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

Raimo P. Hämäläinen, Tuomas J. Lahtinen *

Systems Analysis Laboratory, Department of Mathematics and Systems Analysis, Aalto University School of Science, P.O. Box 11100, 00076 Aalto, Finland

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.

* Corresponding author.
E-mail addresses: raimo.hamalainen@aalto.fi (R.P. Hämäläinen), tuomas.j.lahtinen@aalto.fi (T.J. Lahtinen).

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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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