solving may follow a poor path	The path may need to be redirected if it is not the intended one or satisfying.
Evaluate the model in relation to the objectives and requirements for the model.	Problem solving may follow a poor path	If the model is not satisfying, there may be need to restart model development, or create a competing model.
Investigate whether there is new understanding about the problem to be taken into account in the problem solving process.	Lack of critical evaluation of the path taken	Improved understanding of the problem may call for changes in the approaches used.
Consider the possibility that external factors influencing the system under study have changed.	Incomplete data or information drives thinking	Changes in the external factors may require changes in the assumptions and approaches used.
Consider the possibility that the data used is not up-to-date.	Outdated data drives thinking	If the data set is outdated or incomplete, there may be need to gather more data.
Consider the possibility that stakeholder preferences have changed.	Unnoticed changes in preferences	Reassessment of stakeholder preferences may be needed.

related to the problem solving process constitute the *system of problem solving*. The *system under study* refers to the system in which the problem at hand is embedded.

Building on the phenomena discussed in this paper, the checklist in Table 2 is intended as a tool to help reflect on the path when planning and managing a modelling project. The tasks described can help detect forks, evaluate alternative paths, and recognize and act on situations where backtracking or changing the path may be desirable. The checklist can be used, for example by the modelling team, stakeholders, the problem owner, the commissioner of the modelling project, or by the steering group related to the project. Practitioners are encouraged to tailor the checklist to suit the contexts they work with.

9. Conclusions

The path perspective can be relevant to anyone working with model based problem solving and policy decision making, and in particular to the environmental modeler. In projects with a prescriptive goal, the consideration of paths is essential. This paper describes how path related phenomena and effects are pervasive and can lead to poor modelling results. Paying attention to the path perspective challenges modelers to identify critical forks along the modelling path and to be aware of the phenomena influencing their choices at the forks. The number of critical forks can be high in complex policy problems involving deep uncertainties, such as climate policy. We provide a path checklist, which can help the practitioners to cope with path dependence and to successfully navigate their paths in a reflective mode.

The term path helps distinguish between a planned modelling process and its actual realization. This distinction helps when discussing and communicating about the practice of modelling. Even if a prescribed ‘best practice’ process is followed, the resulting path can be influenced by the human biases of modelers, hidden motives, unexpected changes in the modelling environment, and systemic effects.

The concept of path offers an integrative perspective to capture the overall impact of behavioral phenomena in modelling. These phenomena do not occur in isolation of each other and the sociotechnical system of problem solving. The behavioral phenomena interact and their effects can accumulate along the path consisting of sequential modelling steps. The path perspective helps the practitioner to take a systemic big picture view of the problem solving situation. Understanding the role of behavioral effects is critical.

A natural theme for future studies is to analyze how best practice procedures for environmental modelling are realized in practice. What is the range of variation in the application paths and does it matter in practice? It would also be interesting to keep a *problem solving logbook* tracking all the forks along the path of a modelling project with justifications for the major choices made. Such a logbook would indicate what other paths could have been followed as well. This would help others continue from the work done. Greater understanding of path related phenomena in environmental modelling will advance our field by helping us work with these phenomena and run more successful modelling projects.

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Path dependence and biases in the even swaps decision analysis method

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ABSTRACT

There are usually multiple paths that can be followed in a decision analysis process. It is possible that these different paths lead to different outcomes, i.e. there can exist path dependence. To demonstrate the phenomenon we show how path dependence emerges in the Even Swaps method. We also discuss the phenomenon in decision analysis in general. The Even Swaps process helps the decision maker to find the most preferred alternative out of a set of multi-attribute alternatives. In our experiment different paths are found to systematically lead to different choices in the Even Swaps process. This is explained by the accumulated effect of successive biased even swap tasks. The biases in these tasks are shown to be due to scale compatibility and loss aversion phenomena. Estimates of the magnitudes of these biases in the even swap tasks are provided. We suggest procedures to cancel out the effects of biases.

1. Introduction

This paper studies and discusses the phenomenon of path dependence in decision analysis (DA). By path we mean the sequence of steps taken in the decision analysis process. Path dependence refers to the phenomenon that the outcome of the analysis process depends on the path followed. We find this an important theme to be considered in the field of decision analysis in general. Decision analysis works directly with subjective data elicited from people and therefore biases are likely to be an important driver of path dependence in DA. Biases can be related to e.g. problem framing, preference assessment tasks and to how information is presented. The effects of biases can accumulate in sequential preference assessment processes and also in the whole decision analysis process. In each step biases can work in favor of some alternative. In the end, the effects of biases can have accumulated so much that one alternative becomes favored. It can also happen that the effects of biases cancel out. Path dependence is directly related to the emerging area of Behavioral Operational Research (Hämäläinen, Luoma, & Saarinen, 2013) because biases as well as other behavioral and social phenomena are likely to be major drivers of path dependence (Hämäläinen & Lahtinen, 2015).

The term path dependence has not been earlier used in OR but we see it as a useful integrative term that refers to different effects arising during problem solving processes (Hämäläinen & Lahtinen, 2015). The possibility that two valid but different modeling paths can lead to different outcomes has been noted already early in the Operational Research (OR) literature (Landry, Malouin, & Oral, 1983). Also the literature on best practices in OR (see, e.g. Morris, 1967; Walker, 2009) does implicitly acknowledge the possibility of path dependence since alternative practices are seen to be possible. Moreover, the concept of constructed preferences discussed in psychological literature (Lichtenstein and Slovic 2006; Slovic, 1995) relates closely to path dependence in decision making as noted by Payne, Bettman, and Schkade (1999). According to the concept, people do not have stable underlying preferences but construct them during the decision making process. Thus the path of the process can have an impact on the preferences that are formed. The effects of paths have been studied earlier also in the context of multi-criteria optimization (MCO). French (1984) notes that the decision maker (DM) can be anchored to the initial point in interactive MCO. This is later confirmed experimentally by Buchanan and Corner (1997). The experiment of Korhonen, Moskowitz, and Wallenius (1990) suggests that path dependence in MCO can be caused by prospect theory related effects. Still, the literature on path dependence remains very limited.

In many contexts we would naturally want to minimize the possibility and effects of path dependence. This is the case in particular in prescriptive decision support. One problem area where decision analysis is widely used and where the risk of path dependence is likely to be high is environmental management (see, e.g. Gregory et al., 2012; Huang, Keisler, & Linkov, 2011). In important policy decision problems, such as climate policies, one should at least be aware of the possibility of path dependence and its origins and of the possible range of its consequences. Yet, there are situations where the main benefits expected from the decision analysis project are related to learning and to the creation of a shared understanding of the problem as a

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whole. Then path dependence might not be a serious concern. In fact, reaching different conclusions along different paths could improve learning.

The Even Swaps method (Hammond, Keeney, & Raiffa, 1998, 1999) is simple and uses clearly defined paths: A path consists of the sequence of even swap tasks that the decision maker carries out to eliminate alternatives and attributes one by one until the 'best' alternative is found. Multiple strategies exist for carrying out the Even Swaps process, each leading the decision maker to a different path. This paper demonstrates how path dependence can emerge in the Even Swaps method. We show the existence of path dependence by experiments where the Even Swaps method is used with the Smart-Swaps software (Hämäläinen et al., 2004; Mustajoki & Hämäläinen, 2005, 2007). Different paths are shown to lead to different choices. This is explained by the accumulation of the effects of biases in successive even swap tasks. The biases in the even swap tasks are shown to be due to scale compatibility and loss aversion phenomena. Estimates of the magnitudes of these biases in the even swap tasks are also provided. We suggest ways to reduce the risk of path dependence in the Even Swaps method.

2. Scale compatibility and loss aversion as causes of path dependence in the Even Swaps method

2.1. The Even Swaps method and the measuring stick attribute

The Even Swaps method (Hammond et al., 1998, 1999) helps to identify the 'best' alternative out of a set of multiattribute alternatives. The DM carries out a sequence of *even swaps* in which she changes an alternative in two attributes such that the modified alternative is preferentially equivalent to the original one. The goal is to make swaps so that alternatives become dominated and can be eliminated or so that attributes become irrelevant. The process continues until only one alternative remains. The conducted sequence of even swaps forms the path of the process. The method allows to choose the path freely. Ideally, one would end up with the same alternative on each path.

The DM carries out the even swap in two steps. First she selects a change in one attribute of the alternative. This we call a *reference change*. Then she gives a compensating *response change* in another attribute which we call the *measuring stick attribute*.

A straightforward strategy for carrying out the Even Swaps process, suggested by Hammond et al. (1998), is to use even swaps to repeatedly make attributes irrelevant until only one remains. At this point the most preferred alternative can be readily identified. We call this the *attribute elimination strategy.* The *pricing out* method by Keeney and Raiffa (1976) is an attribute elimination strategy in which all attributes but the monetary one are made irrelevant and money is used as the measuring stick in every swap.

The Even Swaps method is less complicated than many other multi-criteria decision analysis methods that are based on the use of value models. For example, Even Swaps does not require the user to understand the idea of value functions or weights. It is simply, a "clear framework for making trade-offs" (Hammond et al., 1998).

2.2. Scale compatibility

It is known that people tend to give extra weight to the response attribute, i.e. the measuring stick, in two-attribute matching tasks (Anderson & Hobbs, 2002; Bleichrodt and Pinto 2002; Delquié, 1993, 1997; Tversky, Sattath, & Slovic, 1988). This is referred to as the scale compatibility bias. The task of determining the response change of an even swap is equivalent to giving a response in a two-attribute matching task. Therefore one can expect that the scale compatibility bias is found in a similar manner in even swaps as in matching tasks. The bias would cause the measuring stick attribute to get extra weight in the even swap. This would cause the result of an Even Swaps process to depend on the measuring stick attributes used.

When a single measuring stick attribute is used throughout the Even Swaps process, the DM repeatedly carries out even swaps in which this same attribute receives extra weight. This way the effects of the scale compatibility bias can accumulate. This leads us to the following hypothesis:

Hypothesis 1. An Even Swaps process where only one measuring stick is used favors the alternatives that are good in this measuring stick attribute.

2.3. Loss aversion

Loss aversion refers to people's tendency to give extra weight to losses compared to corresponding gains (Tversky & Kahneman, 1991). Bleichrodt and Pinto (2002) show that people are loss averse in two-attribute matching tasks. Asking for the response change in an even swap task is equivalent to a two-attribute matching task. Therefore one can expect that the loss aversion bias also exists in the even swap tasks.

In the even swap task an alternative is changed in two attributes. One of these changes made in the alternative is always a gain and the other one is a loss. A loss averse DM will give extra weight to the loss. This results in the situation where this alternative becomes more attractive in each swap. If the reference change of the even swap is a loss then the compensatory response change is a gain. In this case, the DM overstates the response change because she gives extra weight to the reference change. If the reference change of the even swap is a gain then the compensatory response change is a loss. In this case, the DM understates the response change because she gives extra weight to it. In either case the even swap increases the attractiveness of this alternative.

When the same alternative is repeatedly swapped, then loss aversion can make this alternative better and better. This way the effects of the loss aversion bias can accumulate in favor of this alternative. This leads us to the following hypothesis:

Hypothesis 2. The Even Swaps process favors the alternative in which the most swaps are conducted.

2.4. Modeling scale compatibility and loss aversion

We present a simple approach to model the effects of scale compatibility and loss aversion biases in even swaps. This approach is based on the Anderson and Hobbs (2002) model to estimate the magnitude of scale compatibility. We include a new loss aversion parameter in the model and assume that the value function for each attribute is linear. We use this model to provide a theoretical illustration of how path dependence can occur in the Even Swaps method in Section 2.5. The model is also used to estimate magnitudes of biases in even swap tasks performed during our experiments in Section 4.2.

The following notation is used. The reference change of an even swap in attribute k is $x_k \to x'_k$ and the response change in the measuring stick attribute m is $x_m \to x'_m$. The magnitude of the corresponding trade-off ratio is denoted by

$$r_{mk} = \left| \frac{x'_m - x_m}{x_k - x'_k} \right|. \tag{1}$$

The weights of attributes m and k are denoted by w_m and w_k. The coefficients describing the increase in weight due to biases are S and L for scale compatibility and loss aversion respectively. For unbiased DM they would equal to one. Using these notations the trade-off ratio is given in the following way.

Table 1
Consequences tables on path 1.

Initial consequences table.

Attribute	Alternative A	Alternative B
X	2	0
Y	1	0
Z	0	4
Overall value	3	4

Consequences after swap 1. Attribute Z becomes irrelevant.

Attribute	Alternative A	Alternative B
X	-0.8	0
Y	1	0
~~Z~~	~~4~~	~~4~~
Overall value	4.2	4

Consequences after swap 2. Alternative B becomes dominated.

Attribute	Alternative A	Alternative ~~B~~
X	0.05	~~0~~
~~Y~~	~~0~~	~~0~~
~~Z~~	~~4~~	~~4~~
Overall value	4.05	4

Table 2
Consequences tables on path 2.

Initial consequences table

Attribute	Alternative A	Alternative B
X	2	0
Y	1	0
Z	0	4
Overall value	3	4

Consequences after swap 1. Attribute Z becomes irrelevant.

Attribute	Alternative A	Alternative B
X	2	3.4
Y	1	0
~~Z~~	~~0~~	~~0~~
Overall value	3	3.4

Consequences after swap 2. Alternative A becomes dominated.

Attribute	Alternative ~~A~~	Alternative B
X	~~2~~	2.7
~~Y~~	~~1~~	~~1~~
~~Z~~	~~0~~	~~0~~
Overall value	3	3.7

If the reference change $x_k \to x'_k$ in attribute k is a loss:

$$r_{mk} = \frac{w_k \cdot L}{w_m \cdot S} \cdot e. \tag{2}$$

If the response change $x_m \to x'_m$ in the measuring stick attribute m is a loss:

$$r_{mk} = \frac{w_k}{w_m \cdot S \cdot L} \cdot e. \tag{3}$$

The coefficient e represents a random error which is assumed log-normally distributed with one as the median as in Anderson and Hobbs (2002).

To obtain estimates for the bias coefficients we can use the following model (4) which we get by taking logarithms of (2) and (3),

$$\ln(r_{mk}) = \ln(w_k) - \ln(w_m) - \ln(S) \pm \ln(L) + \ln(e), \tag{4}$$

where the sign of $\ln(L)$ depends on whether the loss is in the attribute m or in the attribute k. This model can be estimated with ordinary least squares regression.

2.5. Illustration of path dependence in Even Swaps

To help the reader understand how the loss aversion and scale compatibility biases can lead to path dependence we provide the following simple illustrative example. The initial consequences table is given in Table 1 on the left. In this illustration we assume the DM's preferences to follow a linear additive value function with equal attribute weights. For illustrative purposes, overall values of the alternatives are shown below each consequences table. These overall values would not be available in a real case because we would not know the DM's preferences.

When the DM conducts even swaps she exhibits scale compatibility and loss aversion such that her swaps follow Eqs. (2) and (3) with bias coefficients $S = 1.3$ and $L = 1.1$. These magnitudes for bias coefficients are selected because they are close to the average magnitudes observed in our experiments. Theoretically, when S or L differs from 1 we can always construct a similar illustrative example where the outcome depends on the path followed.

When there are no biases, alternative B gives the highest value for the DM. Alternative A would contribute 75 percent of the value of B. However, when biases are assumed the DM can end up with either alternative. That is, there exists path dependence. We show this by considering the following two paths:

Path 1: Attribute X is used as the measuring stick and all swaps are carried out in A.

Path 2: Attribute X is used as the measuring stick and all swaps are carried out in B.

On both paths the DM has to conduct two swaps in order to find a non-dominated alternative. The scale compatibility bias works in favor of A on both paths because A is better than B in attribute X which is used as the measuring stick on both paths. On each path, the loss aversion bias works in favor of the alternative in which all swaps car-

Table 3
Consequences table for Task 1 (job).

Attribute	Alternative A	B	C	D
Salary	2600€	1850€	2800€	2100€
Daily working hours	7.5 hours	9 hours	8.5 hours	7 hours
Job atmosphere	2	3	1	2
Commuting time	60 minutes	45 minutes	30 minutes	35 minutes
Flexibility	1	3	1	2

Table 4
Consequences table for Task 2 (apartment).

Attributes	Alternatives			
	A	B	C	D
Size	25 square meter	27 square meter	20 square meter	32 square meter
Commuting time	40 minutes	5 minutes	15 minutes	25 minutes
Rent	300€	450€	350€	500€
Condition	3	1	2	3

Table 5
Consequences table for Task 3 (job).

Attributes	Alternatives			
	A	B	C	D
Salary	2600€	1850€	2800€	2100€
Daily working hours	7.5 hour	9 hour	8.5 hour	8 hour
Job atmosphere	2	3	1	2
Commuting time	60 minutes	45 minutes	30 minutes	35 minutes
Flexibility	1	3	1	2

Table 6
Consequences table for Task 4 (apartment).

Attributes	Alternatives	
	B	D
Size	27 square meter	32 square meter
Commuting time	5 minutes	25 minutes
Rent	450€	500€
Condition	1	3

ried out. When the DM goes along path 1 she ends up with alternative A (Table 1). When the DM goes along path 2 she ends up with alternative B (Table 2).

Swaps on path 1 explained:

Swap 1. Reference change: Alternative A improved in the attribute Z from 0 to 4.

Response change: Alternative A worsened in the measuring stick attribute X from 2 to α.

The response change is a loss so α is based on Eq. (3):

$$\left|\frac{\alpha-2}{0-4}\right| = \frac{1}{1\cdot 1.3\cdot 1.1} \Leftrightarrow \alpha = -4\frac{1}{1\cdot 1.3\cdot 1.1}+2 \Leftrightarrow \alpha \approx -0.80.$$

Swap 2. Reference change: Alternative A worsened in the attribute Y from 1 to 0.

Response change: Alternative A improved in the measuring stick attribute X from −0.8 to β.

The reference change is a loss so β is based on Eq. (2):

$$\left|\frac{\beta-(-0.80)}{1-0}\right| = \frac{1\cdot 1.1}{1\cdot 1.3} \Leftrightarrow \beta = 1\cdot\frac{1\cdot 1.1}{1\cdot 1.3}-0.80 \Leftrightarrow \beta \approx 0.05.$$

3. Experiment

The subjects were Finnish speaking, mostly second year engineering students ($N = 148$) from Aalto University. The subjects used the Even Swaps method with the Smart-Swaps software (Hämäläinen et al., 2004; Mustajoki & Hämäläinen, 2005, 2007) in decision tasks related to selecting a rental apartment or a summer job.

Each session consisted of two steps. First the subjects were given a 15 minute tutorial on the method and they practiced using it for 10 minutes. Then the subjects were given a sheet that contained the instructions for carrying out the experiment. The subjects proceeded at their own pace. Completing the tasks took from half an hour to one and a half hours. Incomplete responses and those which do not follow the instructions are excluded from analysis.

3.1. The decision tasks

Four different decision tasks are used in the experiment. The consequences tables for each of them are given in Tables 3–6. The subjects were told to think that the alternatives are equally good with respect to any other attribute that is not shown in the table. The 1–3 scales used for the attributes condition, atmosphere and flexibility are from the worst to the best. These scales were described to the subjects in more detail on the instruction sheets of the experiment.

3.2. Paths

Each subject carried out one apartment related task and one job related task. Both tasks were carried out two or three times. Each time the subject followed a different path, i.e., conducted a different sequence of swaps. The different paths resulted from different instructions given (Table 7).

The Pricing (PRI) and Hours (HRS) paths are based on the use of the attribute elimination strategy.

The dominance (DOM) and irrelevance (IRR) paths are used as references for these paths. The DOM and IRR paths are based on the use of the Even Swap proposal features of the Smart-Swaps software. The software allows the user to ask for proposals which help her to complete the Even Swaps process with as few swaps as possible (Mustajoki & Hämäläinen, 2005).

- The proposals for dominance aims at domination of alternatives with as few swaps as possible.
- The proposals for irrelevance aims at making attributes irrelevant with as few swaps as possible.

Each proposal specifies the alternative that would be modified, the reference change and the measuring stick attribute. The user gives the response change based on her preferences. Fig. 1 illustrates a proposal for dominance.

The subjects were divided into two groups with different tasks and instructions (Table 8). Tasks 1 and 2 were used with the first group, Tasks 3 and 4 were used with the second group. The subjects repeatedly carried out a job related task followed by an apartment related task. The order in which the subjects followed the paths was altered across subjects.

4. Results

4.1. Path dependence

Path dependence is studied by comparing the subjects' choices across the paths. Path dependence exists if different paths lead to different final alternatives. We can only compare the results between paths but cannot determine which the 'true' most desirable alternative is for each subject.

For the analysis the alternatives in each task are grouped into two sets (Table 9). In Task 1 and Task 2 the alternatives are grouped based on their performance in the money attribute which is used as the measuring stick on the PRI path. In Task 3 the alternatives are grouped based on their performance in daily working hours which is used as the measuring stick on the HRS path.

Table 7
Paths related to different instructions.

Path	Subjects instructed to
Pricing (PRI)	Use an attribute elimination strategy to make all attributes but the monetary one irrelevant. Money used as the measuring stick in every swap.
Hours (HRS)	Use an attribute elimination strategy to make all attributes but daily hours irrelevant. Daily hours used as the measuring stick in every swap.
Dominance (DOM)	Follow the suggestions provided by the feature 'even swap proposals by *dominance*' of the Smart-Swaps software.
Irrelevance (IRR)	Follow the suggestions provided by the feature 'even swap proposals by *irrelevance*' of the Smart-Swaps software.
Swaps in one alternative (Swaps in B/D)	Carry out all swaps in the same alternative, B or D.[a]

[a] This instruction was used only in Task 4 which includes only two alternatives.

Table 8
The experiments.

Task	N	Paths		
Task 1 (job)	98	PRI	DOM	IRR
Task 2 (apartment)		PRI	DOM	IRR
Task 3 (job)	50	HRS	DOM	–
Task 4 (apartment)		Swaps in B	Swaps in D	–

Hypothesis 1 predicts that the percentage of subjects ending up with any of the alternatives in Set 1 is higher on the PRI path than on the IRR and DOM paths. Hypothesis 1 also predicts that the percentage of subjects ending up with any of the alternatives in Set 1 is higher on the HRS path than on DOM path. The reason is that only one measuring stick attribute is used on PRI and HRS paths and the alternatives in Set 1 are better in this attribute.

Hypothesis 2 predicts that the percentage of subjects ending up with alternative B is higher on the Swaps in B path than on the Swaps in D path. The reason is that on the Swaps in B path all swaps are conducted in alternative B.

Table 10 (column 5) gives the percentage of subjects ending up with an alternative in Set 1 on each path. This illustrates the effect sizes and shows that the results of the experiment align with the predictions by hypotheses 1 and 2. Additionally, we checked whether the results for either Task 1 or Task 2 change if only those subjects which have completed the task on all paths are included in the analysis. We found the same pattern of results. None of our conclusions would change if that data was used.

The statistical test results are presented in Table 11. McNemar's test (1947) is used because we have binomial paired data. The test is based on comparing the results of the *same* subjects between a pair of paths. Therefore, only subjects with data from both paths are included in each comparison. The null distribution of the test statistic k is binomial (K, 0.5) where K is the number of subjects who end up with alternatives in different sets on each of the two paths. The statistic k is the number of subjects who end up with any of the alternatives in the Set 1 on the PRI, HRS or Swaps in B path *and* end up with any of the alternatives in the Set 2 in the other path.

The difference between two paths is statistically significant with $p < 0.001$ in two cases, $p < 0.01$ in one case and $p < 0.05$ in one case (Table 11). In the remaining two cases the difference between the paths is small and statistically insignificant but in the direction predicted by the hypothesis.

Table 10 shows that the subjects used money as the measuring stick more frequently on the IRR than on the DOM path. This possibly explains why the IRR path has been more favorable than the DOM path for the alternatives that are good in the monetary attribute.

We also compare the choices by subjects who conducted Task 1 (job) on the PRI path and the choices by subjects who conducted Task 3 (job) on the HRS path. Two statistically significant differences are found. Job C is chosen more often on the PRI path (40 percent) than on the HRS path (11 percent) (Z-statistic: 3.35, p-value: 0.0004). Job D is chosen more often on the HRS path (53 percent) than on the PRI path (36 percent) (Z-statistic: −1.84, p-value: 0.03). These results are in line with hypothesis 1 because Job C has better salary and Job D has lower working hours.

We conclude that these results show the existence of path dependence. Hypothesis 1 is clearly supported when a monetary attribute is used as the measuring stick. Hypothesis 2 is supported.

4.2. Magnitudes of loss aversion and scale compatibility

Altogether the subjects carried out several thousand even swap tasks during the experiment. We form eight data sets out of this data and estimate the model (4) separately for each of them. The data set *Apartment task – All attributes* includes all swaps conducted in a task related to choice of an apartment. The data set *Job task – All attributes* includes all swaps conducted in a task related to choice of a job. The rest of the data sets are formed such that each contains all swaps where the same pair of attributes was traded-off against each other. Only those pairs of attributes are studied in which the measurement scale for both attributes is continuous. Table 12 shows the estimates of the bias coefficients.

We make the following three observations.

Observation 1. The scale compatibility and loss aversion biases are found in even swaps similarly as in matching tasks. The bias coefficients S and L are greater than one in all data sets. This confirms our initial assumption that these biases exist in Even Swaps.

Observation 2. The estimates of magnitude of scale compatibility obtained for data sets "Apartment task – All attributes" and "Job task – All attributes" are 1.21 and 1.34 respectively. These are close to the average of the subject specific scale compatibility estimates by Anderson and Hobbs (2002) which is 1.32 when their subject 4 is excluded as an outlier. This suggests the interesting conclusion that the average magnitude of scale compatibility can be a general bias effect which is of the same magnitude in different contexts. The experiment by Anderson and Hobbs (2002) was in the context of fisheries management and the subjects were managers instead of students. They report Bayesian posterior probability distributions of bias for each subject. The means of these distributions are (1.5, 2.07, 1.01, 10.9, 1.25, 1.45, 0.65) (R. Anderson, personal communication, September 10, 2013).

Observation 3. The estimates obtained for S range from 1.12 to 1.43 and the estimates obtained for L range from 1.05 to 1.16. A possible explanation is that the magnitude of the bias depends on which attributes are traded-off against each other. This would be contrary to the assumption by Anderson and Hobbs (2002) that the bias coefficient *do not* depend on which attributes are traded-off against each other. This matter could be investigated in a further study.

We conducted residual analysis that suggests the assumption of homogeneity of variance and the assumption of normality to be reasonable. Multicollinearity is not found in the data sets.

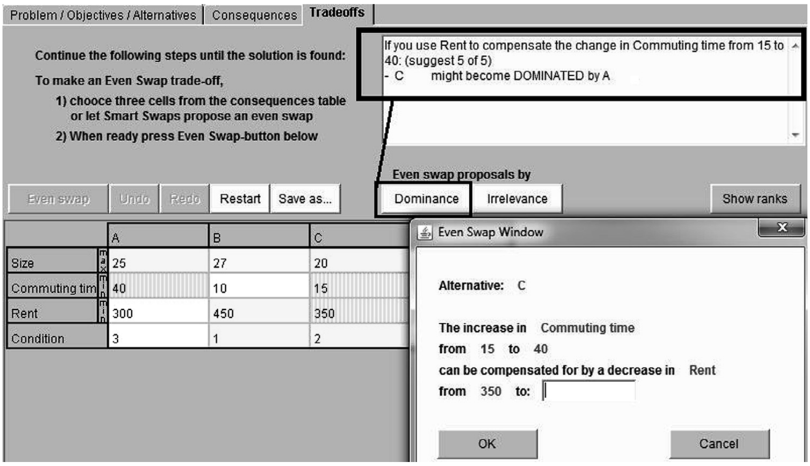

Fig. 1. Interface for the Smart-Swaps software (Hämäläinen et al., 2004). Even swap proposal by dominance is highlighted with the bolded frame.

4.3. Summary of results

When the subjects go through the Even Swaps process and use money as the measuring stick in the even swap tasks, i.e. they give responses in money, they end up favoring those alternatives which are good in the monetary attribute. When two alternatives are compared such that the same alternative is modified in every swap, the subjects favor the modified alternative. These results can be explained with the accumulated effect of successive statements biased by scale compatibility and loss aversion. These biases are found in the trade-off data provided by the experiments.

5. Reducing the accumulation of bias effects in the Even Swaps process

The general question of reducing the possibility of biases, or debiasing, in decision analysis has not been studied very much. There has been a number of suggestions including: Use consistency checks and give feedback (Keeney & Raiffa, 1976), average the responses given (Kleinmuntz, 1990), give better training (Anderson & Clemen, 2013; Carlson & Bond, 2006; Hämäläinen & Alaja, 2008) and calibrate the responses given (Anderson & Hobbs, 2002; Bleichrodt, Pinto, & Wakker, 2001; or Jacobi & Hobbs, 2007). However, there remains a limited number of studies on how successful these advice are. Currently, the general observation is that some biases, such as the splitting bias (Pöyhönen, Vrolijk, & Hämäläinen, 2001; Weber, Eisenführ, & von Winterfeldt, 1988), are very persistent and difficult to eliminate whereas some are easier to be reduced (Montibeller & von Winterfeldt, 2015). For example, in the study by Hämäläinen and Alaja (2008) they found that training did not help stakeholders to avoid the splitting bias. Yet, the studies by Carlson and Bond (2006) and Anderson and Clemen (2013) suggest that training can help to reduce biases related to priming, framing, asymmetric dominance and the prominence effect.

Table 9
Sets of alternatives.

Task	Set 1	Set 2
Task 1 (job)	‘High-salary jobs’ A and C	‘Low-salary jobs’ B and D
Task 2 (apartment)	‘Low-rent apartments’ A and C	‘High-rent apartments’ B and D
Task 3 (job)	‘Low-hours jobs’ A and D	‘High-hours jobs’ B and C
Task 4 (apartment)	Alternative B	Alternative D

Table 10
Number and percentage of subjects who ended up with an alternative in Set 1.

Task	Path	*N*	Number of subjects who ended up with	Percentage of subjects who ended up with	Percentage of swaps with money as measuring stick
Task 1 (job)			High-salary job	High-salary job	
	PRI	67	42	63	100
	IRR	98	56	57	55
	DOM	98	28	29	19
Task 2 (apartment)			Low-rent apartment	Low-rent apartment	
	PRI	45	36	80	100
	IRR	97	61	63	34
	DOM	96	51	53	31
Task 3 (job)			Low-hours jobs	Low-hours jobs	
	HRS	45	34	76	N/A [a]
	DOM	45	32	71	N/A
Task 4 (apartment)			Apartment B	Apartment B	
	Swaps in B	38	19	50	N/A
	Swaps in D	38	8	21	N/A

[a] N/A = Not available.

Table 11
Results of statistical tests.

Task	Paths	Prediction by hypothesis 1 or 2	N	K	k	p-value
Task 1 (job)	PRI, IRR	Hypothesis 1: PRI favors high-salary alternatives	67	18	11	0.24
	PRI, DOM	Hypothesis 1: PRI favors high-salary alternatives	67	34	28	0.0004***
Task 2 (apartment)	PRI, IRR	Hypothesis 1: PRI favors low-rent alternatives	45	18	13	0.05*
	PRI, DOM	Hypothesis 1: PRI favors low-rent alternatives	45	20	18	0.0002***
Task 3 (job)	HRS, DOM	Hypothesis 1: HRS favors low-hours alternatives	45	16	9	0.4
Task 4 (apartment)	Swaps in B,Swaps in D	Hypothesis 2: Swaps in B favors alternative B	38	15	13	0.004**

Statistical significance level:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 12
Estimates of magnitudes of biases for different data sets.

Data set	N	R^2	ln(L)	p-value	ln(S)	p-value	Loss aversion coefficient L	Scale compatibility coefficient S
Apartment task								
All attributes	2155	0.95	0.1	3.6E−13	0.19	2.7E−31	1.11	1.21
Rent, commuting time	474	0.89	0.078	0.12	0.36	3.9E−10	1.08	1.43
Size, commuting time	419	0.52	0.12	0.0048	0.16	1.6E−5	1.13	1.17
Size, rent	554	0.97	0.058	0.0043	0.11	8.1E−7	1.06	1.12
Job task								
All attributes	3096	0.98	0.12	3.2E−23	0.29	1.1E−90	1.13	1.34
Salary, commuting time	576	0.95	0.074	0.12	0.33	1.1E−11	1.08	1.39
Working hours, commuting time	305	0.95	0.15	0.0030	0.3	5.1E−9	1.16	1.35
Working hours, salary	592	0.99	0.053	0.10	0.21	6.5E−12	1.05	1.23

Table 13
Illustration of path where cumulative effect of bias is reduced.

Initial consequences table.

	Alternative	
Attribute	A	B
X	2	0
Y	1	0
Z	0	4
Overall value	3	4

Consequences after swap 1. Attribute X becomes irrelevant.

	Alternative	
Attribute	A	B
~~X~~	~~0~~	~~0~~
Y	2.7	0
Z	0	4
Overall value	2.7	4

Consequences after swap 2. Alternative A becomes dominated.

	Alternative	
Attribute	~~A~~	B
~~X~~	~~0~~	~~0~~
Y	~~2.7~~	3.4
~~Z~~	~~0~~	~~0~~
Overall value	2.7	3.4

Here we suggest a strategy for carrying out the Even Swaps process so that the accumulation of the effects of biases is reduced. Our idea does not rely on reducing biases in single even swap tasks. Instead, we suggest a way to design the path of the process so that the effects of biases do not accumulate in favor of any single alternative.

To reduce the accumulation of the effects of the loss aversion bias, one can carry out even swaps evenly in all of the alternatives. This way the effects of the bias do not accumulate in favor of a single alternative but are distributed evenly across the alternatives. To reduce the accumulated effect of the scale compatibility bias one can use a measuring stick in which the consequences of the alternatives differ the least. Scale compatibility gives extra weight to the measuring stick attribute. This extra weight does not matter if the alternatives differ only a little in this attribute.

These ideas can be illustrated with the example of Section 2.5. The DM should choose the attribute Y as the measuring stick because the alternatives' consequences differ the least in this attribute. One swap should be conducted in each of the alternatives to distribute the effect of loss aversion evenly. Following these suggestions would lead to a path shown in Table 13. Along this path the DM would end up with the alternative B which theoretically gives her the highest value.

Another idea to reduce the accumulated effect of biases is to restart the Even Swaps process with the original consequences of the remaining alternatives at certain points during the process. This would remove any error or bias that has accumulated in the remaining alternatives. One possibility would be to restart the process with the remaining alternatives every time when an alternative is eliminated. The following example illustrates this idea: The decision task includes three alternatives A, B and C. The DM conducts four swaps in B which result in the elimination of C. Here loss aversion has accumulated and made the modified B more attractive than the original B because all swaps were conducted in B. Thus the DM is biased towards B if she continues the Even Swaps process with A and modified B. The accumulated bias could be removed by restarting the Even Swaps process with alternative A and the original, unmodified, alternative B. This idea can be applied in the Smart-Swaps software by using the backtracking feature which allows the DM to cancel previously made swaps. Every time an alternative is dominated the DM can backtrack to the start of the process and then eliminate the dominated alternative and continue with the remaining ones.

One can utilize all of the above mentioned ideas together with the following step-by-step procedure for carrying out the Even Swaps process:

Continue steps 1 to 3 until only one alternative remains.

1. Identify a pair of alternatives which are close to each other in some attribute that can be used as the measuring stick attribute.
2. Carry out swaps to make the consequences of these two alternatives equal in all other attributes. Alternate between conducting swaps in the two alternatives.
3. Eliminate the dominated alternative and restart the Even Swaps process with the original consequences of the reduced set of alternatives.

Using the step-by-step procedure described above will take at most $(N-1)(K-1)$ swaps where N is the number of alternatives and K is the number of attributes. One needs $N - 1$ pairwise comparisons to eliminate all but one alternative. In each pairwise comparison at most $K-1$ swaps must be conducted to make all but one attribute irrelevant. In the attribute elimination strategies, e.g. the pricing out method, the upper limit for the number of swaps is the same.

It should be noted that using the procedure described above or other methods that use averaging or calibration of responses do not always lead to the most accurate judgments. For example, some decision makers might give the most thoughtful responses when using money as the measuring stick if they are used to evaluating benefits in terms of money. In such a case simply using money as the measuring stick can be the best option. Therefore, the procedure proposed here or other methods based on averaging or calibrating responses should be employed with consideration.

One could also think that sensitivity analysis can help to identify and avoid path dependence in Even Swaps. However, performing sensitivity analysis in a 'traditional way' is difficult in the Even Swaps method. This is because of the sequential nature of the swapping process. For example, changing the response change in the first swap by 10 percent might cause the subsequent swaps to be unfeasible. Thus the DM might have to revise all swaps accordingly. Instead, as a form of sensitivity analysis, one could carry out the whole Even Swaps process along multiple paths and compare the results.

6. Discussion

All decision analysis processes consist of a sequence of steps and typically different paths can be followed. The sequential character of the analysis process can give rise to path dependencies due to the accumulation of biases and possibly also due to other behavioral phenomena. We chose to study path dependence in the Even Swaps method because it is simple and consists of a clear sequential preference elicitation process. This hopefully makes our argumentation easier to follow and the experiments easier to replicate. In general, the drivers of path dependence are likely to depend on the method used as well as the problem context. In the following discussion we provide examples of how path dependence might occur in some well-known decision analysis methods.

The starting point effect is one path related phenomenon that can exist in decision analysis methods. Different starting points can set the decision analysis process on different paths. This can happen, for example, in structuring the value tree. A decision maker could give most attention to the one higher level objective she considers first and generate the richest set of lower level objectives under this objective. This would lead to the situation where extra weight is given to the objective considered first due to the splitting bias (Hämäläinen & Alaja, 2008; Pöyhönen et al., 2001; Weber et al., 1988).

Path dependence can exist when a sequence of trade-off tasks is performed to determine the weights for an additive value model. The choice of measuring stick attributes can matter because of the scale compatibility effect. Whether changes in the consequences are framed as gains or losses can have an impact due to the loss aversion effect. Laskey and Fischer (1987) suggest that in sequential preference elicitation the response given in one task could become an anchor for the next one. It is also possible that the problem context could evoke use of heuristics that can cause path dependence in the weight elicitation process.

We have shown that the scale compatibility bias can create path dependence in the Even Swaps method. In trade-off and even swap tasks the bias gives extra weight to the measuring stick attribute. The scale compatibility bias could possibly also play a role in the SWING and SMART weighting (von Winterfeldt & Edwards, 1986). In the SWING procedure one gives 100 points to the most important attribute and then proceeds by giving points to the other attributes. In the SMART procedure one gives 10 points to the least important attribute and then proceeds by giving points to the other attributes. One might possibly perceive the attribute with fixed points as the measuring stick and overvalue it. As a result the SWING procedure would create a greater spread of weights than the SMART procedure. Spread of weights is the ratio of the weights of the most important and least important attribute. Overvaluing the most important attribute would increase this ratio and overvaluing the least important attribute would decrease this ratio. In the experiments by Bottomley & Doyle (2001) and Pöyhönen and Hämäläinen (2001) the SWING procedure has, indeed, created a greater spread of weights than the SMART procedure. Other explanations are naturally possible as well, and there is clearly a need for further studies.

The existence and possible causes of path dependence in the Analytic Hierarchy Process (AHP) by Saaty (1990) is also an interesting research topic which has not been addressed before. In AHP the decision maker performs a sequence of pairwise comparison tasks. It is possible that the order of these tasks has an impact on the result. If path dependence is found to exist in AHP, one can ask whether there is a sequence of pairwise comparison tasks which would minimize the effects of biases in AHP.

7. Conclusions

In decision analysis path dependence is likely to emerge from behavioral origins because the decision analysis processes directly involve people and work with subjective data elicited from them. This paper demonstrates how path dependence can emerge in the Even Swaps method. We also discuss possible ways in which path dependence could exist in other decision analysis methods.

Our experiment shows that when the subjects go through the Even Swaps process and use money as the measuring stick in the even swap tasks, i.e. they give responses in money, they end up favoring those alternatives which are good in the monetary attribute. When two alternatives are compared such that the same alternative is modified in every swap, the subjects favor the modified alternative. These results can be explained with the accumulated effect of successive even swap tasks biased by scale compatibility and loss aversion. We provide estimates of the magnitudes of these biases in the even swap tasks.

Finding ways to avoid problems related to path dependence is important in normative decision support where the aim is to give one correct outcome to be implemented. One option is to analyze the same problem following different paths. This can increase confidence in the solutions obtained. Debiasing methods can also be considered. In this paper we suggest a strategy for reducing the effect of biases in the Even Swaps method. Our idea is not based on reducing biases in single even swap tasks. Instead, we suggest to design the path of the process so that the effects of biases cancel out and do not accumulate in favor of any single alternative. This way there is no need to explicitly manipulate or calibrate the DM's judgments.

The drivers of path dependence are likely to depend on the method used as well as the problem context. Besides biases there can be other human related drivers of path dependence, including motivational and strategic behavior. These drivers can be related to the facilitator and to the problem owners as well as to the stakeholders involved. In future studies a natural next step is to consider the decision analysis process and the people engaged in the system created in the problem solving as a whole. More research is clearly needed to identify different forms of path dependence, to understand the causes of path dependence in different context and to find ways of dealing with it.

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Paper IV

Lahtinen, T.J., Hämäläinen, R.P., Jenytin, C. 2017. A Systemic Perspective on Bias Mitigation in Decision Analysis. *Submitted manuscript, 22 pages*.

A systemic perspective on bias mitigation in decision analysis

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Abstract

A systemic overall perspective is needed in the mitigation of biases in practical decision analysis processes. There has been a limited interest in analyzing the overall effects of biases. Biases occur at different sequential steps in the decision process and become an issue especially if their effects build up in favor of certain alternatives. This paper presents bias mitigation techniques and evaluates them computationally. These techniques are: 1. Introducing a virtual reference alternative in the decision problem. 2. Introducing an auxiliary measuring stick attribute. 3. Rotating the reference point. 4. Restarting the decision process at an intermediate step with a reduced set of alternatives. We analyze settings where decision makers exhibit the loss aversion bias, the measuring stick bias, and make random response errors. We demonstrate that the techniques help to mitigate biases in the Even Swaps process. These techniques are likely to be applicable also with other multi-criteria approaches.

1. Introduction

In the practice of decision analysis the importance of coping with biases has been recognized for long (see, e.g. Howard 1980, Keeney 1982). There have been various suggestions on how to mitigate the effects of cognitive biases in individual preference elicitation tasks (see, e.g. Clemen 2008, Montibeller and von Winterfeldt 2015). However, only a few studies have analyzed the effectiveness of debiasing methods in practical preference elicitation processes (see, e.g. Anderson and Hobbs 2002, Jacobi and Hobbs 2007).

In practical decision analysis, preference elicitation is just one phase in the overall process where behavioral phenomena such as biases can affect the outcome. A systemic approach is needed when coping with the overall effects of behavioral issues (Hämäläinen et al. 2013, Franco and Hämäläinen 2016). The path perspective (Hämäläinen and Lahtinen 2016, Lahtinen and Hämäläinen 2016, Lahtinen et al. 2017) offers a systemic view on bias mitigation in decision analysis. Path is the sequence of steps or tasks carried out in the decision analysis process. In bias mitigation, we should seek paths along which the overall effect of biases will be minimal. The effects of biases may build along the steps taken and create a large overall bias. It is also possible that the effects of biases cancel out each other (Kleinmuntz 1990, Anderson and Hobbs 2002). Looking for bias minimizing paths can be a more attractive approach than trying to reduce biases in the individual steps that form the path. Then one would not need to find ways to debias or force decision makers to avoid their natural ways of responding. Training people to avoid biases is not necessarily easy nor very successful (Hämäläinen and Alaja 2008). Furthermore, reducing biases by adjusting the numerical judgments obtained from experts or stakeholders (see, e.g. Bleichrodt et al. 2001, Anderson and Hobbs 2002, Jacobi and Hobbs 2007) can be problematic. People may not trust results that have been technically adjusted or corrected by the analyst.

This paper demonstrates four techniques that can help to create paths with a reduced overall effect of biases. The first technique is to introduce a virtual reference alternative in the decision problem. The second technique is to introduce an auxiliary measuring stick attribute to be used in the assessment of trade-offs between attributes. The third technique is to rotate the reference point used. The fourth one is to restart the decision making process at an intermediate step with a reduced set of alternatives.

Mitigating biases by introducing a virtual alternative in the decision problem is a new idea. This possibility has not received attention previously although virtual alternatives are, in fact, commonly used in standard preference elicitation procedures. A virtual alternative is a fictitious hypothetical alternative that is not included in the original set of decision alternatives. For example, in trade-off tasks, which are sometimes called two-attribute matching tasks, the decision maker adjusts a given virtual alternative to make it equally preferred to another virtual alternative. The design of these virtual alternatives can impact the results obtained (Delquié 2003, Deparis et al. 2015). In swing weighting (von Winterfeldt and Edwards 1986) the decision maker is instructed to imagine a virtual alternative, which serves as an initial reference point. Typically, this alternative has the worst possible consequence in every attribute. It is well known, e.g. in marketing, that introducing an additional alternative can influence the results of a decision process (Huber et al. 1982, Farquhar and Pratkanis 1993). Introducing a new alternative may create a reference point that can affect the decision maker’s responses, for example, due to the loss aversion bias (Tversky and Kahneman 1991).

The introduction of an auxiliary measuring stick attribute can help to mitigate the effect of the measuring stick bias, which is also called the scale compatibility bias (Tversky et al. 1988). This bias refers to the tendency to give extra weight to the response attribute in trade-off tasks (Delquié 1993). The modified trade-off technique by Delquié (1997) is one earlier approach for mitigating the measuring stick bias. Anderson and Hobbs (2002) suggested to mitigate this bias by adjusting the decision maker’s responses with estimated bias coefficients or by using an averaging procedure. Lahtinen and Hämäläinen (2016) described how the overall effect of the measuring stick bias can be reduced by the choice of the measuring stick attribute.

The idea to rotate the reference point used in a decision process was suggested by Lahtinen and Hämäläinen (2016). A related idea is to use multiple anchor points in the estimation of consequences (see, e.g. Montibeller and von Winterfeldt 2015). Lahtinen and Hämäläinen (2016) also suggested the possibility of restarting the decision process after finding dominated alternatives and excluding them from the decision problem. This can eliminate the impacts of biases that have built up during the earlier steps.

This paper also shows how a computational approach can support the evaluation of bias mitigaton methods. A computational approach helps, in particular, in the assessment of the aggregate effect of successive biases that occur at different steps along the decision analysis process. Extensive testing of debiasing methods with behavioral experiments can be very laborious, as the subjects need to carry out exceedingly many evaluations. Naturally, a prerequisite for a computational analysis is that one has a model of the effects of the biases considered. Examples of such models can be found in the literature (see, e.g. Bleichrodt et al. 2001, Anderson and Hobbs 2002, Delquié 2003, Jacobi and Hobbs 2007, and Lahtinen and Hämäläinen 2016). In multi-criteria decision analysis, computational analyses have earlier been used, for example, to study the impact of approximations of value functions (Stewart 1996), to compare weighting methods in the presence of response errors (Jia et al. 1998), and to analyze the value of information in portfolio decision analysis (Keisler 2004). In the multi-criteria optimization literature, computational analyses have been used to assess the effects of cognitive biases and to find improved interactive methods (see, e.g. Stewart 1999, Stewart 2005, Ojalehto et al. 2016).

This paper presents a computational example, where new bias mitigation methods are evaluated for the Even Swaps process (Hammond et al. 1998), which is the final phase in the PrOACT decision making framework described in Hammond et al. (1999). In our analysis, the decision maker is assumed to exhibit the loss aversion bias, the measuring stick bias, and to make non-systematic response errors (see, e.g. Laskey and Fischer 1987). The bias mitigation methods are based on the techniques described above. In the computational analysis, these methods are compared against each other and against a reference method, which is the attribute elimination method with a fixed reference alternative. The settings studied vary in the size of the decision problem, consequences of alternatives, weight profiles, and in the magnitudes of biases and random response error. The performance measure used in the evaluations is the share of cases where a method leads to the same alternative as one would get in a bias free process. In our analysis, four of the new bias mitigation methods perform better than the reference method and one performs worse.

2. Even Swaps and biases

The Even Swaps process (Hammond et al. 1998, 1999) supports choosing an alternative from a set of alternatives that are described with multiple attributes (see, e.g. Table 1). In an even swap, an alternative is replaced with a preferentially equivalent virtual alternative, which differs from the original alternative in two attributes. The decision maker conducts even swaps to make attributes irrelevant and to find dominated alternatives. These can be eliminated from the decision problem. An attribute is irrelevant if all alternatives have the same consequence in it. The decision maker carries out swaps until only one alternative remains in the consequences table.

The decision maker conducts an even swap in two steps. First, the decision maker defines a *reference change* in one attribute describing an alternative. This attribute is called the *reference attribute*. For example: "The size of the apartment B is changed from 40 to 35 square meters." Second, the decision maker specifies a compensatory *response change* in another attribute called the *measuring stick attribute*. For example: "The decrease in the size of the apartment B is compensated if the rent decreases from 900 to 810 euros." Table 2 shows the modified alternative B, which is dominated by the alternative C.

Table 1: A simple illustrative consequences table related to the choice of an apartment.

	Apartment alternatives		
Attributes	A	B	C
Rent (euros per month)	700	900	800
Size (square meters)	30	40	35
Condition (constructed scale)	4	6	10

Table 2: An even swap has been carried out in alternative B, which is now dominated by alternative C.

	Apartment alternatives		
Attributes	A	B	C
Rent (euros per month)	700	~~900~~ 810	800
Size (square meters)	30	~~40~~ 35	35
Condition (constructed scale)	4	6	10

Lahtinen and Hämäläinen (2016) have shown that in the even swap task people give extra weight to the measuring stick attribute, and to the attribute where the change is a loss. These behaviors exhibit the measuring stick bias and the loss aversion bias that have been found also in two-attribute matching tasks (Delquié 1993, 1997, Anderson and Hobbs 2002, Bleichrodt and Pinto 2002, Deparis et al. 2015). In the Even Swaps process, the measuring stick bias works in favor of those alternatives that are the best in the measuring stick attribute used. Due to the loss aversion bias, response changes that are gains are overstated and response changes that are losses are understated. This causes an alternative to become more attractive every time it is swapped. We assume that the increase in attractiveness depends positively on the size of the reference change. The increase of the attractiveness of an alternative in the even swap task also reflects a common mistake in trade-off tasks (Keeney 2002). Some people may knowingly accept a swap only if they think that the modified alternative is more attractive than the original one.

The attribute elimination method described in Hammond et al. (1998) is a basic method for completing the Even Swaps process. The idea is to make attributes irrelevant one by one until only one attribute remains. This measuring stick attribute reveals the 'best' alternative. In a simple version of the attribute elimination method, the decision maker has one fixed *reference alternative* throughout the process, and she uses the same measuring stick attribute in all swaps. The decision maker carries out swaps to make the attribute specific consequences of all other alternatives equal to those of the reference alternative in all attributes besides the measuring stick attribute. If this method is used, the measuring stick attribute has to be chosen such that for every alternative there is initially enough room for gains and losses in the attribute. Otherwise one may reach a situation where a required response change in an alternative cannot be carried out. The Smart-Swaps software (Mustajoki and Hämäläinen 2007) supports the use of the attribute elimination method.

One can also use the attribute elimination method combined with pairwise comparisons of alternatives. In this method, the decision maker considers two alternatives at a time, and uses the attribute elimination method to find the better out of these two. After each pairwise comparison, the dominated alternative is removed from the consequences table.

Due to the measuring stick bias, the attribute elimination method is likely to favor those alternatives, which are the best in the measuring stick attribute. Due to the loss aversion bias, the method is likely to favor those alternatives whose consequences, in attributes other than the measuring stick attribute, differ the most from the consequences of the reference alternative.

3. Bias mitigation techniques and methods

This section presents four techniques and five methods for mitigating the overall effect of biases in the Even Swaps process. Techniques 1 and 3 are alternative techniques for mitigating the loss aversion bias. Technique 2 can help to mitigate the measuring stick bias. Technique 4 can help to prevent the accumulation of biases and response errors when alternatives are eliminated one at a time. Methods A, B, C, D, and E make use of different combinations of these techniques. More methods can be developed by combining the techniques in different ways and by using variations of them.

Technique 1: Introduce a virtual reference alternative.

To even out the effect of loss aversion, the reference changes in the swaps with each of the original alternatives should be as equal sized as possible. One approach is to create a virtual reference alternative whose consequence in each attribute is the average of the consequences of the original alternatives. In cases with two alternatives this ensures that the reference changes made in both alternatives are of equal size. In the computational analysis, it is studied if this technique works also in cases with more than two alternatives. Table 3 provides an example. If the decision maker aims to make condition an irrelevant attribute, the sizes of the reference changes needed are 3, 1, and 3 in alternatives A, B, and C, respectively. The sizes of the reference changes would be more unequal if the reference alternative would be one of the original alternatives.

Table 3: A consequences table with a virtual reference alternative.

	Apartment alternatives			
Attributes	A	B	C	Virtual
Rent (euros per month)	700	900	800	800
Size (square meters)	30	40	35	35
Condition (constructed scale)	4	6	10	7

Technique 2: Introduce an auxiliary measuring stick attribute.

The extra weight to the measuring stick attribute does not matter, or matters very little, if all alternatives have the same, or about the same, consequence in this attribute. Sometimes such an attribute can be found among the attributes originally left out of the analysis because they did not differentiate the alternatives. For example, commute time might be such an attribute if one is choosing between different apartments located in the same area (Table 4).

Table 4: Commute time has been introduced in the table to be the auxiliary measuring stick attribute.

	Apartment alternatives		
Attributes	A	B	C
Rent (euros per month)	700	900	800
Size (square meters)	30	40	35
Condition (constructed scale)	4	6	10
Commute time (minutes)	60	60	60

Technique 3: Repeatedly rotate the reference point.

When the attribute elimination method is used, the reference alternative can be rotated each time an attribute is eliminated. This can help even out the effect of loss aversion. For instance, if a decision maker wants to find the better out of two alternatives, she can switch the reference alternative after each swap. This way the effect of loss aversion does not build in up favor of one alternative only.

Technique 4: Intermediate restarting of the process with a reduced set of alternatives.

It is possible to restart the Even Swaps process with the original consequences of the remaining alternatives each time an alternative is eliminated. This removes the effects of biases and response errors that have built-up in the remaining alternatives during the earlier steps. This technique can be useful in particular when the attribute elimination is used with pairwise comparisons of alternatives.

The Reference method: Attribute elimination method with a fixed reference alternative.

Initialization: Choose a reference alternative and a measuring stick attribute among the set of original alternatives and attributes.

Do even swaps such that the consequences of all alternatives become equal to the consequence of the reference alternative in all attributes besides the measuring stick attribute. Use the same measuring stick attribute and reference alternative in every swap.

Method A: Attribute elimination method with a virtual reference alternative (technique 1).

Initialization: Introduce a virtual reference alternative. In each attribute, the consequence of the virtual reference alternative is the average of the consequences of the original alternatives. Choose a measuring stick attribute among the set of original attributes.

Do even swaps as in the Reference method.

Method B: Attribute elimination method with an auxiliary measuring stick (technique 2).

Initialization: Choose a reference alternative among the set of original alternatives. Introduce an auxiliary measuring stick attribute in which every alternative has the same consequence.

Do even swaps as in the Reference method.

Method C: Attribute elimination method with a virtual reference alternative (technique 1) and an auxiliary measuring stick (technique 2).

Initialization: Introduce a virtual reference alternative and an auxiliary measuring stick.

Do even swaps as in the Reference method.

Method D: Pairwise comparisons of alternatives using an auxiliary measuring stick (technique 2), alternating reference alternative (technique 3), and intermediate restarting of the process (technique 4).

Initialization: Introduce an auxiliary measuring stick attribute.

Do even swaps in a pair of alternatives such that their consequences become equal in all attributes besides the measuring stick attribute. Change the reference alternative after each swap. Eliminate the dominated alternative. Restore the original consequences of the remaining alternative. Carry out pairwise comparisons until only one alternative remains.

Example: The decision maker carries out the following swaps to compare apartments A and B described in Table 4. Apartment A's rent is made equal to apartment B's rent, B's size is made equal to A's size, A's condition is made equal to B's condition. All response changes are given in commute time. Assuming, for example, that apartment A becomes dominated, the decision maker should next carry out a similar process starting with apartment C and the original unmodified apartment B.

Method E: Pairwise comparisons of alternatives using an auxiliary measuring stick (technique 2), virtual reference alternative (technique 1), and intermediate restarting of the process (technique 4).

Initialization: Introduce an auxiliary measuring stick attribute.

Select a pair of alternatives. Introduce a virtual reference alternative whose consequence in each attribute is the average of the consequences of the two alternatives under comparison. Do even swaps such that the consequences of both alternatives become equal to the consequence of the reference alternative in all attributes besides the measuring stick attribute. Eliminate the dominated alternative and the virtual reference alternative. Restore the original consequences of the remaining alternative. Carry out pairwise comparisons until only one alternative remains.

The number of swaps required is usually about the same with all methods expect with Method E, which requires about twice as many swaps as the other methods. We denote the number of alternatives with N and the number of attributes with K. The number of swaps required is at most $(N-1)(K-1)$ with the Reference method, $N(K-1)$ with Method A, $(N-1)K$ with method B, NK with Method C, $(N-1)K$ with Method D, and $2(N-1)K$ with Method E.

Method E can be proved to eliminate the effects of biases if the decision maker's behavior is assumed to follow the model described in Section 4 with no random response errors. If these assumptions hold, introducing an auxiliary measuring stick completely eliminates the measuring stick bias. Creating a new virtual reference alternative for each pairwise comparison perfectly evens out the effect of the loss aversion bias. Intermediate restarting prevents the effects of biases from accumulating.

4. Computational analysis

The effectivity of each method described in Section 3 is studied computationally in very different settings. The settings differ in the number of alternatives, the number of attributes, the consequences of the alternatives, the weight profiles describing the preferences of the decision makers assumed, the magnitudes of biases, and whether random response errors are included or not. The performance criterion to evaluate a method is how often using it gives the same result as a bias free process would give.

In the even swap task, the assumed decision maker specifies a response change Δ_m in the measuring stick attribute *m*. This change compensates for a given reference change Δ_r in the reference attribute *r*. If the decision maker would be unbiased, her responses would follow an additive linear value function. However, due to the measuring stick bias the weight of the measuring stick attribute, w_m, is increased by a factor *S*. Due to the loss aversion bias, the weight of the attribute in which the change is a loss is increased by a factor *L*. In addition, the decision maker can make random response errors. These are modeled with a random variable *e*.

If the reference change is a loss, the decision maker's response change is given by:

$$\Delta_m = \frac{L\, w_r}{S\, w_m} \Delta_r\, e. \; (1)$$

If the reference change is a gain, the decision maker's response change is given by:

$$\Delta_m = \frac{w_r}{L\, S\, w_m} \Delta_r\, e. \; (2)$$

In the settings studied, the number of alternatives is 2, 5, or 8 and the number of attributes is 3, 5, or 8. We generate 5000 consequences tables for each combination of the number of alternatives and the number of attributes. In total, this means 45000 different consequences tables. Each table includes only non-dominated alternatives. To generate one table, the attribute specific consequences of the alternatives are drawn from a uniform distribution. The table is then normalized such that in each attribute, the value 0 is assigned to the alternative that has the worst performance and the value 1 to the alternative that has the best performance. If there is a dominated alternative in the table, the table is rejected and a new one is generated.

We generate 100 weight profiles for each number of attributes. In every profile, the weights sum to 1 and all weights are greater than 0.05. These weight profiles are drawn from a uniform distribution over the space of possible weights (see, e.g. Rubinstein 1982).

The bias coefficient *S* is 1.0, 1.1, 1.2, 1.3 or 1.4, and *L* is 1.0, 1.1, 1.2, 1.3 or 1.4. These values are assumed to describe typical magnitudes of biases and they cover the point estimates obtained in Lahtinen and Hämäläinen (2016). Random response errors are included in half of the cases studied. The random variable *e* follows a log-normal distribution with median 1.0 and standard deviation 0.10. These properties are assumed to describe typical random response errors.

It is assumed that when the Reference method or Method A is used, one of the attributes in the consequences table is randomly selected to be the measuring stick attribute. When the Reference method or Method B is used, one of the alternatives available is randomly selected to be the reference alternative. The auxiliary measuring stick attribute for Methods B, C, D and E is created such that its weight is the average of the weights of the original attributes. After the auxiliary attribute is introduced, the weights are rescaled so that they sum to 1. When Method D or E is used, the pair of alternatives compared at each iteration is randomly selected among the remaining alternatives.

5. Results

In overall performance, Methods A, C, D, and E are better than the Reference method. The overall performances of Methods A, C, and D are within 1 percentage point (Table 5). Relative to the Reference method, Methods A, C, and D are better by 6 to 7 percentage points. Method E performs the best. It finds the same result as a bias-free process in 98 percent of all cases studied. If there is no random error, Method E gives the correct solution in all settings (Figure 3). The Reference method and Method B are the worst in overall performance. Still, they outperform Methods A, C and D in a small percentage of the cases without random response error (Table 6).

Table 5: Overall performances with each method.

Method	Percentage of correct results
Reference	87
A	93
B	86
C	94
D	93
E	98

Table 6: Pairwise comparison of methods in settings without response error. Each cell gives the percentage of cases in which the method on the row gives the correct result and the method on the column does not give.

	Reference	A	B	C	D	E
Reference		2	3	2	3	0
A	7		9	1	4	0
B	2	3		1	3	0
C	9	3	9		4	0
D	9	4	10	3		0
E	11	6	12	4	6	

Figures 1 to 6 show the performances of the methods in different types of cases. The overall conclusion is that Methods A, C, D, and E are effective across a variety of settings. The performances shown in Figures 1 to 5 are calculated over all cases where one parameter describing the cases has the same value. The performances shown in Figure 6 are based on the cases with five alternatives and five attributes. There are also some interesting observations that can be made. When the magnitude of the loss aversion bias is 1.3 or higher, the performances of Methods A and C are almost the same (Figure 2). Thus, there seems to be no extra benefit from using an auxiliary measuring stick attribute in addition to a virtual reference alternative when the magnitude of loss aversion is high. Figure 7 shows that, although Method B has the worst overall performance, this method can be effective when the magnitude of loss aversion bias is low relative to the magnitude of the measuring stick bias.

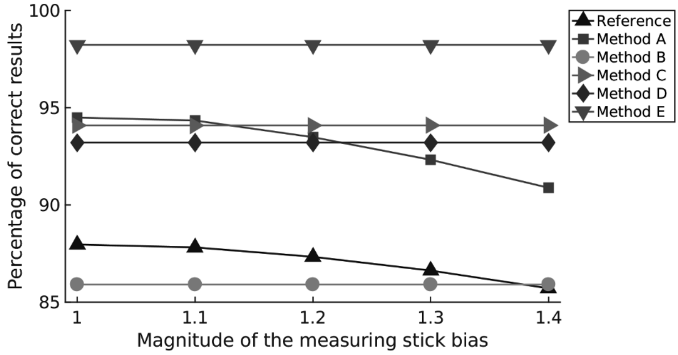

Figure 1: The effect of the magnitude of the measuring stick bias.

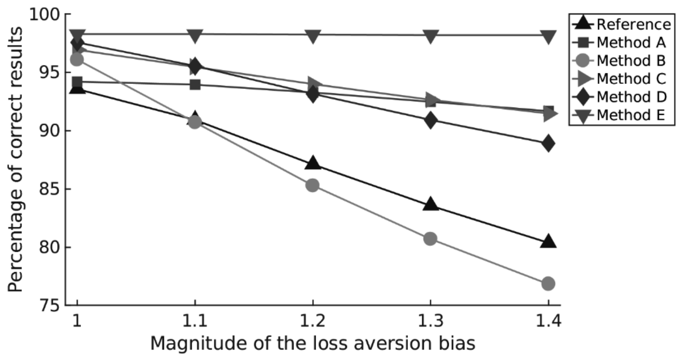

Figure 2: The effect the magnitude of the loss aversion bias.

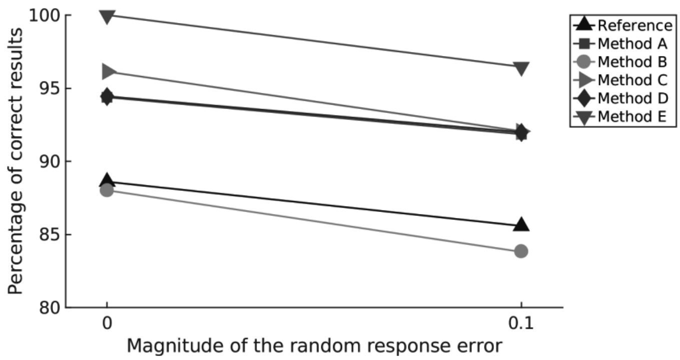

Figure 3: The effect of random response errors.

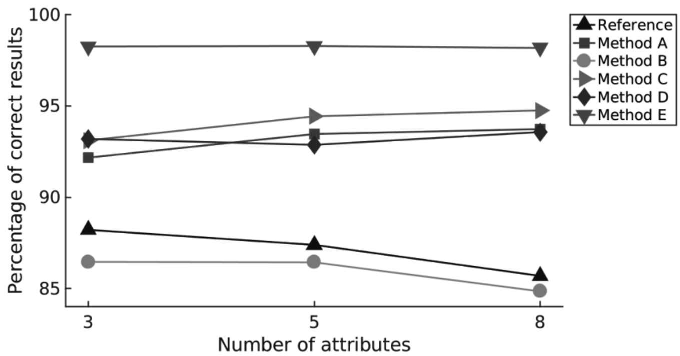

Figure 4: The effect of the number of attributes.

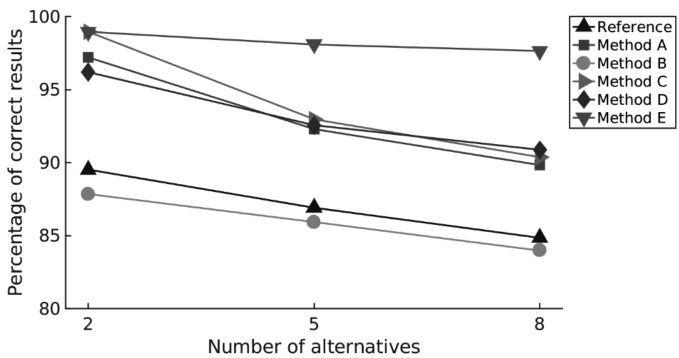

Figure 5: The effect of the number of alternatives.

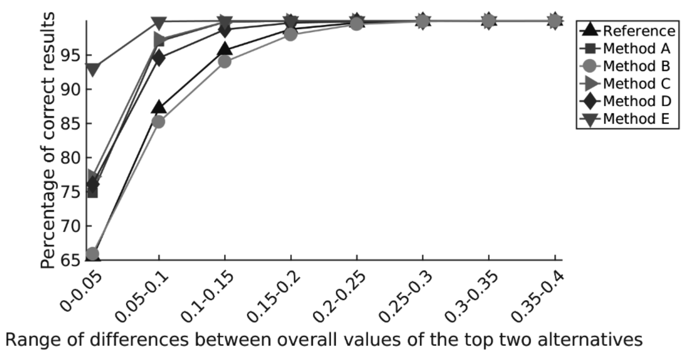

Figure 6: The effect of the difference between the overall values of the top two alternatives.

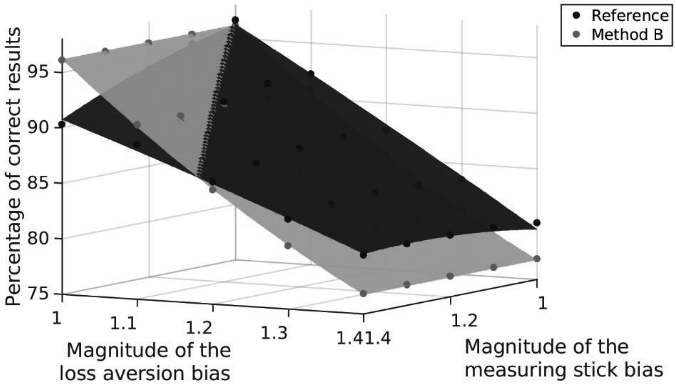

Figure 7: Comparison of the Reference method and Method B with different magnitudes of biases. Quadratic surfaces are fitted to the data in order to illustrate the results more clearly.

6. Discussion

All of the proposed new bias mitigation techniques are shown to help reduce the overall effects of biases in the Even Swaps process. We evaluated the methods computationally across a number of different settings. In practice, the method to be used should be chosen based on more specific information about the case at hand. Such information can include, e.g., the number of alternatives, the number of attributes, the consequences of the alternatives, as well as estimates of the magnitudes of biases of the person using the Even Swaps process.

The debiasing techniques demonstrated in this paper with the Even Swaps method are likely to be applicable also in other multi-criteria approaches including interactive multi-criteria optimization. When trade-off tasks are used in weight elicitation, using an irrelevant attribute as the measuring stick can help to mitigate the measuring stick bias. In swing weighting, the usual procedure is to first introduce a virtual reference alternative that performs at the lowest consequence level in every attribute. Attributes are then weighted by assigning importance points to so called attribute swings. The swing related to an attribute is a hypothetical change where the reference alternative is improved in this attribute from the lowest to the highest consequence level. The most important attribute is typically used as the measuring stick. The swing related to this attribute is given a fixed number of importance points, e.g. 100. A possible modification to the procedure could be to first introduce a virtual reference alternative that performs at the highest consequence level in every attribute. Another approach could be to introduce a virtual reference alternative with attribute specific consequences that are between the lowest and the highest consequence levels.

The intermediate restarting technique could also be used with swing weighting, e.g. in the following way. 1. Elicit attribute weights and use them to score the alternatives. 2. Eliminate some of the lowest scoring alternatives such that the ranges of the attribute swings are reduced. 3. Repeat steps 1 and 2 until the ranges of attribute swings cannot be reduced anymore. In the end of this process, the decision maker will face only the attribute ranges that are differentiating between the final alternatives. A process like this might help cope with the fact that the attribute ranges used in swing weighting can influence the ranking of alternatives (see, e.g. Fischer 1995).

7. Conclusions

A systemic overall perspective is needed in bias mitigation in order to find the most effective ways to improve decision analysis processes and to help decision makers. It is not enough to focus on the effects of individual biases in isolated steps of decision making processes. The role of biases is critical especially if they can cause changes in the rank ordering of the alternatives under consideration. In this paper, we demonstrate that it can be possible to find paths along which the effects of biases cancel out each other. Then the decision maker will not be directly faced with the challenges in trying to avoid biases.

The bias mitigation techniques introduced in this paper could easily be taken into use in real decision support processes. In our computational analysis, these techniques are shown to help mitigate biases in the Even Swaps process. These techniques are likely to be useful also with other multi-criteria decision making methods, such as the trade-off method, the swing method, and in interactive multi-criteria optimization.

Testing debiasing approaches in behavioral experiments is not easy when the whole process is included in the analysis. Therefore, we believe that computational approaches could be more generally used when studying biases and when developing improved bias mitigation techniques.

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Paper V

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Portfolio decision analysis methods in environmental decision making

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Modern portfolio theory

A B S T R A C T

Environmental modellers recurrently work with decisions where a portfolio of actions has to be formed to effectively address the overall situation at hand. When creating the portfolio, one needs to consider multiple objectives and constraints, identify promising action candidates and examine interactions among them. The area of portfolio decision analysis deals with such tasks. This paper reviews portfolio modelling approaches and software that are applicable in environmental management. A framework for environmental portfolio decision analysis is provided that consists of steps ranging from problem framing to modelling and optimization, as well as to the analysis of results. The use of this framework is demonstrated with an illustrative case describing planning of urban water services. The problem is analyzed with a recently introduced portfolio decision analysis method called Robust Portfolio Modelling, which enables the use of incomplete preference information and consequence data. This feature can be particularly useful in environmental applications.

Software availability

Name of the software: RPM-Decisions
Requirements: Windows 7–10, Java runtime environment
Contact: http://rpm.aalto.fi

1. Introduction

Environmental management decisions are often portfolio problems where the task is to find a portfolio of actions to meet the overall objectives, targets, and constraints. For example, when the goal is to cut greenhouse gas emissions by a certain amount, the decision makers seek to identify a portfolio, i.e. a combination of actions, whose combined effects result in reaching the target reduction level. The actions can be, e.g., energy saving measures, investments in renewables, educational projects, technology development, or regulation policies. Typically, the decision makers also have to consider the overall performance of the portfolio across other relevant dimensions or criteria, such as, costs, social and political impacts, as well as environmental risks. In this paper the following terminology is used. Attributes refer to the measures used to describe the consequences of alternatives. Objectives refer to higher level goals. In the literature attributes are sometimes called criteria. This paper uses the term multi-criteria evaluation when referring to decision analysis approaches where alternatives are evaluated with respect to multiple criteria.

In practice, environmental portfolio problems are often addressed so that experts first generate a number of feasible portfolio alternatives, which are combinations of actions that satisfy the overall requirements. These alternatives are then compared by stakeholders using multi-criteria evaluation to identify the most preferred one. The quality of the resulting decision naturally depends on the experts' ability to initially construct good portfolio alternatives. This task is particularly challenging when the number of action candidates is high and there are many conflicting objectives. There can also be non-linearities or interactions across the set of actions and their consequences. If this is the case, the overall performance of a combination of actions is not necessarily the sum of the action specific performances. Surprisingly, the extensive literature on environmental multi-criteria decision making has so far given very little attention to the possibilities offered by portfolio modelling (see, e.g. Linkov and Moberg, 2011; Huang et al., 2011; Gregory et al., 2012).

The current paper contributes to the literature by making the portfolio approach more easily accessible. This paper explains how the emerging area of portfolio decision analysis (PDA; Salo et al., 2011) can benefit the practitioners and researchers in

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environmental management and decision making. A comparative description of five major portfolio modelling approaches is given. These approaches offer modelling and optimization support to find the best portfolio of actions or the non-dominated portfolios. The final choice of a portfolio should be made among the non-dominated portfolios. If a portfolio is dominated, there exists another portfolio of actions, which is better in some attribute and at least equally good in all other attributes. The model based portfolio generation process advocated here can help to consider multiple objectives and resource constraints, interactions related to the actions, as well as uncertainties. The portfolio perspective can also help mitigate the overall risk related to a set of actions (see, e.g. Keisler and Linkov, 2010; van der Honert, 2016).

This paper develops a general framework for environmental portfolio decision analysis which aims at providing environmental researchers and practitioners an easy entry into implementing decision processes that utilize portfolio models. The use of the framework is demonstrated with an illustrative case related to urban water service planning (Mitchell et al., 2007). The case is analyzed using the recently introduced portfolio decision analysis method called Robust Portfolio Modelling (RPM; Liesiö et al., 2007), which enables the use of incomplete preference and consequence information (Salo and Hämäläinen, 1995). This possibility can be useful in environmental management problems. Perfect data about the environmental impacts of the action candidates is rarely available. The stakeholders may not want to give exact numbers to represent their opinions on the relative importance of each decision objective.

The framework described in this paper incorporates elements from both top-down and bottom-up decision support approaches (see, e.g. Montibeller et al., 2009; Linkov et al., 2014). The first phase within the framework is to describe the overall problem and goals. This represents the top-down perspective. The idea is to direct the problem solvers to reflect on the desired overall consequences. Having the big picture in mind can often help in generating new action candidates (Keeney, 1992). The bottom-up perspective, in turn, is naturally present almost always in environmental problem solving processes: When a problem solving project is set up, it is often based on the existence of some already available action candidates. In addition, the stakeholders usually bring with them their own ideas of actions, which are related to their interests. One major contribution of the portfolio approach is that all action candidates can be included in the same analysis. The participants and stakeholders can easily bring their ideas and possible actions to the table. This is likely to increase the participants' commitment to the problem solving process and create a sense of shared ownership of its outcomes, which is important in environmental problem solving (Voinov et al., 2016).

So far, the main areas in the environmental management literature where portfolio modelling has been used are conservation network design and investment decisions related to the development of natural capital and ecosystem services. Conservation network design problems typically include a very high number of actions, which relate to areas of land to be included in the network (see, e.g. Ando et al., 1998; Possingham et al., 2000; Moilanen, 2007; Kreitler et al., 2014). A similar setting is encountered in conservation auctions where landowners bid pieces of land to be included in conservation networks and the decision makers need to choose which pieces of land to purchase (see, e.g. Hajkowicz et al., 2007). Models related to environmental investments typically deal with the problem of choosing a set of costly improvement or restoration actions with uncertain outcomes (see, e.g. Hajkowicz et al., 2008; Higgins et al., 2008; Marinoni et al., 2009, 2011). These studies employ a variety of approaches based on multi-criteria evaluation, optimization, multi-objective optimization, benefit-cost analysis and modern portfolio theory. Yet, the opportunities to utilize portfolio approaches in environmental management problems are much wider. Many environmental multi-criteria decision making processes include an implicit portfolio generation stage in creating the alternatives. The ideas and the framework presented in this paper help to include the portfolio approach explicitly already in the initial stages of these processes.

The paper is structured as follows. Section 2 discusses behavioral issues in unaided portfolio generation. Section 3 provides an outlook on different portfolio modelling approaches. Section 4 introduces a framework for environmental portfolio decision analysis. Section 5 provides the illustrative example demonstrating both the framework and the RPM approach and software. Section 6 discusses software support for portfolio decision analysis. Section 7 summarizes our conclusions.

2. Behavioral issues in portfolio generation

Behavioral issues can easily arise when the problem solving team generates portfolio alternatives. The task is complex and there can be behavioral biases originating from, e.g., motivational, social, and cognitive phenomena (Fasolo et al., 2011). The outcome of an unaided portfolio generation process is likely to be path dependent (Lahtinen and Hämäläinen, 2016; Hämäläinen and Lahtinen, 2016; Lahtinen et al., 2017), i.e. depend on the starting point and the order in which different actions are considered. For general discussions on behavioral issues in operations research and environmental modelling, see Hämäläinen et al. (2013) and Hämäläinen (2015).

The traditional approach (Fig. 1) used in environmental portfolio problems is that the problem solving team generates portfolio alternatives to be compared against each other with multi-criteria evaluation (see, e.g., Marttunen and Hämäläinen, 1995; Prato and Herath, 2007; Linkov and Moberg, 2011, p. 144; Gregory et al., 2012, pp. 155–171). These alternatives are typically constructed in a stepwise process where new actions are included into a portfolio following the feedback obtained from the stakeholders. The goal is to generate combinations of actions, which are non-dominated with respect to the criteria. In such a process there is a risk that there are better portfolios, which are not found and are left out of the evaluation.

Paying attention to the overall performance of each portfolio can be an overwhelming challenge in portfolio generation without modelling and optimization support. There can be many action candidates, multiple objectives, and interactions across the actions and their consequences. Interactions can relate to the effects of the actions, to their resource consumption, and give rise to constraints that prevent some of the actions to be jointly included in the same portfolio (see, e.g. Fox et al., 1984). Due to interactions, the consequences of an action can depend on other actions included in the portfolio. For instance, emissions from cars can be reduced by developing improved emission reduction technologies or by reducing the total miles driven. The effect of reducing the miles driven clearly depends on the technology available for the emission reductions in the cars. It can be very difficult to consider such interactions without computational support. For example, the well-known climate wedge game (http://cmi.princeton.edu/wedges/game.php) based on Pacala and Socolow (2004) includes such interactions. Furthermore, if actions are considered and added in the portfolio one at a time, it can happen that only those actions are selected, which score well in every attribute. Yet, it can be a mistake to discard an action which is weak in some attributes but has strong positive impact across the other attributes. The right choice can be to select such actions into the portfolio and compensate their weaknesses with some other actions.

Path dependence (Lahtinen and Hämäläinen, 2016; Hämäläinen

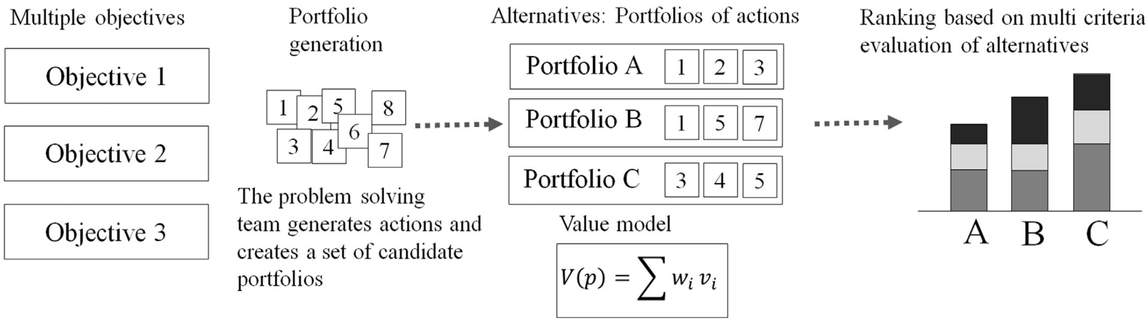

Fig. 1. Traditional approach: Multi-criteria evaluation of portfolios.

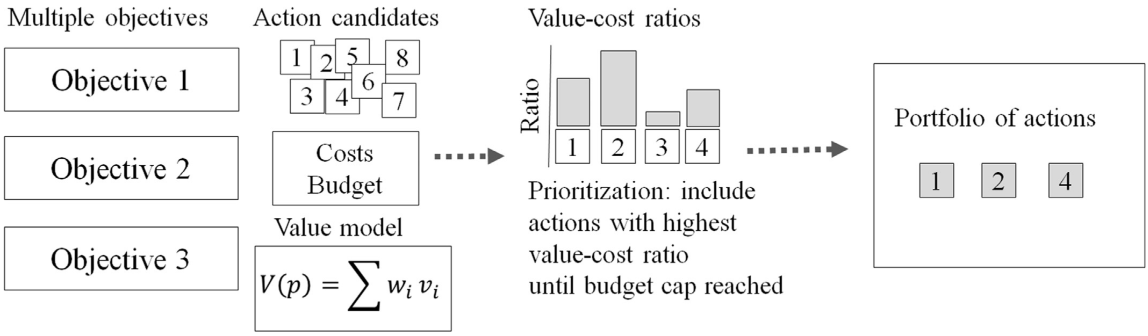

Fig. 2. Value-cost approach: Prioritize actions according to value-cost ratio.

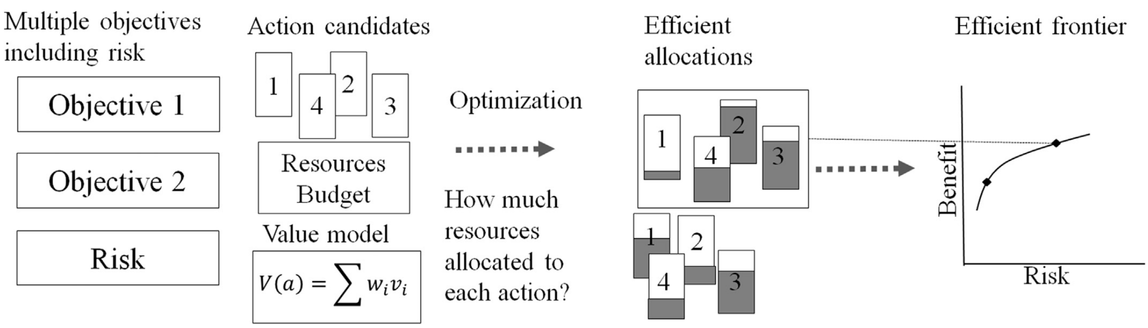

Fig. 3. Modern portfolio theory approach: Identify the optimal resource allocation for each risk level.

and Lahtinen, 2016; Lahtinen et al., 2017) can easily emerge in the stepwise portfolio generation process. How the first step is taken can influence the path followed in the process, and the outcome of the process can be path dependent. For example, after the first action is included in a portfolio, the problem solving team can myopically start looking only for synergies that this first action can benefit from and ignore other elements of the problem. The first action can be selected, e.g. based on a 'champion' argument (Fasolo et al., 2011). Champion actions with wide support from the participants of the process can easily be included in a portfolio without trying to create a portfolio without them. There is a risk that a champion action does not perform well together with the other actions. Including it in the portfolio of actions does not necessarily lead to a non-dominated portfolio.

When portfolio modelling is used, all action candidates are included simultaneously in the same optimization model which generates the non-dominated portfolios. This can mitigate the risk of path dependence and biases.

3. Modelling portfolio decisions

This section describes five portfolio modelling approaches, which help identify a portfolio of actions (Figs. 2 and 5), or a set of non-dominated portfolios (Figs. 4 and 6), to best meet multiple objectives while satisfying the problem constraints. The goal can also be to find the efficient resource allocations (Fig. 3). Heuristic

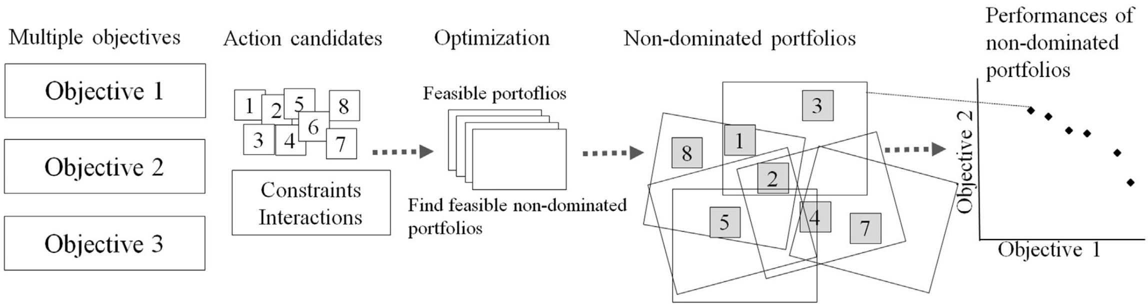

Fig. 4. Multi-objective optimization approach: Identify the non-dominated portfolios.

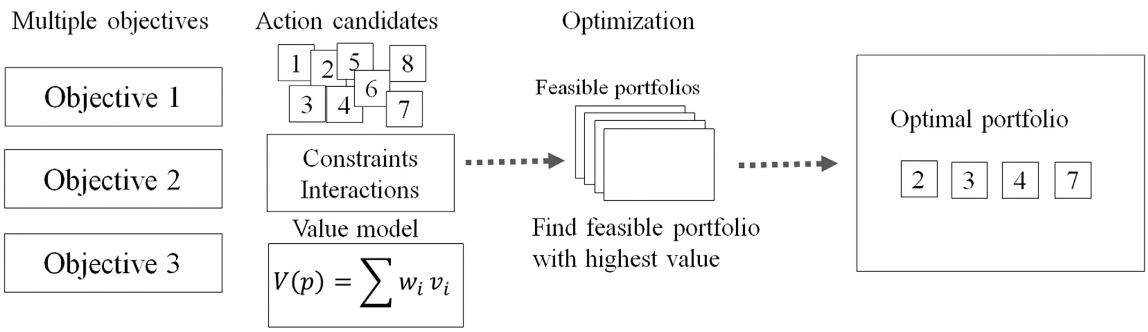

Fig. 5. Portfolio decision analysis approach: Find the optimal portfolio.

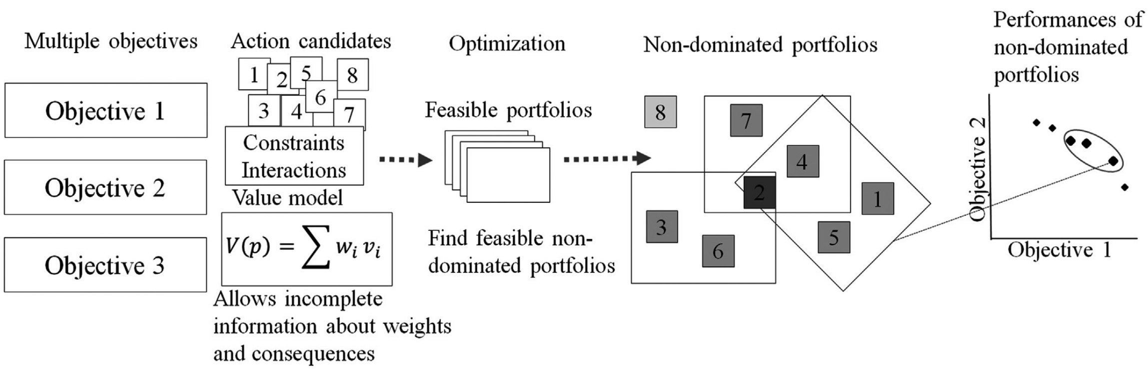

Fig. 6. Portfolio decision analysis with incomplete information: Identify the non-dominated portfolios.

model based portfolio generation approaches are also discussed in this section. An illustrative list of environmental applications of these approaches is given in Table 1.

The roots of portfolio decision models go back to the work of Markowitz (1952) on risk diversification in financial investments. The mean-variance model of Markowitz and the capital asset pricing model by Sharpe (1964) support investment decisions related to purchasing financial assets with uncertain future returns. In another strand of research, capital budgeting methods were developed to support comparison of projects based on net present value and other economic attributes (Lorie and Savage, 1955). Later, a variety of approaches also incorporating non-economic objectives, group decision making, and an array of optimization methods have been developed to support project portfolio selection (see, e.g. Heidenberger and Stummer, 1999; Salo et al., 2011).

The value-cost approach (Fig. 2), also called value-to-cost, or benefit-cost approach, is a simple portfolio generation method (see, e.g., Kleinmuntz, 2007; Phillips and Bana e Costa, 2007) where multi-criteria evaluation of the actions is first performed and their costs are estimated. Actions are then selected into the portfolio in a descending order of their value-cost ratios until the budget limit is reached. If there are no synergies or interactions between the actions, the resulting portfolio of actions provides the optimal use of the resources spent. Otherwise, optimality is not guaranteed. This

Table 1
Illustrative papers on environmental portfolio problems.

Approach	Problem	Examples of attributes	Solution method
Value-cost			
Marinoni et al. (2011), case 1	Improving sites in a river catchment	Pollutant reduction, rehabilitation, recreational effect, site access	Value-cost based prioritization
Hajkowicz et al. (2008)	Enhancing water quality	Nitrogen reduction, phosphorus reduction, strategic benefits	Value-cost based prioritization with heuristic procedure to find improved solutions
Portfolio Decision Analysis (PDA)			
Kreitler et al. (2014)	Agricultural land conservation	Agricultural viability, conservation priority, flood liability	Integer optimization
Convertino and Valverde, (2013)	Restoration planning in coastal areas	Habitat quality and species richness	Integer optimization
Multi-objective optimization (MOO)			
Zheng and Hobbs (2013)	Removals of dams	Effect to fish populations, public safety, cost	Multiple objective integer optimization
Higgins et al. (2008)	Improving landscapes	Biodiversity, water run-off, carbon sequestration	Heuristic multiple objective integer optimization
Modern Portfolio Theory (MPT)			
Paydar and Qureshi (2012)	Irrigation related investments under climate uncertainty	Monetary expected value and variance calculated with climate change scenarios	Monte Carlo simulation
Marinoni et al. (2011), case 2	Investments in river catchment sites	Expected multi-criteria benefit and variance calculated with climate change scenarios	Monte Carlo simulation
Crowe and Parker (2008)	Forest restoration under climate uncertainty	Adaptation score and variation of the score under climate scenarios	Quadratic programming
Heuristic			
Kurttila et al. (2009)	Developing forest management plans	Monetary net present value, saw log volume, cutting removal	Heuristic routine combined with heuristic integer optimization
Moilanen (2007)	Conservation network design	Number of animals within the area, connectivity, costs	Heuristic routine similar to the gradient descent method
Possingham et al. (2000)	Forming a representative conservation network	Number of species within the network, number of sites selected	Heuristic integer optimization

approach is often not sufficient in environmental problems where interactions can play a major role.

The modern portfolio theory approach (Fig. 3) helps forming a portfolio when the goal is to find a balance between expected benefits and risks. Benefits can be measured with an aggregate score based on multiple objectives. Risk is typically quantified as the variance of the benefit score. The decision problem is to choose the level of resources spent on each action. The outcome of the analysis is an efficient frontier showing the maximum possible expected benefit with each risk level. Each point on the frontier corresponds to one efficient allocation of resources to the actions. In environmental applications, the computation of expected benefits and risks is typically based on scenarios related to, e.g., future climate (see, e.g. Marinoni et al., 2011; Paydar and Qureshi, 2012).

In the multi-objective optimization (MOO) approach (Fig. 4) the goal is to identify non-dominated portfolios. Interactions among the actions and portfolio constraints can be considered. A multi-objective optimization problem is formulated and solved to find the feasible non-dominated portfolios of actions. The performance profiles of these portfolios can be visualized in different ways, e.g., by 2D scatterplots, which help the decision makers choose the most preferred portfolio from the set of non-dominated portfolios (see, e.g. Stummer et al., 2009). In interactive MOO approaches only a subset of all non-dominated solutions is solved and displayed to the decision makers at once. This set of portfolios is iteratively updated in response to preference information given by the decision makers until they are satisfied with the solutions obtained (see, e.g. Korhonen, 1988; Stummer and Heidenberger, 2003; Alves and Clímaco, 2007).

The portfolio decision analysis approach (Fig. 5) combines multi-criteria evaluation and mathematical optimization. The basic goal is to form one portfolio of actions out of a set of action candidates while taking into account multiple objectives, interactions, and resource constraints. The decision makers' preferences regarding the objectives are captured with a multi-attribute value function. Integer optimization is used to find the feasible portfolio with the greatest overall value. Interactive 'what-if' analyses can be performed to see how the optimal portfolio of actions changes in response to changes in model parameters or constraints. For instance, the decision makers can be interested in comparing the optimal portfolios that are obtained when different budget limits are used.

Portfolio decision analysis with incomplete information (Fig. 6) admits the use of intervals to describe the consequences. Ordinal preference statements can also be used regarding the preference weights in the value model (Salo and Hämäläinen, 1995; Liesiö et al., 2007). A stakeholder can state, for example, that the reduction of one ton in annual nitrogen emissions is more important than the reduction of two tons in annual phosphorus emissions without specifying the precise trade-off ratio. Optimization is used to identify the non-dominated portfolios of actions with regard to the incomplete information given. A portfolio dominates another if it is better with some combination of possible weights and consequences, and at least equally good with all other combinations (Liesiö et al., 2007). Stricter preference statements typically result in a lower number of non-dominated portfolios. The number of non-dominated portfolios usually remains much smaller than with the multi-objective optimization approach, because the multi-objective optimization models do not utilize any preference information. If the decision makers cannot make a choice between the non-dominated portfolios, one option is to obtain more precise information and solve the model again.

In heuristic approaches a heuristic solution procedure is followed instead of using optimization to find the portfolio of actions with the highest overall value. In these approaches the goal is to find a feasible portfolio with an overall performance which is considered satisfactory. The Zonation method by Moilanen (2007) is one such approach developed to support the choice of land areas to be included in a conservation network. The solution procedure in Zonation starts with the situation where all land areas are included in the network. Land areas are then repeatedly removed from the network until a feasible and satisfactory solution is found. Different rules can be used to select the land area to be removed at each iteration. One possibility is to remove the land area whose removal reduces the overall environmental value the least relative to the cost of the area.

Possingham et al. (2000) describe another procedure to form a conservation network. The idea is to find the minimal set of land areas, which satisfies the constraint that all species must be represented within the total area. This task can be formulated as an integer optimization problem.

The method by Kurttila et al. (2009) uses incomplete preference information in the development of forest management plans. The plans specify the action to be taken at each forest stand. The actions differ with respect to the timing and the extent of cutting. In this method, one first solves a set of management plans which are

Table 2
A portfolio decision analysis framework for environmental decision making.

Steps	Tasks
1. Problem framing	Determine context and scope
	Specify initial resource constraints and performance targets
	Identify stakeholders
	Design the participation and analysis process
2. Objectives and actions	Generate the initial set of objectives and actions
	Use objectives to generate additional actions
	Use actions to identify missing objectives
	Screen and specify the objectives, constraints, and actions
	Specify attributes and measurement scales
3. Interactions and overall consequences	Identify interactions between the actions
	Specify constraints related to the interactions
	Specify models for calculating the overall consequences
	Collect data and estimate the consequences of actions
4. Value model	Determine the forms of the value functions on the attributes
	Elicit weights for the attributes
5. Computation and analysis of results	Find optimal or non-dominated portfolios of actions
	Perform what-if analyses
	Communicate and visualize results
	Compare results between stakeholder groups

optimal for some plausible preference parameters. The decision makers then analyze these plans and fix the actions for some of the forest stands. After this, they repeatedly re-analyze the situation and fix the actions for more forest stands until the final management plan is formed.

4. A framework for environmental portfolio decision analysis

The framework outlined in Table 2 contains the most important steps and tasks that the portfolio decision analysis process includes. It is not always necessary to implement every step of the framework. Depending on the application, some information may be available from the outset and some model elements may not be needed. Although the steps of the framework are presented in a sequential order, this does not rule out the possibility of iterating between the steps.

4.1. Step 1: problem framing

Framing the problem is an essential phase in environmental problem solving in general (see, e.g. Bardwell, 1991; Gregory et al., 2012). The frame guides all the subsequent problem solving steps and helps the problem solving team focus their thinking.

Context refers to the system or systems where improvements or solutions are sought. Scope directs the attention of the problem solving team to specific issues and concerns within the context. One possibility is to specify what types of solutions are looked for. Consider, for example, the context of managing water resources in a river basin. The problem solving team could focus only on the operation of the hydro power plants to control the water level, or consider also other factors, such as nutrients produced by the agriculture, or the possibility to invest in water treatment facilities. Broader context and scope generally leave more possibilities for creativity and overall optimization (see, e.g. Evans, 1989). For instance, it is less expensive to tackle global problems related to energy, air-pollution and global warming simultaneously rather than addressing each problem separately (McCollum et al., 2013). Yet, taking a broader frame cannot always be advocated since it can make the problem too difficult to analyze. The breadth of topics that can be considered in the analysis depends on the time and modelling resources available for the project.

In environmental decision problems, the performance targets and resource constraints can stem from regulatory standards, aspirations of policy makers, or budgetary reasons, for instance. Resource constraints limit the amount of money, energy or other resources that can be consumed by the chosen portfolio of actions. A performance target specifies a level of performance that has to be achieved by the portfolio. Such targets typically relate to specific attributes such as emission reductions. The constraints or targets can be negotiable if, for example, relaxing a constraint enables to form a portfolio with significantly improved overall performance.

Before proceeding to the generation of objectives and actions, the stakeholder participation process should be planned. Facilitation and stakeholder engagement are important for the overall success of decision analysis and model based problem solving processes in general (Franco and Montibeller, 2010; Voinov and Bousquet, 2010; Voinov et al., 2016). Phillips and Bana e Costa (2007) describe ways in which stakeholders can be engaged in a portfolio decision analysis process. They find strongly engaged stakeholders to be more committed to implementing the results of the analysis. Many of the tools and principles followed in standard decision analysis are applicable also in portfolio decision analysis. Examples are the decision structuring dialogue (Slotte and Hämäläinen, 2015), decision analysis interviews (Marttunen and Hämäläinen, 2008), decision conferences (Phillips and Bana e Costa, 2007), tools for public engagement (Hämäläinen et al., 2010), and the structured decision making framework by Gregory et al. (2012).

4.2. Step 2: objectives and actions

In the iterative process of defining the objectives and generating the actions, the objectives guide the search for promising action candidates, and the actions can help identify missing objectives (Keeney, 1992). The objectives can refer to any tangible and intangible concerns, goals, and aims related to the problem. In the portfolio optimization model, these can be included in the value function, as performance targets, or as constraints. The goal is to generate concrete and well specified objectives, constraints, and actions. At first, all stakeholders and participants in the process should be allowed to bring their ideas on the table. Unnecessary constraints should be discarded because this can enable forming a better portfolio. Initially suggested objectives can be discarded if they are of negligible importance. If basically the same action or objective is suggested multiple times in slightly different forms, these can be merged into one. An action can be discarded if it individually violates the constraints or does not sufficiently contribute to reaching the objectives.

The idea that people generate better actions when given a list of objectives as a stimulus has been suggested by Keeney (1992). Recently this claim has gained experimental support (Selart and Johansen, 2011; Siebert and Keeney, 2015). Gregory et al. (2012) and Gregory and Keeney (1994) describe how to use objectives to generate alternatives in participatory environmental problem solving.

Attributes are the measures to describe the consequences of alternatives. Ideally, the set of attributes is comprehensive and non-redundant. When possible, the attributes should use quantitative natural measurement units, which are directly linked to the fundamental objectives of the decision (Keeney and Gregory, 2005). Such a measurement unit could be, for example, the number of organisms belonging to a particular rare species within a conservation area. It is also possible to use a proxy attribute or develop a constructed scale (Keeney and Gregory, 2005). When developing the list of attributes one should pay attention to the behavioral splitting bias phenomenon. It refers to the situation where people give more weight to an attribute if it is split into multiple more detailed attributes (Pöyhönen et al., 2001; Hämäläinen and Alaja, 2008). Therefore, one should avoid going into too much detail in the development of attributes.

4.3. Step 3: interactions and overall consequences

An essential contribution of creating and solving a portfolio model is that the interactions and synergies related to the actions will be taken into account. These interactions and synergies can relate to the effects of the actions, and to the way they use the available resources. Interactions can also impose constraints on the actions that can be in the same portfolio (Fox et al., 1984).

Mutual exclusivity constraints can arise from technical or physical restrictions, for instance. Actions are mutually exclusive if only one of them can be selected into the portfolio. There can also be ‘follow-up’ actions which can be selected only together with its prerequisite action. Technically, it is straightforward to incorporate exclusivity or follow-up constraints in the portfolio optimization model (see, e.g. Kleinmuntz, 2007).

The analysts should tell apart attributes in which the overall consequence of a portfolio of actions can be obtained by summing up the consequences of individual actions, and attributes in which the overall consequence of a portfolio results non-linearly from the consequences of the actions that are selected. For example, there can be a 'one-shot' effect related to a group of actions. The effect takes place if at least one of the actions is implemented. Such an effect could be due to a common initialization effort or a physical equipment that has a fixed cost irrespective of how many actions share it (Keisler, 2005). Technically, a one-shot effect can be modeled as a dummy action that is forced into the portfolio if the condition for the effect to take place is met (see, e.g. Stummer and Heidenberger, 2003).

In some applications there are attributes in which a known non-linear formula captures how the overall consequence of a portfolio of actions results from the consequences of the individual actions. For example, a multiplicative formula can be appropriate when there are several actions causing percentage improvements in the performance of a system (see, e.g. Grushka-Cockayne et al., 2008). Other techniques to model interactions and synergies are discussed, for example, in Dickinson et al. (2001) and Toppila et al. (2011).

Furthermore, there is always the option to estimate the possible overall consequences related to a small group of actions by separately considering all combinations of these actions. If the number of combinations is too large, the analysts can first try to run a lighter process with experts to identify the most promising combinations and subsequently only consider these. Technically, the different combinations of actions can be inserted in the portfolio optimization model as distinct mutually exclusive actions.

4.4. Step 4: value model

A standard value function can be used to obtain the overall scores of portfolios of actions once their overall consequences can be calculated in all attributes. The additive multi-attribute value function is practical and the most widely used value model. It gives the overall score of a portfolio as the weighted sum of the attribute-specific scores of the portfolio. Elicitation of the additive value function consist of two parts. The first part is to specify the attribute-specific value functions that map the portfolio level measurement scales of attributes (e.g. CO_2 reduction in tons) to attribute-specific scores. The shape of such function can capture, for instance, decreasing marginal value on an attribute. The second part is to assess the attribute importance weights, which determine the relative increases in the overall score resulting from unit improvements in the attribute-specific scores.

A rich literature exists on the methods to construct the attribute specific value functions and to assess the weights (see, e.g., von Winterfeldt and Edwards, 1986). Montibeller and von Winterfeldt, (2015) discuss a number of cognitive and motivational phenomena that can distort the construction of the additive value function. One example is the range insensitivity phenomenon (von Nitzsch and Weber, 1993). It refers to the tendency to give too low weights for attributes with a wide range. In response, one of the recommendations by Montibeller and von Winterfeldt, (2015) is to use a weighting protocol such as SWING (von Winterfeldt and Edwards, 1986) which explicitly considers the whole range of each attribute. Use of multiple methods to assess the weights can also be a good idea. If the results are sensitive to the method used, then one should try to understand why. Obtaining similar weights with different methods can increase confidence in the results.

Incomplete information about the weights can also be used (Salo and Hämäläinen, 1995). For instance, rather than using precise weights $w_1 = 0.7$ and $w_2 = 0.3$ for attributes 'CO_2 reduction' and 'Societal impact', robust value models can capture the statement 'change from the worst level to the best level in attribute CO_2 reduction is at least as important as a similar change in attribute Societal impact' by considering all weights satisfying the constraint $w_1 \geq w_2$. With incomplete information one can try to find decision recommendations that stay the same with all weights within the boundaries given. For example, if portfolio A is worse than portfolio B with all possible weights, then it can be recommended that A should not be selected (Liesiö et al., 2007).

There are several examples in the literature which follow a value modelling approach that differs from the approach described above. In these examples, the additive value function is first developed for individual actions. Portfolio overall scores are then obtained by aggregating the action specific scores (see, e.g. Golabi et al., 1981; Liesiö, 2014; Morton et al., 2016).

4.5. Step 5: computation and analysis of results

The computations and analyses of results are often intertwined. Analysing some results produced by the model can raise questions that call for more analyses, which are based on different parameter values or an updated model. The basic computational task is to use integer optimization algorithms to find the portfolio of actions which maximizes the portfolio value function subject to constraints on the portfolio composition. With modern computers this task often takes only a few seconds in problems with up to hundreds of action candidates and an additive portfolio value function.

In the interactive use of the model, the decision makers and stakeholders can be interested in various 'what-if' analyses. These include finding how the optimal portfolio of actions changes; if resource constraints or performance targets are changed, if an action is forced in the portfolio, and if weights or other model parameters are changed.

Sensitivity to a resource constraint can be studied by solving the optimal portfolio of actions with different limits on the resource expenditure. Such analysis can reveal, for example, whether an additional expenditure could result in a significant increase in the overall value. Results of the analysis can be visualized by displaying the overall scores of the optimal portfolios as a function of the budget limit. In the same way the analysts can study what happens if a performance target is relaxed in some attribute. This may enable to form a portfolio with a higher overall score or less cost.

The stakeholders may want to find out how the composition and the performance of the optimal portfolio change if a certain action is forced into the portfolio (see, e.g. Phillips and Bana e Costa, 2007). For example, stakeholders could bring up a new perspective that justifies selecting an action, which was not part of the original optimized portfolio. It can be interesting to calculate the difference in overall value between the new modified portfolio and the original one. This value difference can be informally weighed against the new perspective given. Based on such a comparison, the problem solving team may choose to keep or not keep the forced-in action in the portfolio, or revise the model to incorporate the new perspective given. Revising the model may require the development of a new attribute, for instance.

Table 3
Action candidates.

j	Description
1	Toilets with reduced water consumption
2	Showers and faucets with reduced water consumption
3	Washing machines with reduced water consumption
4	Raintanks for toilet and garden water use (3 kL)
5	Improving action 4 with extra capacity of 1.5 kL
6	Raintanks for residential hot water (3 kL)
7	Small scale recycling for irrigation
8	Aquifer usage for irrigation of public open space
9	Dual reticulation system for recycling water

Table 4
Attributes.

i	Attribute	Abbreviation	Measurement unit
1	Reduction in phosphorus release	Phosphorus	Tonnes per year
2	Reduction in nitrogen release	Nitrogen	Tonnes per year
3	Climate change impacts	Climate	Score based on expert assessment
4	Long-run savings	Savings	Millions of dollars (net present value)
5	Implementation costs	Cost	Millions of dollars
6	Reduction in water demand	Water	Percentage reduction

When visualizing optimization results, the analysts typically wish to communicate both the composition of the optimal portfolio of actions, as well as its performance in each attribute. The visualization task is more challenging when the compositions or performance profiles of multiple portfolios need to be depicted in a single graph. The parallel coordinates plot and the heat map are two options for displaying the performance profiles. The experimental research by Kiesling et al. (2011) suggests the parallel coordinates graph to be the better alternative out of these two.

When incomplete information is used, there are typically many non-dominated portfolios. Core index (CI) is a metric to communicate information about the compositions of the non-dominated portfolios (Liesiö et al., 2007). For each action, the core index is the share of non-dominated portfolios that include this action. Core index can serve as a basis for recommendations about which actions to select in the final portfolio. The core indexes of actions with CI of 0% or 100% cannot change in response to obtaining more precise preference information, if the overall consequences of each portfolio are obtained by summing up the consequences of individual actions, and the portfolio value function is linear. Then one can be recommended to choose core actions (core index 100%) and reject exterior actions (core index of 0%). Further attention should be focused to choosing between borderline actions with CI strictly between 0% and 100%. Based on applications, visualizing core indices using bar charts seems to be an intuitive way to communicate the effects of incomplete information to decision makers. Heat maps can be used to visualize the core indices of actions as a function of the budget limit.

In group decision making settings it can be interesting to compare the optimal portfolios of actions that are obtained with weights given by different stakeholder groups. This can serve as the basis for negotiation. One possibility is to look for actions that are in the optimal portfolio of every stakeholder group, and for actions that are not included in the optimal portfolio for any group (Vilkkumaa et al., 2014).

5. An illustrative example with Robust Portfolio Modelling

This illustration concretizes the tasks and concepts related to each step of the framework outlined in the previous section. Since the example is fictitious, it focuses on the modelling and analysis steps. The example case is adopted from Mitchell et al. (2007). It is analyzed using the RPM-Decisions software, which supports the use of incomplete information in portfolio decision analysis. Although incomplete information is used, the example should be instructive also for those practitioners who wish to use a standard portfolio decision analysis approach with crisp data.

5.1. Problem framing

The city of Bass has decided to have a new development constructed in the Bridgewater region near the metropolitan area of Bass. This will increase the demand of water services in the area. The core services include supplying water to households and for irrigation. Due to scarcity of existing sources of water, the city searches for means to cut the water demand of the new development. The city has allocated a budget of 45 million Australian dollars to implement a portfolio of actions with the target of cutting the water demand of the new development to half when compared to similar developments constructed earlier.

5.2. Objectives and actions

The problem solving team identifies three other objectives in addition to the goals stated in the problem definition. These are the long-term financial effects, climate change related impacts, and effects to the local water system. Nine action candidates are developed (Table 3).

Together with environmental and financial experts the problem solving team defines six attributes and corresponding measurement units which are given in Table 4. Effects to the local water system are captured by reductions in phosphorus and nitrogen releases ($i = 1, 2$). Natural scales can be used for these attributes, as well as for implementation costs ($i = 5$) and reductions in water demand ($i = 6$). For climate change impacts ($i = 3$) the problem solving team develops a constructed scale where the score of 0 refers to no impact and 1 refers to the positive impacts of a certain reference action. The other actions are evaluated in comparison with these scores. For example, an action which has twice as large positive impacts than the reference action is given the score of 2. An

Table 5
Constraints.

Constraint	Description
Follow-up action	Action #5 can be included only if action #4 is included
Mutual exclusivity A	Actions #4 and #6 cannot be included in the same portfolio
Mutual exclusivity B	Actions #7 and #8 cannot be included in the same portfolio
Mutual exclusivity C	Actions #7 and #9 cannot be included in the same portfolio
Budget constraint	Overall implementation cost must be less than 45M$
Water demand target	Overall water demand reduction must be greater than 50%

Table 6
Estimated consequences of actions. The numbers inside brackets correspond to lower and upper bound estimates respectively.

j	Phosphorus	Nitrogen	Climate	Savings	Cost	Water
1	[0.9, 1.1]	[0.09, 0.11]	[0, 0]	[1.8, 2.2]	1	3%
2	[1.1, 1.3]	[0.09, 0.11]	[0, 0]	[1.8, 2.2]	1	7%
3	[1.3, 1.7]	[0.14, 0.17]	[0.5, 1.5]	[1.8, 2.2]	2	4%
4	[0, 0]	[0, 0]	[-1.5, −0.5]	[1.8, 2.2]	10	15%
5	[0, 0]	[0, 0]	[0, 0]	[0.9, 1.1]	8	10%
6	[0, 0]	[0, 0]	[0.5, 1.5]	[9, 11]	11	38%
7	[0.50, 0.60]	[0, 0]	[0, 0]	[32, 40]	43	15%
8	[0, 0]	[0, 0]	[0, 0]	[14, 18]	23	34%
9	[4.0, 4.8]	[0.40, 0.48]	[-2.5, −1.5]	[3.5, 4.5]	20	46%

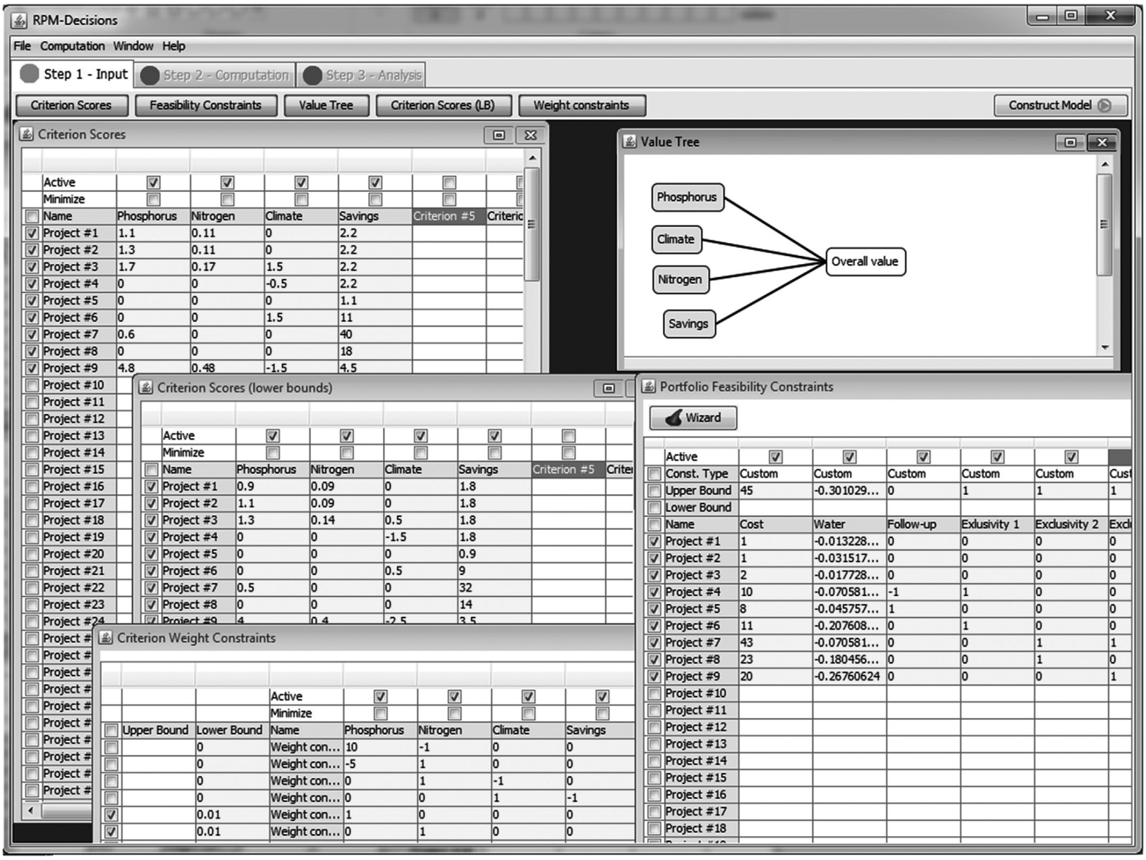

Fig. 7. Screenshot of input data in the RPM-Decisions software.

action with negative impacts of equal magnitude as the reference action's impacts is given the score of −1. For long-run savings (i = 4) the experts develop a scale based on the concept of net present value.

5.3. Interactions and overall consequences

The problem solving team identifies four interactions that impose constraints on the choice of actions (Table 5). The follow-up action constraint is specified to account for the fact that action #4 consists of installing tanks for collection of rainwater whereas action #5 consists of installing extra capacity to these tanks. Three mutual exclusivity constraints are defined. Mutual exclusivity A is defined because in most buildings it is technically too difficult to construct two separate rain tanks (actions #4, 6) on the roof and connect them to the piping of the building. Mutual exclusivity constraint B is created because actions #7 and #8 are both related to irrigation and implementing both of them would be redundant. Mutual exclusivity constraint C is specified because both actions #7 and #9 are based on the recycling of waste water. Implementing both of these actions would make the piping system of the development too complicated and therefore significantly increase the risk of failure. The list of constraints (Table 5) also includes the budget constraint and the target for water demand reduction.

The overall water demand reduction (i = 6) of a portfolio is obtained with a multiplicative function over the action specific reductions. For example, implementing either action 8 or 9 alone would reduce the water demand by 34% or 46%, respectively. Implementing both of them would reduce the water demand by $(1-0.66\cdot 0.54)\cdot 100\% = 64\%$. In the rest of the attributes (i = 1, 2, 3, 4, 5), the overall consequence of a portfolio is obtained by summing up the consequences of the actions included in the portfolio.

The problem solving team obtains estimates of the attribute specific consequences of the actions (Table 6). Point estimates are used in the attributes related to implementation costs and water

Table 7
The non-dominated portfolios.

Action	Portfolio A	Portfolio B	Portfolio C	Portfolio D	Core index
#1	included	included	included	not	3/4
#2	included	included	included	not	3/4
#3	included	included	not	included	3/4
#4	not	not	not	not	0/4
#5	not	not	not	not	0/4
#6	included	included	not	not	2/4
#7	not	not	not	not	0/4
#8	not	included	included	included	3/4
#9	included	not	included	included	3/4

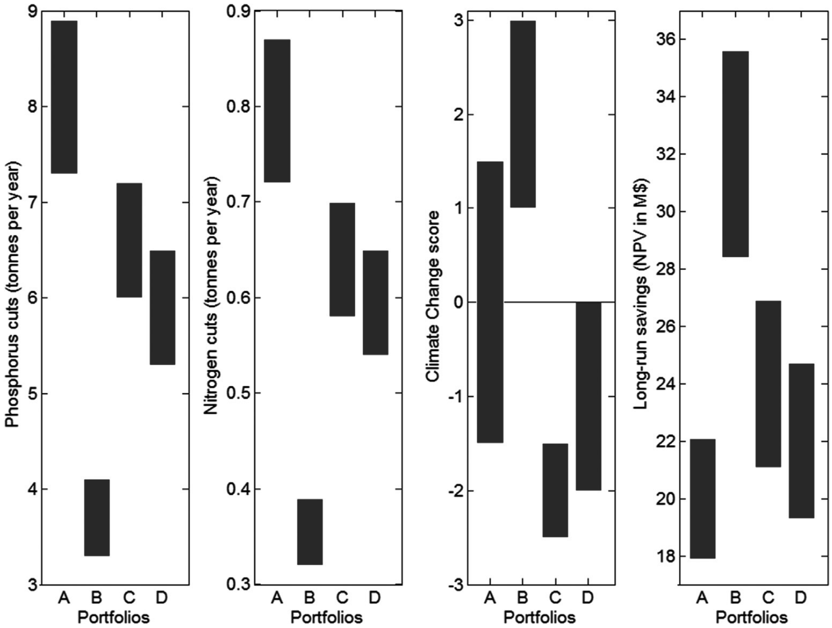

Fig. 8. Ranges of overall consequences of the non-dominated portfolios.

demand reductions (i = 5, 6). The estimates are conservative to reduce the risk of exceeding the budget or failing to reach the target for reductions in water demand. To capture uncertainty about the actions' effects in the rest of the attributes (i = 1, 2, 3, 4), lower and upper bound estimates are obtained for each attribute specific consequence that is expected to differ from zero. In the attributes related to phosphorus, nitrogen and long-run savings (i = 1, 2, 4) experts believe the consequences to fall within the bounds with a probability of 80%. The climate change impact (i = 3) related bounds are obtained simply by taking experts' best estimates and adding ±0.5 units to them.

5.4. Value model

The problem solving team together with the city representatives decide to include attributes 1–4 in the value model. They use the additive value function to model portfolio overall value. This is justified because they consider the attributes to be independent in such a way that the increase in the portfolio value due to an improvement in one attribute does not depend on the performance of the portfolio in the other attributes. Moreover, they find linear single attribute value functions to be appropriate. The reason is that the ranges of possible attribute 1–4 related effects of this decision are not large relative to the aggregate effect of all other attribute 1–4 related environmental and economic impacts that take place in the area.

To model the portfolio optimization problem, a decision variable $z = (z^1, \ldots, z^9)$ is used, where z^j is 1 if the action j is included in the portfolio and 0 if it is not included. The overall consequence of the portfolio in attributes i = 1, 2, 3, 4 is given by $\sum_{j=1}^{9} x_i^j z^j$, where x_i^j refers to the consequence of action j in attribute i. The value of portfolio z is given by

$$V(z) = \sum_{i=1}^{4} w_i \sum_{j=1}^{9} x_i^j z^j, \tag{1}$$

where w_i is the weight of the attribute i. The weights are scaled such that they sum to one. Initially, no preference information is used regarding the weights besides requiring each of them to exceed 0.01. Additional information can be obtained during the analysis phase.

5.5. Computation and analysis of results

The portfolios of actions are compared with each other based on the concept of dominance because incomplete information about weights and consequences is used. Portfolio z dominates the portfolio z', if z has greater overall value with some weights and action specific consequences, and has at least as high overall value as z' with all possible combinations of weights and action specific consequences. Non-dominated portfolios are solved with the RPM-Decisions software. Fig. 7 shows a screenshot of the input data in this software.

Four non-dominated portfolios of actions are found when no preference information regarding weights is used and action specific consequences are within the bounds given in Table 6. Table 7 shows these portfolios and the core indices of the actions. Actions #1, 2, 3, 8 and #9 are in three out of the four non-dominated portfolios and action #6 is in two. Actions #4, 5 and #7 are not in any of the non-dominated portfolios. Fig. 8 shows the ranges of overall consequences of the non-dominated portfolios in the attributes 1–4. One can see, for example, that portfolio B has the highest long-run savings and climate change score but rates the worst in nitrogen and phosphorus reductions.

Next, the city representatives give the following preference

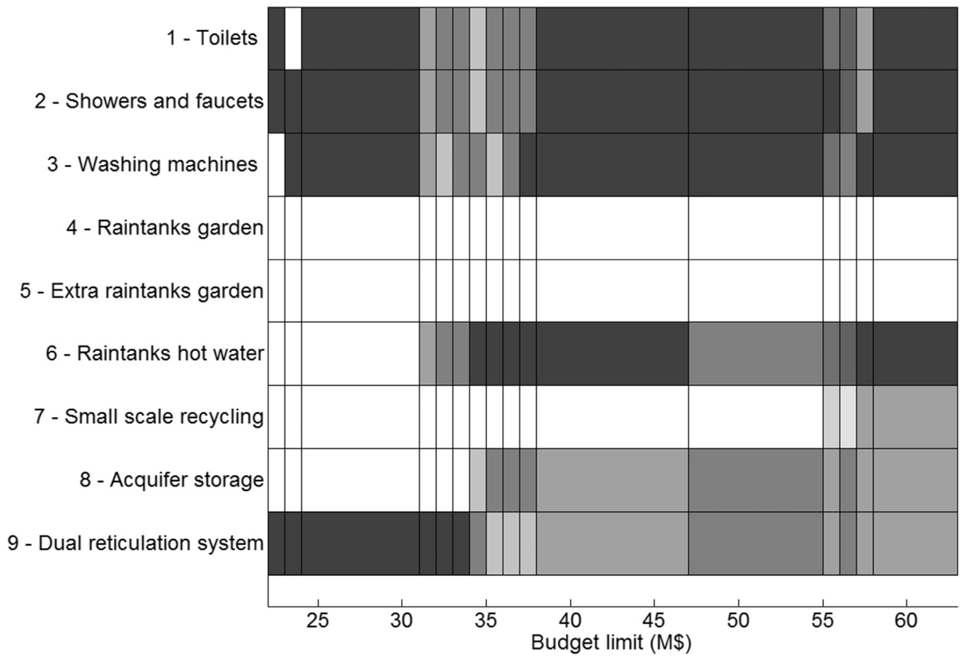

Fig. 9. Core indices of the actions with different budget limits. Dark gray corresponds to core index of 1 and white corresponds to core index of 0.

statements. One unit of climate change score is more valuable than one ton of annual nitrogen reduction, i.e. $w_3 \geq w_2$. One ton of annual nitrogen reduction is more valuable than two tons of annual phosphorus reduction, i.e. $w_2 \geq 2w_1$. One ton of annual phosphorus reduction is more valuable than two million dollars in net present value, i.e. $w_1 \geq 2w_4$.Ten million dollars in net present value is more valuable than one unit of climate change score, i.e. $10w_4 \geq w_3$. With this preference information, the portfolios A and B are the only non-dominated ones. Considering this, the recommendation can be made to choose actions #1, 2, 3 and #6 as they are included in both of the non-dominated portfolios. If this recommendation is followed, the remaining task of the city representatives would be to choose between actions #8 and #9.

The problem solving team is interested to find whether the results are sensitive to the budget limit used. The initial results were calculated with the budget limit of 45 million Australian dollars. Fig. 9 depicts the core indices of the actions with different budget limits. When the budget cap is between 38 and 47 million dollars, the core indices of the actions stay the same, i.e. the portfolios A and B are the only non-dominated ones. If the budget limit is reduced by 7 million dollars or more, then portfolio B can no longer be afforded. If the limit is increased by two million dollars, then a third non-dominated portfolio of actions becomes feasible. This portfolio does not include action #6 but instead it includes both actions #8 and #9.

The final decision is made to choose the actions #1, 2, 3, 6 and #8 that constitute the portfolio B. The estimated cost of this portfolio is 38 million Australian dollars. The city representatives find the higher long-run savings and better climate change score of portfolio B to outweigh the importance of cuts in nitrogen and phosphorus emissions that portfolio A would enable.

This example demonstrated the new possibilities offered by the use of incomplete information in portfolio decision analysis and the RPM-Decisions software. Stakeholders can perceive the analysis as more credible when preference parameters and consequence data do not need to be specified precisely. The workflow, where more precise information is gradually incorporated in the analysis can increase transparency of the solution process. At first, the model typically identifies multiple non-dominated portfolios of actions. The number of non-dominated portfolios is reduced as more precise information is incorporated in the model. Such process can help stakeholders better understand how their preference statements influence the outputs of the model.

This example is intended only as an illustration of portfolio decision analysis to help the reader in using the portfolio approach in her future work.

6. Software support for portfolio decision analysis

Software support for portfolio decision analysis is readily available. This section briefly introduces possibilities offered by dedicated portfolio decision analysis software packages, spreadsheets software, and general purpose mathematical software.

The strengths of dedicated portfolio decision analysis software packages include ready-made user interfaces, simple data inputs, as well as tools for visualization and sensitivity analysis. These software have built-in optimization algorithms that can handle large problems with up to hundreds of actions. However, they impose some restrictions on the portfolio model. Non-linear value functions defined over portfolio overall consequences are not explicitly supported by any of the dedicated software packages considered in this section. The freely available software by Marinoni et al. (2009) supports only a single resource constraint and a linear portfolio value function with no interactions. The four commercial software packages reviewed by Lourenço et al. (2008) enable specifying multiple resource constraints, and offer support for modelling certain types of interactions, such as, 'choosing the actions A and B creates a certain synergy benefit' or 'the action C can be chosen only if D is chosen'. The PROBE software (Lourenço et al., 2012) adds support for general linear constraints on the actions. This makes it possible to model multiple resource constraints, performance targets, as well as various types of interactions related to the actions. PROBE can also analyze the robustness of the optimal portfolio found using crisp data. The user can give incomplete information on some model parameters (e.g. actions' costs and scores) and the software uses it to check whether there exists a less expensive portfolio whose value could exceed that of the optimal portfolio.

RPM-Decisions is a portfolio decision analysis software whose distinguishing feature is the way it enables the use of incomplete information. It can identify *all* non-dominated portfolios in view of incomplete information on the weights and the consequences of the actions. Moreover, it also accepts any number of general linear constraints on the actions. The website http://rpm.aalto.fi can be a useful resource for the reader interested in the RPM-Decisions software. The website gives general information on the software, on its use, and on the Robust Portfolio Modelling method. References to several papers that have made use of the RPM-Decisions software are also provided.

Spreadsheet software are an easily accessible tool for building portfolio models. In many applications all possible portfolios, i.e. combinations of actions, can be enumerated. The main factor limiting applicability of this approach is the number of action candidates. To provide some insight on these limits, our experiences suggest that it is relatively straightforward to structure and solve a model with 15 actions, i.e. $2^{15} = 32768$ portfolios, with Microsoft Excel running on a standard laptop (Intel Core i5 2.4 GHz, 4 GB memory). The enumeration approach does not restrict the types of constraints, interactions, or value functions that can be used in the model.

Finally, working with portfolio models including a large number of actions and complicated constraint structure can require the use of a general purpose mathematical software, e.g. Matlab or Python. A high performance optimization solver, such as CPLEX or Gurobi, can be needed to identify the optimal portfolios. Examples of real-life portfolio decision analysis applications harnessing such an approach are reported by Mild and Salo (2009) and Toppila et al. (2011), for instance.

7. Conclusions

Multi-criteria evaluation methods have proven to be very useful in environmental decision making. Today, it is natural to take the next step in environmental decision support and start using portfolio decision analysis methods and tools. Many environmental decisions are, in fact, portfolio problems where the decision makers need to consider a set of actions and create a management policy incorporating relevant concerns and interests in a balanced way. The portfolio decision analysis approach enables stakeholders to constructively engage in the decision making process at an early stage. Both experts and stakeholders can suggest actions to be included in the analysis without restrictions. This is a major advantage compared to the standard multi-criteria approaches. It helps to create shared ownership of the process, which is likely to increase the participants' commitment to the implementation of the management decision.

Portfolio decision analysis can also be useful in integrated environmental assessment tasks. In these assessments, the aim is to measure interdependent environmental impacts with multiple indicators, which relate to different perspectives and scales (see, e.g. Jakeman and Letcher, 2003; Laniak et al., 2013). Such problems can be addressed as portfolio assessment problems.

The model based portfolio generation process can mitigate some of the risks arising from behavioral phenomena in unaided portfolio generation. One risk in the unaided process is that the problem solving team myopically builds the portfolio around certain champion actions and fails to see better combinations of actions. This risk can be reduced by considering all actions simultaneously in the same analysis. Such an analysis can be carried out with one of the readily available software approaches. Spreadsheet software is an easily accessible tool, which can be used when the number of action candidates is moderate, e.g. less than fifteen.

Once the opportunities offered by portfolio approaches are more widely recognized, a great number of environmental applications is likely to be seen. An interesting direction of research in the future will be to develop and test practical portfolio decision analysis procedures when working interactively with stakeholders. This paper hopefully encourages and helps the practitioners to engage in portfolio decision analysis in environmental management problems.

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