



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.

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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; Delqu e, 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 $x_k \rightarrow x'_k$ and the response change in the measuring stick attribute m is $x_m \rightarrow x'_m$. The magnitude of the corresponding trade-off ratio is denoted by

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

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.

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