MUST

Managing Deep Uncertainty in Planning for Sustainable Transport

Project report: phase 1

ITRL – INTEGRATED TRANSPORT RESEARCH LAB
KTH ROYAL INSTITUTE OF TECHNOLOGY

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Executive summary

There is a growing recognition that traditional forecasting and decision-making approaches might fall short considering the many uncertainties and complexities facing the development of the transport system. The project Managing deep Uncertainty in planning for Sustainable Transport (MUST), funded by Trafikverket and conducted by KTH ITRL and VTI, aims to explore emerging methods for improving the handling of deep uncertainty in the long-term planning of future transport systems. The core of MUST is to explore, develop, and demonstrate tools and methods grounded in Decision Making under Deep Uncertainty (DMDU) and Exploratory Modeling and Analysis (EMA). These approaches are intended to support a shift towards more robust and adaptable planning methodologies.

The project is performed in two phases, with the first phase dedicated to laying a foundational understanding of deep uncertainty in transport planning. This report covers the first phase which has included the following tasks:

- A literature review on deep uncertainty and existing decision-making and system analysis methods under such conditions, with a focus on transportation.
- A workshop series with Trafikverket identifying transport planning challenges marked by deep uncertainty.
- A case study of applying DMDU through a case study on climate policy robustness (primarily reported in other deliverables).

The literature review covers how the nature of uncertainty in socio-technical systems can be understood, classified, and analyzed. For policy analysis and decision making, the literature underscores the importance of considering multiple futures in model-based analysis when faced with deep uncertainties. DMDU and EMA methods are reviewed and summarized, and their application to transport are discussed. The literature also summarizes studies on uncertainty in model-based transport planning and policy analysis and concludes that the primary location of deep uncertainty is in the model inputs in the form of “scenario uncertainty”. In the workshop series, uncertainty related to producing the base forecast (Swe: basprognos) and policy analysis for domestic transport climate policy was analyzed. This analysis suggested that scenario uncertainty is a main source of deep uncertainty, but also uncertainty related to the system boundaries where highlighted. Furthermore, potential benefits and drawbacks of EMA and DMDU were discussed. In the case study, it is explored how the Scenario tool can be further leveraged by DMDU. More specifically, MORDM (see Section 2.2.3) is applied to assess to what extent it may allow a broader set of policy options to be explored, and how it can provide a better understanding of the robustness and vulnerabilities of different types of policies.

A key takeaway from MUST phase 1 is that DMDU and EMA could provide several potential benefits and that methods and tools for applying them are maturing. However, it is possibly a long way to go before DMDU and EMA can be integrated as a regularly used method during the planning process. This is due to organization and process-related issues, as well as technical issues on how to effectively apply DMDU and EMA to Trafikverket’s national transport models. These technical issues will partly be explored in MUST phase 2.

Extended summary

The purpose of the MUST project is to enhance Trafikverket's ability to manage deep uncertainty in long-term analysis and planning for the future transport system. This is done by exploring, developing, and demonstrating tools and methods for Decision Making under Deep Uncertainty (DMDU) and Exploratory Modeling and Analysis (EMA). These are emerging approaches from the field of policy analysis for analyzing systems and decisions when there is significant uncertainty for how the system, or its inputs, will behave in the future. The project is performed by KTH ITRL and VTI and financed by Trafikverket.

The MUST project is performed in two phases. In this first phase, the primary goal is to establish a knowledge foundation by identifying transport planning challenges that are characterized by deep uncertainty and reviewing methods for decision-making and system analysis under such uncertainty. A further objective is to explore and showcase methods for DMDU and EMA through a case study in which the robustness of various climate policy packages is analyzed. Phase 1 constitutes of two work packages (WPs): WP1 which includes a literature review and workshop series with participants from the project partners, and WP2 which consists of a case study where DMDU is applied to Trafikverket's Scenario tool for transport climate policy analysis. This report summarizes research performed during phase 1 and constitutes one of the phase 1 deliverables. However, the majority of WP2 is delivered and described in other deliverables in the form of a scientific paper and a code repository. Following the introduction, the report consists of three main chapters: Chapter 2 presents a literature review of decision making under deep uncertainty in sociotechnical systems with focus on transportation, Chapter 3 describes the workshop series, Chapter 4 provides a description of the Scenario tool and discusses its applicability. Finally, Chapter 5 provides a concluding discussion.

Literature review
The purpose of this literature review is to provide a basis for the MUST project by reviewing central theoretical concepts for understanding complexity and uncertainty in sociotechnical systems and methods for decision making under deep uncertainty. The review will also survey research and previous work analyzing uncertainty in model-based analysis in the transport sector and how uncertainty has been dealt with. While not intended as a fully exhaustive review, the focus is on introducing key concepts from the literature that are relevant for the MUST project. The literature review is organized around three thematic questions: i) what is (deep) uncertainty and how can it be understood? ii) how can (deep) uncertainty be accounted for in model-based policy analysis? iii) how, and to what extent, has (deep) uncertainty been accounted for in transport planning?

The literature stresses that uncertainty has multiple dimensions and ranges from complete determinism, an ideal we cannot achieve, to total ignorance. *Deep uncertainty* arises in situations where it is challenging to assign probabilities due to system complexity, scarce information, or inherent unpredictability of complex systems. Deep uncertainty leads to a need to consider a multiplicity of futures, which is typically challenging in decision-making situations. Historically, various methods have been used to think about the future, such as: narratives, group narratives like Delphi and Foresight, simulation modelling, decision analysis, and scenario-based planning. However, each of these approaches has limitations, especially in addressing the multitude of plausible futures (Lempert et al., 2003). Maier et al (2016) highlight the importance of considering multiple futures in

model-based quantitative policy analysis. They recommend describing uncertainty using distinct plausible scenarios, measuring system performance based on its robustness to future changes, and designing adaptive strategies that can be adjusted as conditions evolve.

Decision Making Under Deep Uncertainty (DMDU) is a collection of tools and methods used to identify strategies that are robust and adaptive in the face of deep uncertainty (Marchau et al., 2019). DMDU is based on three key ideas: exploratory modelling, adaptive planning, and decision support. When applying DMDU, quantitative policy models are used to simulate a range of scenarios and assess policy alternatives. There are many different DMDU techniques and tools, of which many are complementary. For the MUST project, two of these methods are in focus: Robust Decision Making (RDM), and Exploratory Modeling and Analysis (EMA).

RDM focuses on identifying strategies that are robust against a wide variety of future conditions. It challenges the prevailing notion of basing policy analysis on a prediction of a system's future state, aiming instead to support decision-making in cases of deep uncertainty when definitive forecasts cannot be made. Moreover, if RDM is performed in collaboration with relevant stakeholders, it can enhance the understanding of the policy problem, generate additional policy alternatives, and provide deeper insights into the inherent trade-offs of policies.

EMA is a more general approach which involves creating, exploring, and analyzing many alternative policies, models or scenarios to understand the impact of uncertainties on system behavior and decision outcomes (Kwakkel and Pruyt 2013). EMA utilizes several methods and techniques, such as sampling, sensitivity analysis, uncertainty analysis, scenario discovery, and (multi-objective) optimization. To structure EMA problems, the XLRM framework is often used to specify the external uncertainties (X), policy levers (L), relationships in the system (R), and outcomes of interest (M). EMA is essentially an analysis of how regions of uncertainty (X and R) and the decision space (L) relate to the outcome space (M). EMA differentiates between two applications: open exploration and directed search. Open exploration systematically samples uncertainty or decision space while directed search uses mathematical optimization to search the decision or uncertainty space, aiming to identify policies or scenarios of interest.

Often, EMA problems have multiple objectives involving trade-offs. In these cases, multi-objective optimization is performed, often using a multi-objective evolutionary algorithm (MOEA). Directed search can be used to generate candidate policies within the RDM framework. One such approach is Many Objective Robust Decision Making (MORDM), where a MOEA is used to generate Pareto-optimal policies based on a reference scenario. Thereafter, the robustness and vulnerabilities of these candidate policies are evaluated using RDM. There are also closely related methods to MORDM designed to put more emphasis on robustness during the policy search phase such as multi-scenario MORDM and multi-objective robust search (MORO). For all these approaches, specifying relevant robustness metrics is crucial, with robustness understood either as low uncertainty or minimization of undesirable outcomes. Different robustness metrics emphasize various aspects of robustness, underscoring the need for careful selection tailored to the problem at hand and use of complementary metrics.

In the transport planning field, it has for several decades been common practice to make a transport forecast of a future year (typically around 20 years in the future) and to calculate costs and benefits of transport projects for the forecast of this forecast year. In some cases, sensitivity analyses have been made in which the planner tries a few changes to the input data such as changes to assumed population growth or assumed future fuel prices. The accuracy of these transport forecasts has been evaluated in several studies (Andersson et al., 2017; Cruz & Sarmento, 2020; Hoque et al., 2021) coming to the conclusion that transport forecasts are more often optimistic rather than pessimistic, over-estimating demand and under-estimating costs when compared to actual outcome statistics. Thus, the uncertainty in the forecast is not purely random, there is a systematic bias. In the reviewed studies, the over-estimation of forecast traffic flows/vehicle kilometers compared to actual outcome statistics is in the order of 5%-20%. It is also found that rail traffic forecasts in general deviate more from actual outcomes compared to road traffic forecasts.

Rather than conducting a handful of sensitivity analyses of selected input parameters, researchers and planners have in the latest years tried to deal with uncertainty in transport planning and transport forecasting in a more all-encompassing way, applying approaches from the DMDU field. This implies that policies/measures are tested against a large set of scenarios with varying input parameters within defined ranges, and that the policies/measures that are most robust across the different scenarios are selected. The prominent example of this is a U.S. model called TMIP-EMAT (Lemp et al., 2021; Milkovits et al., 2019). TMIP-EMAT applies EMA together with a travel forecasting model to give a range of outcomes given uncertainties in employment levels, values of travel time etcetera.

Workshop series

The purpose of the workshop series is to bring together experts within various areas of model-based analysis at Trafikverket with researchers from the project partners to identify, analyze and discuss deep uncertainty and the challenges it poses for Trafikverket's long-term planning and policy analysis processes, and methods for managing it. The workshop series consists of two workshops, Workshop 1 (WS1) and Workshop 2 (WS2), which build on each other. In WS1, focus is on the concept of deep uncertainty and to analyze how it relates to some of Trafikverket's analysis needs. During the workshop, a framework for classifying and communicating deep uncertainty in model-based foresight or policy analysis is introduced. Exercises are performed to identify and categorize Trafikverket's analysis needs, and to perform an analysis of uncertainty for one of the analysis needs, producing the reference forecast (basprognos) for the Swedish transport system, by applying the aforementioned framework. WS2 is focused on the concept of decision making under deep uncertainty and introduces a framework for uncertainty in the policy analysis process and an overview of exploratory modelling and analysis by presenting the case study in WP2. The exercises are centered on the case of identifying and analyzing policies for reaching the national climate targets for the transport system. WS2 is concluded by a brainstorming session on the implications for Trafikverket and to generate ideas of potential activities Trafikverket could undertake to improve its ability to manage deep uncertainty.

An important finding, which is also in line with what the literature has reported, is that typically, scenario uncertainty (i.e. model input) uncertainty tend to be a larger issue than model uncertainty. In other words, the forecasting models can be expected to give fairly accurate results given that analysts were able to correctly forecast the state of the world for the forecast year. A complication is that much of the scenario assumptions for national transport forecast are "inherited" from forecast made by other agencies (e.g. about economic development).

While several workshop participants could see the benefits of EMA and DMDU as tools for a systematic account of uncertainty in various types of analyses, it was stressed that different types of sensitivity and uncertainty analyses are already performed. It was also brought up that it is important that the result of the analyses, which are to be used for decision support for policymakers, cannot be too complicated, and that it is not obvious if DMDU can ensure that.

Trafikverket's Scenario Tool: description and applicability
One task in work package 2 is to assess Trafikverket's Scenario tool for climate policy analysis *(the Scenario tool*) (Trafikverket, 2020a) and the application of it to generate policy scenarios for reaching the climate targets as part of the governmental task to develop alternative scenarios for the transport system (Trafikverket, 2020d). A few years ago, Trafikverket was given a task by the Swedish government to provide alternative forecast scenarios for the transport sector and how they relate to the political goals for the transport area, including the climate targets (Trafikverket, 2020d). This in turn triggered the development of the Scenario tool. The Scenario tool (Trafikverket, 2020a) is an Excel-based tool that is intended to support the analysis of whether various climate strategies (combinations of policy measures) lead to a future which meets the climate goals or not. The Scenario tool covers domestic[1] road transport including light vehicles (cars and light trucks[2]), heavy trucks and, partly, bus traffic. The scenario tool is developed to study climate strategies that include three types of policy measures 1) an increased share of electric vehicles and more fuel-efficient vehicles, 2) an increased share of renewable fuels, 3) reduced road traffic activity.

Trafikverket did, using the Scenario tool, identify eight climate strategies that manage to reach the climate target for the base scenario, which vary in the combination of policies applied to reach the goal (Trafikverket, 2020d). In other words, these climate strategies are by design goal fulfilling and illustrate different ways of reaching the climate targets, assuming the development of other factors in line with the reference scenario.
Two of the policy strategies identified using the Scenario tool, namely: B and C2 were thereafter analyzed more in-depth, see Trafikverket (2020e) for details. This analysis was made using the national forecasting models Sampers and Samgods in which the corresponding policy strategies were represented. Following this analysis, one of the analyzed policy strategies, which relied on a high amount of biofuel usage, has been adopted as the presumed transport climate policy in subsequent base forecasts up until currently (Trafikverket, 2020c).

The main aim of the Scenario tool is according to Trafikverket (2020a, p. 6) to *simplify analyses of the road transport sector's CO2 emissions*. Furthermore, it is stated that the conventional forecast models that produce more disaggregate and detailed forecasts (Sampers and Samgods) are complex, require a large and broad set of input and are time- and resource intensive to run. Therefore, they are practically unsuited to use for identifying goal-fulfilling scenarios by iterating over parameter

[1] Traffic activity performed at Swedish territory

[2] With maximum permissible weight less than 3.5 tonnes

space of policy lever combinations. The Scenario tool can therefore be used to quickly test, on an overarching level, a large number of policy combinations, to identify a set of policy candidates. To summarize, Trafikverket describes the Scenario tool as an option to quickly perform rough, aggregate analyses of climate policies iteratively and exploratory. The Scenario tool can be used in a sequential process in conjuncture with the conventional forecasting models in which the Scenario tool is first used to identify policy candidates based on their estimated impacts. The candidate polies can then be analyzed more in detail with these models to provide data for more comprehensive decision support

In the case study in work package 2, it is explored how the Scenario tool can be further leveraged by DMDU. More specifically, MORDM (see Section 2.2.3) is applied to assess to what extent it may allow a broader set of policy options to be explored, and how it can provide a better understanding of the robustness and vulnerabilities of different types of policies. For the case study, the following modifications to the scenario tool have been made:

- Identified bugs were corrected,
- The reference scenario was updated to align with the base forecasts of 2023,
- A module to enable crude analysis of potential impacts of automated driving technology (driverless vehicles) was added,
- A simplified method for specifying the degree of biofuel admixture was added,
- Minor adaptations were made to simplify the set up and to run the Scenario tool via Python, using the open-source library EMA-workbench (Kwakkel, 2017).

Concluding discussion
The results from the literature review and workshop series both suggest that the deep uncertainty in model-based analysis in the transportation domain often relates to specification of model inputs, so called *scenario uncertainty.* Another important area of uncertainty relates to the modelling of policies, or combinations thereof, which have previously not been implemented or properly evaluated. An overarching insight from MUST phase 1 is that DMDU has potential to improve transport planning and policy analysis, since it offers systematic approaches to account for scenario uncertainty and policy impact uncertainty.

The literature on DMDU developed substantially during the last decade and there is also a growing number of case studies applying different DMDU methods to various problems. Furthermore, the development of well-maintained open-source software supporting DMDU has lowered the barrier for experimenting and implementing DMDU for researchers and practitioners. However, the DMDU literature has to a large extent so far been focused on method development and prospective case studies with limited effort on the policy making context and how DMDU can be successfully applied for real world policy making.

For specific, stand-alone, infrastructure investment analyses or policy analyses, it may be relatively straightforward to implement DMDU without significant additional effort. For instance, many methods for robust decision making are simple to apply in cases where there are predefined planning or policy options, given that the system model can be used to represent the deep uncertainties of interest. It is, however, presumably a fairly long way to go for DMDU to become a core approach within the standard national transport infrastructure planning practice. A central issue is to consider and assess to what extent DMDU can and should be used during different stages of the planning process. Also, it needs to be analyzed to what extent it can and should constitute a complement to existing practices or whether it would be required to fundamentally adjust certain parts of the planning process. Applying DMDU to existing national transport models (Sampers and Samgods) requires a non-negligible amount of work to adapt the models and their infrastructure to enable EMA or DMDU. It requires the development of tools that supports to automatically generate, implement, run and store results from hundreds or thousands of scenarios. Furthermore, the rather long computation time of these models is an issue that needs to be accounted for and managed. In phase 2 of MUST, EMA is applied to the Samgods model and some of these issues will be explored.

Contents

1 Introduction

As the pace of technological and societal development continues to accelerate, it brings with it a complex landscape of uncertainties for the transport sector. The capability required to make long-term forecasts regarding the transport system becomes increasingly intricate. The emergence of new technologies comes with a need for understanding their multifaceted implications. This understanding is important in many aspects of transportation planning and policy making. For instance, to analyze the need of policy measures for achieving sustainability and transport policy goals or making appraisal of societal costs and benefits of policies or investments.

To a large extent, conventional transport planning relies on forecasting methods using large-scale transportation models within a predict-then-act paradigm for policymaking. One, or a few, specific predictions of the demand- and supply side for the future transport system are made based on which policy needs are identified, and policy alternatives are evaluated. This approach, although systematic, may not be appropriate to account for the deep uncertainties that surround the development of the future transport system since it relies on that policymakers and analysts can agree upon a most likely scenario for the development of society, technology, and the economy, how to reflect these factors in model inputs, and the appropriate ways to model the interactions within the transport system. Agreeing on these factors cannot be expected in situations of deep uncertainty.

The purpose of the MUST project is to strengthen Trafikverket's ability to manage deep uncertainty in long-term analysis and planning for the future transport system. This is done by exploring, developing, and demonstrating tools and methods for Decision Making under Deep Uncertainty (DMDU) and Exploratory Modeling and Analysis (EMA). These are emerging approaches from the field of policy analysis for analyzing systems and decisions when there is significant uncertainty for how the system, or its input, will behave in the future.

The MUST project is performed in two phases. For this first phase, the primary goal is to establish a knowledge foundation by identifying transport planning challenges that are characterized by deep uncertainty and reviewing methods for decision-making and system analysis under such uncertainty. A further objective is to explore and showcase methods for DMDU and EMA will through a case study in which the robustness of various climate policy packages is analyzed. This report summarizes the research performed during Phase 1 and is one of the project deliverables for phase 1 along with the additional deliverables listed in Table 1. Phase 1 is organized into two work packages (WP): WP1 and WP2.

Work package 1 Knowledge foundation for understanding and managing deep uncertainty in long-term planning for a sustainable transport system
Key activities:

- Literature review on methods for analysis and decision-making under uncertainty
- A series of workshops with Trafikverket

The goal of WP 1 is to conceptualize and delineate the challenges that uncertainties in technical and societal developments pose for long-term planning for a sustainable transport system. The literature study aims to 1) provide a theoretical foundation for the project's themes around complex sociotechnical system uncertainty and its implications for analysis and policymaking for the future transport system, 2) review existing approaches for analysis and decision-making under deep uncertainty, and 3) provide an overview of research addressing uncertainty in the transport sector. The workshop series consists of two workshops with participants from Trafikverket and researchers from KTH and VTI.

Work package 2 Case study: Uncertainty and robustness analysis of policy strategies for reaching the climate targets for the transport sector

Activities:

- Assessment of the current version of Trafikverket's scenario tool and previously conducted policy analysis.
- Development of the scenario tool with a module for autonomous vehicles.
- Robustness analysis of policy strategies to achieve climate goals.

The purpose of Work package 2 (WP2) is to serve as a pilot study within MUST for applying EMA and/or DMDU to support analysis and decision making for a sustainable planning or policy issue of relevance for the Swedish Transport Administration (STA). The focus for this pilot is to broaden a previous analysis that STA has performed for identifying different types of policy packages that enables the climate goals for the Swedish transport sector to be achieved (Trafikverket, 2020d). The previous analysis used a simplified climate policy assessment model (hereafter denoted as *the Scenario tool*) to identify fulfilling policy packages that fulfill the Swedish climate target if other factors assumed to be in line with the base forecast. The pilot study in WP2 applies EMA and DMDU to the Scenario tool to evaluate the robustness of the proposed policy packages against a large number of scenarios that accounts for uncertainty in the assumptions for the base forecast as well as uncertainties in model parameters which affect the modeled magnitude of policy impacts. It also compares the robustness of the policy packages presented in the previous analysis with policies that are generated using DMDU. To include the potential impacts of driverless vehicles, which is one technology uncertainty with potential to substantially affect transport demand and climate emissions, the Scenario tool is extended to model these effects in a simplistic way.

While the findings of this pilot study are interesting in itself, it also serves the project by building a foundation of knowledge and tools (code) for applying EMA and DMDU for the more substantial EMA/DMDU study that will be performed Phase 2. It is also used as an example during the workshop series in WP1.

Work package 2 is primarily delivered in other deliverables than this report, namely a research paper and a code repository, see Table 1. Only the review of the Scenario tool is fully covered by this report, and the other tasks are only summarized.

Table 1 Overview of WP2 tasks and their corresponding primary deliverable.

Task	Primary deliverable
Review of the Scenario tool	This report

Extend the scenario tool to study driverless vehicle impacts	Model in code repository
Develop code for applying EMA and DMDU to the Scenario tool	Scripts in code repository
Perform robustness analysis of climate policies	Research paper

The scope for this report is primarily national transport planning and policy analysis performed by, closely related to, the Swedish Transport Administration. When terms such as “transport planning applications”, “planning practices”, etc. it typically refers to applications or practices of the Swedish Transport Administration.

The remainder of this report is organized as follows: Chapter 2, presents the literature review, Chapter 3 summarizes the workshop series, Chapter 4 provides a description of the scenario tool and discusses its applicability, and Chapter 5 provides a concluding discussion.

2 Literature review of decision making under deep uncertainty in sociotechnical systems: an overview and focus on transportation

The purpose of this literature review is to provide a basis for the MUST project by reviewing central theoretical concepts for understanding complexity and uncertainty in sociotechnical systems and methods for decision making under deep uncertainty. The review will also survey research and previous work analyzing uncertainty in model-based analysis in the transport sector and how uncertainty has been dealt with. While not intended as a fully exhaustive review, the focus is on introducing key concepts from the literature that are relevant for the MUST project. The review of theoretical perspectives on uncertainty and methods for managing deep uncertainty is not limited to the transportation sector; rather, it seeks inspiration from work across the broader area of decision-making under deep uncertainty.

The literature review is organized around three thematic questions:

1. What is (deep) uncertainty and how can it be understood?
2. How can (deep) uncertainty be accounted for in model-based policy analysis?
3. How, and to what extent, has (deep) uncertainty been accounted for in transport planning?

By addressing these questions, this literature review aims to provide guidance in terms of useful concepts, frameworks, and methods for other activities in the MUST project. Furthermore, it can serve as an introduction to deep uncertainty for Trafikverket and other actors in the field of transport planning and policy making.

2.1 What is (deep) uncertainty and how can it be understood?

2.1.1 A short note on the history of uncertainty in science

The literature on decision making under deep uncertainty highlights that different fields and disciplines have understood the concept of uncertainty in slightly different ways. The various philosophical viewpoints and epistemological discourses imply various meanings for uncertainty. Furthermore, the understanding and role of uncertainty in science have developed and changed over time. Van Asselt (2000) and Agustdinata (2008) both present overviews on the history of the understanding of uncertainty in science and various epistemologies. Below, a highly condensed summary of these overviews is provided.

The underpinning idea of the Enlightenment, which was influenced by Descartes and succeeding thinkers like Locke, Diderot, Voltaire, Kant, and Hegel, is of science as a provider of certainty. Through systematic investigation using mathematics and quantitative methods, certain knowledge on reality can be obtained and there is a distinct separation between the domain of objective facts and the domain of subjective opinions. The Enlightenment thinking grew into the positivistic epistemology (positivism) which can be defined as "the search for and prediction of empirical regularities to make universal, true statements" (van Asselt 2000 p.78), which ultimately, implies that for positivism, uncertainty is unscientific. Positivism has historically been the dominant epistemology in science well into the 20th century. However, there has always been criticism of positivist epistemology. During the 18th century, Hume and the skepticism school of thought, criticized positivism on the basis that reason is insufficient for bridging the gap between observations and reality since our minds cannot grasp the causal connections among events based on experience. This means that there are inherent limits to our ability to make predictions of future events. The notion of true knowledge was challenged also by some of the Enlightenment thinkers. For instance, Hegel was of the position that systematic examination did produce knowledge, but it was neither perfect nor complete knowledge.

In the early 20th century, the rise of new ideas in physics and mathematics such as statistical mechanics and Einstein's model of mass, time, and space as relative and not absolute concepts, sparked a more serious inquiry of the role of uncertainty in science. During the same period, uncertainty was also becoming a more prominent topic in other fields with a prominent example being the work of Knight (1921) in the field of economics. Knight distinguished the concepts of risk and uncertainty from each other with risk being the part of the unknowable that is calculable and controllable while the remainder of the unknowable is uncertain. In the second half of the 20th century there was more widespread criticism of positivist epistemology. Two "anti-positivism" movements emerged, post-modernism which stemmed from philosophy and social constructivism which emerged within the field of sociology of science and technology.

Post-modernism refutes central viewpoints of the positivistic epistemology. Post-modernists are skeptical to the human ability to represent reality objectively and refute that any knowledge can be certain. Instead, post-modernists claim that reality is a construct of scientific concepts and that there is no objective truth. Furthermore, reason and logic are not understood as being universally valid but are rather valid only within a specific scientific or intellectual context. Prominent post-modernism scholars include Foucault and Derrida who were inspired by the works of scholars such as Nietzsche and Heidegger.

Social constructivism has its empirical foundations from sociological and anthropological studies on the production of scientific knowledge. Social constructivism denies that scientific knowledge can be produced according to purely rational cognitive factors. Instead, the production of science is a social process and scientific knowledge is constructed and negotiated through social processes. Even though it is possible to distinguish between valid and invalid scientific statements, the criterion for such judgments cannot according to social constructivists be derived from an "abstract and universal faculty of reason" but must be socially constructed. van Asselt summarize social-constructivism epistemology as the following theses:

- What knowledge is produced and how knowledge is used are socially driven decisions.
- Central processes in theory building, e.g., acceptance or rejection of theories are entirely social.

- What scientists expect to observe, can observe, and want to observe are outcomes of social negotiations.
- There is no single scientific method to which all scientists can refer. What methods are seen as appropriate is determined by social processes.

Post-modernism and social constructivism have raised fundamental questions about objectivity and certainty in science, which van Asselt synthesizes into the following two statements:

- Science is not a purely objective, value-free activity of discovery – science is a creative process in which social and individual values interfere with observation, analysis, and interpretation.
- Knowledge is not equivalent to truth and certainty.

Another perspective that has shaped the understanding of uncertainty in science during the 20th century is based on Heisenberg's uncertainty principle. In short, the principle states that it is not possible to obtain all information since the act of obtaining the information often alters the phenomena being studied. Also, in economics, the limits of knowledge and achieving certainty by seeking more information was stressed during this period. For instance, the economist Shackle formulated it as follows. "There would be no uncertainty if a question could be answered by seeking additional knowledge. The fundamental imperfection of knowledge is the essence of uncertainty." (Shackle, 2010).

All in all, this points to an epistemological position where uncertainty can still prevail in situations with a lot of information available. In other words, uncertainty is not simply the absence of information. Also, getting more information about a system can increase uncertainty, for instance we may learn the system's processes are more complex and have uncertainties previously not understood when it is studied more. In other words, there are inherent limitations to the reduction of uncertainty through the acquisition of more information or knowledge.

2.1.2 Defining uncertainty and deep uncertainty

In the simplest sense, uncertainty can be defined as a *limited knowledge of future, past, or current events* (Walker et al. 2013). In mathematical terms, this can be expressed as that if the probability of an event is not equal to one or zero, the event is uncertain. This follows the tradition of understanding uncertainty as a lack of knowledge and the distinction between risk and uncertainty which often is attributed to Knight (1921), see Section 2.1.1. As will be apparent in the forthcoming sections of this report, knowledge, and thus uncertainty, consist along a spectrum ranging from *the unachievable ideal of complete determinism* to *total ignorance* on the other side (Marchau et al., 2019). The contemporary literature provides frameworks that supports a nuanced understanding of uncertainty both by separating various degrees of uncertainty along the aforementioned spectrum, but also relating to other dimensions of uncertainty as well as different sources of uncertainty.

Deep uncertainty can be thought of as situations where it is difficult to assign probabilities to different events or predict outcomes due to complexity, lack of information or inherent unpredictability of a system. Deep uncertainty is thus a particular type of uncertainty that resides towards the *total ignorance* end of the uncertainty spectrum. Uncertainty that is more towards the other end of the uncertainty spectrum is sometimes denoted using contrasting terms such as *shallow uncertainty.* A definition of deep uncertainty is provided by (Lempert et al., 2003) and this is commonly referred to in subsequent literature about deep uncertainty (Agustdinata, 2008; Kwakkel & Pruyt, 2013; Maier et al., 2016; W. E. Walker et al., 2013):

> *Deep uncertainty exists when analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate models to describe the interactions among a system's variables, (2) the probability distributions to represent uncertainty about key variables and parameters in the models, and/or (3) how to value the desirability of outcomes. (Lempert et al., 2003, pp. 25–26)*

Maier et al. (2016) describe deep uncertainty as a concept used to encapsulate the notion of multiple plausible futures. They point out that in addition to deep uncertainty, other concepts describing this notion have emerged in the literature, seemingly independently of each other during the same period which may indicate that the realization of the need to deal with multiple plausible futures has been gaining ground in several different disciplines. Two examples of such concepts are Volatility, Uncertainty, Complexity and Ambiguity (*VUCA*) (Bennett & Lemoine, 2014), and *global/local uncertainty* (Mejia-Giraldo & McCalley, 2014) which are both summarized in Section 2.1.3.

2.1.3 Typologies and framework for classifying uncertainty and its dimensions

In addition to the distinctions between risk and uncertainty, and shallow and deep uncertainty, as discussed in the previous section, the literature has also outlined other aspects and dimensions of uncertainty and developed frameworks to represent it. There are various classifications and reviews of sources and types of uncertainties available, see e.g. Functowitz and Ravertz (1990), van Asselt (2000). As noted by Agustdinata (2008), a mainstream conceptualization of uncertainty has emerged in the literature on model-based decision support. The following sections summarizes some of the frameworks for describing and classifying uncertainty that have been developed based on this conceptualization.

In an effort to synthesize and integrate previous research on uncertainty in model-based policy analysis into a joint coherent typology, Walker et al. (2003) developed a framework for uncertainty classification. This framework is intended to provide the foundations for a common language that clarifies and help illuminate the various dimensions, and types, of uncertainty thereby helping to a) facilitate communication among policy analysts, b) enhance communication about uncertainty between policy analysts, policy makers and stakeholders, and, c) help policy analysts understand and appreciate the different dimensions of uncertainty, which can support identification and prioritization of uncertainties and help in the selection of appropriate treatment of a given uncertainty.
Within the framework, three dimensions of uncertainty are distinguished: 1) the location, 2) the level, and 3) the nature of uncertainty. Kwakkel, Walker and Marchau (2010) develop the Walker et al framework further, keeping the three dimensions of uncertainty but justifying several changes to the descriptions of the three dimensions of uncertainty based on subsequent research applying the initial Walker framework.

Location of uncertainty – where uncertainty is located in the system analysis framework.
Walker et al. (2003) identify five generic locations of uncertainty: *Context, Model, Inputs, Parameters, and Model outcomes*.

- Context. The context is mainly defined by the system boundaries, which are the demarcation of aspects of the real world that are included in the model from those that are not included. Context uncertainty includes uncertainty about the external economic, environmental, political, social, and technological situation that forms the context for the problem being examined (Walker et al., 2003).
- Model. Model uncertainty can be either uncertainty in the conceptual model that specifies the variables and relationships inside the system boundaries, or uncertainty in the computer implementation of the conceptual model. It addresses uncertainties related to bugs and errors in the code, or hardware errors. Petersen (2012) calls this ‘technical model implementation’; and Walker et al. (2003) call this ‘computer implementation’.
- Inputs. Input data uncertainty refers to the uncertainties associated with determining appropriate values for the inputs to the model. This data can be separated into uncontrollable (external) factors that are exogenous to the decision maker, which often are estimated based on empirical data or derived from other models, and controllable variables, which are inputs that the decision maker can influence.
- Parameters. Parameter uncertainty is connected to data and methods to calibrate the internal parameters of the model.
- Model outcomes. Uncertainty in model outcomes which is due to how other forms of uncertainties have accumulate after propagating through the model.

Kwakkel et al. (2010) integrate the frameworks of Walker et al. (2003) and Petersen (2012) and update the possible locations of uncertainty into: System boundary, Conceptual model, Computer model, Input data, Model implementation, and Processed output data.

Level of uncertainty – to what extent uncertainty is present in the system analysis framework. Walker et al. (2003) identify three levels (degrees) of uncertainty: Statistical uncertainty, Scenario uncertainty, and Recognized ignorance. These levels can be seen as different regions of the aforementioned *uncertainty spectrum* where the degree of uncertainty is smallest in the case of statistical uncertainty and largest in the case of recognized ignorance. Kwakkel et al. (2010) argue that there have been several problems with the levels of uncertainty defined in Walker et al. (2003), since there is no common understanding of what the terms statistical uncertainty, scenario uncertainty and recognized ignorance means. Therefore, the authors see the need to a redesign of the level dimension. They instead describe level of uncertainty in terms of assignment of likelihood to things or events. Their proposed four levels capture differences in the types of scales that are used in practice.

- Level 1, shallow uncertainty: probabilities can be used to specify the likelihood or plausibility of the uncertain alternatives. Ratio scale can be used.
- Level 2, medium uncertainty: alternatives can be enumerated, and rank ordered in terms of their likelihood, but how much more or less likely cannot be specified. Ordinal scale can be used.
- Level 3, deep uncertainty: alternatives can be enumerated, but for various reasons, such as decision makers or experts cannot agree or do not know, even a rank ordering is ruled out. Nominal or categorical scale can be used.
- Level 4, recognized ignorance. Alternatives cannot be enumerated, admitting the possibility of being surprised.

Nature of uncertainty – which type of uncertainty that is present in the system analysis framework.

Walker et al. (2003) delineate two different natures of uncertainty:

- Epistemic uncertainty (epistemology / lack of knowledge): Uncertainty due to the imperfection of our knowledge, which may be reduced by more research and empirical efforts.
- Variability uncertainty (ontology / inherent variability): Uncertainty due to inherent variability, which is especially applicable in human and natural systems and concerning social, economic, and technological developments.

Kwakkel et al. (2010) add a third nature of uncertainty:

- Ambiguity uncertainty: Uncertainty arising due to different actors interpreting data and results differently because of differences in frames and values.

Walker et al. (2003) propose that their framework can be presented and applied in the form of a so-called uncertainty matrix. The aim of using an uncertainty matrix is to get an overview of where, to what extent and of which type, uncertainty is present in the model-based decision support under discussion. The aim is also to inspire analysts to make an explicit effort to identify, estimate, assess, and prioritize contributions to uncertainty. Several papers have applied the Walker framework, and over the years many different changes were made to the uncertainty matrix. These modifications were counter to the purpose of the original Walker framework to provide a common framework to facilitate communication about uncertainty. Therefore, Kwakkel et al. (2010) took on the challenge to review all applications of the Walker framework and synthesize the changes into an updated uncertainty matrix. The updated uncertainty matrix is shown in the figure below. As described above, the new framework includes an extra category in the nature dimension – Ambiguity, which highlight that uncertainty can arise because differences in frames and values can make actors interpret data differently. Furthermore, the level dimension has been reworked from to the initial framework by Walker et al. (2003) so that it now includes four levels of uncertainty: shallow, medium, deep, and recognized ignorance. The location dimension is also slightly reworked. The template for the uncertainty matrix by (2010) is shown in Figure 1.

		Level				*Nature*		
Location		*Level 1: shallow uncertainty*	*Level 2: medium uncertainty*	*Level 3: deep uncertainty*	*Level 4: recognised ignorance*	*Ambiguity*	*Epistemology*	*Ontology*
System boundary								
Conceptual model								
Computer model	Model structure							
	Parameters inside the model							
	Input parameters to the model							
Input data								
Model implementation								
Processed output data								

Figure 1 Uncertainty matrix, proposed by Kwakkel et al. (2010) as a tool to facilitate classification and communication in model-based policy analysis. The intention is that analysts can use the matrix to comprehensively map analysis-specific uncertainties by listing them in the corresponding cell of the matrix.

For the policy making process there are other factors and types of uncertainty to consider in addition to uncertainty in system analysis. For policy making, uncertainty may be understood as a difference between the available knowledge and the required knowledge for making the best policy decision (Marchau et al., 2019). A framework for classifying uncertainty related to the policy analysis process (which can also be applied to decision making situations in general) is presented by Walker (2000), Walker et al (2013) and Marchau (2019), see Figure 2. The framework is based on the view that decision-making concerns the choice between alternative decisions aiming to affect the system so that its outcomes are changed in a desirable way. At the core of their framework is the system model (R) which specifies the system boundaries and the system's internal structure, that is, the system's elements and their relationships. The system is affected by two types of factors. External forces (X) are forces acting on the system that the decision makers cannot control but that may have a significant impact on the system, for instance technological or social developments. Policies (P) are the forces under control by the actors in the policy domain. Policies are intended to affect the system so that some measure(s) of the system's performance, i.e., outcomes of interest (O) change in a way that is the desirable based on the relative valuation of the goals, objectives, and preferences (W) of the decision makers and stakeholders.

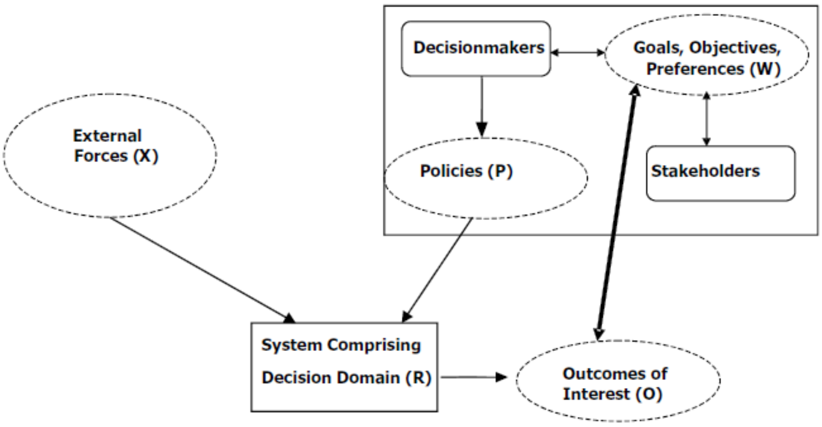


Figure 2 The framework for the policy analysis process, from Marchau et al. (2019).

Based on this framework, a few locations of uncertainty that may arise can be outlined.

- Scenario uncertainty. The development of external forces may be highly uncertain which makes it challenging to identify which potential developments will be most relevant and important for the future performance of the system.
- Structural uncertainty. It may be uncertain how the system responds to external factors (X and P). This means that even if the developments of external factors are not uncertain, structural uncertainty may be a major source of uncertainty. Complex systems may undergo structural change when affected by external factors. Furthermore, sociotechnical systems can also undergo endogenous structural change due to feedbacks, delays, emergent or self-organizing behaviors and it may be the case that the internal causal mechanisms are not fully known.
- Uncertainty in valuation of outcomes. Different stakeholders may have contesting views on the relative importance of various outcomes of interest and there may be disputes on what grounds empirical valuation should be done (e.g., social cost of carbon versus shadow price) or uncertainty from poor empirical methods or lack of data. Furthermore, over time, new stakeholders of relevance might emerge, or the perception of the importance of existing or new problems may change, meaning that the future relative valuation of outcomes is also a source of uncertainty.

Marchau et al. (2019) provide a classification scheme (Figure 3) for the level of uncertainty in each of the domains in the framework for the policy analysis.

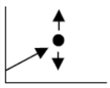
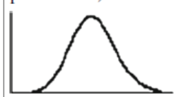
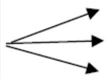
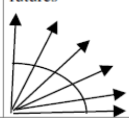
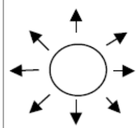
	Complete determinism	Level 1	Level 2	Level 3	Level 4 (deep uncertainty)		Total ignorance
					Level 4a	Level 4b	
Context (X)		A clear enough future 	Alternate futures (with probabilities) 	A few plausible futures 	Many plausible futures 	Unknown future 	
System model (R)		A single (deterministic) system model	A single (stochastic) system model	A few alternative system models	Many alternative system models	Unknown system model; know we don't know	
System outcomes (O)		A point estimate for each outcome	A confidence interval for each outcome	A limited range of outcomes	A wide range of outcomes	Unknown outcomes; know we don't know	
Weights (W)		A single set of weights	Several sets of weights, with a probability attached to each set	A limited range weights	A wide range of weights	Unknown weights; know we don't know	

Figure 3 Levels of uncertainty in relation to the domains in the framework for the policy analysis process from Marchau et al. (2019).

The frameworks summarized above all stem from the need to understand various aspects of uncertainty in analysis- and decision situations characterized by deep uncertainty. As mentioned in Section 2.1.2, other concepts than deep uncertainty, such as VUCA and global/local uncertainty, have emerged based on the need to manage the challenge of multiple plausible futures. VUCA has primarily been discussed and applied within the business literature and refers to management situations characterized by four distinct types of challenges, volatility, uncertainty, complexity and ambiguity (Bennett & Lemoine, 2014). Maier et al. (2016) summarize the four terms as follows. Volatility refers to a deviation from an expected mean or due to extreme unpredictable events. Uncertainty refers to the unknown range of inputs and the impact of external events. Complexity refers to issues with many interconnected variables which means that the change in one variable (e.g., due to an intervention) can result in unpredictable impacts, and possibly also changing the structure or magnitude of relations in the system. Ambiguity relates to when different stakeholders hold different beliefs about the causal structure of a system. Bennet and Lemoine (2014) describe that the difference between complexity and ambiguity mainly has to do with the nature and degree of uncertainty for a situation: complexity is a result of a system with many interconnected parts which might make it overwhelming, but not impossible, to analyze (compare with *epistemological uncertainty*); ambiguity refers to situations where causal relationships are completely unclear (compare with *ontological uncertainty*). The concept of global and local uncertainty was developed to support flexible electricity generation infrastructure planning (Mejia-Giraldo & McCalley, 2014). Global uncertainty is uncertainty about trends that can yield distinctly different future states of the world (i.e. multiplicity of futures) while local uncertainty is due to the imperfect knowledge of the exact realization for a specific plausible different future state of the world. Global uncertainties can thus be seen as uncertainties that generate context uncertainty at Level 3 and Level 4 in Figure 3 while local uncertainty yields context uncertainty at Level 2 in Figure 3. Maier et al. (2016) stress the need to combine analysis of both global and local uncertainty and therefore highlights that many problems include both deep and shallow uncertainty.

2.1.4 Inherent uncertainty in policy issues and complex sociotechnical systems

The scientific study of societal systems and the use of science to inform policy decisions is a domain where the role of uncertainty often is central. It has for a relatively long period of time been acknowledged that applying scientific methods to policy problems and analysis of complex societal systems is associated with uncertainty and inherent limitations due to the different nature of policy problems and conventional scientific problems, for instance in the natural sciences. The physicist AM Weinberg (Weinberg, 1972) argued that many policy issues related to the interactions between society and science, or technology are of a kind that they can be phrased as scientific questions, but they cannot be unambiguously answered by science. Weinberg puts it that these questions transcend science, they are “trans-scientific questions”. van Asselt (2000) outlines four types of trans-scientific questions based on Weinberg (1972), i) questions that would require impracticably expensive or lengthy, or even impossible experiments, for instance, determining the probability of extremely improbable events; ii) questions referring to human behavior since it does not allow for strict rationalization and the human creativity and adaptability is uncertain; iii) questions about the future since uncertainty always arise when extrapolating into new and unknown circumstances; and iv) questions that involve value judgements since they involve subjective moral judgements. Weinberg’s specification of trans-scientific questions illustrates that there are multiple types of uncertainties associated for policy matters on the relationships between technology and society.

Another influential notion for describing the challenges for science to deal with many policy issues is the concept of *wicked problems* which is used to denote the complex and poorly defined nature of many policy issues which means that they are fundamentally different from the well-defined problems that natural sciences typically deal with (Rittel & Webber, 1973). Wicked problems are characterized by that they lack a definitive, comprehensive, and objective problem formulation or solution, making it difficult to establish clear boundaries or parameters for the issue at hand. Therefore, it is nearly impossible to determine when a solution to a wicked problem has been found, as there are no universally accepted criteria for success. This further implies that solutions to wicked problems cannot be evaluated as true or false, but just good or bad based on subjective judgements and oftentimes, several stakeholders have valid rights to judge the solution based on their varying specific subjective perspectives.

The sheer scope and complexity of modern societal systems is highlighted as another reason to why policymakers and decision makers often face intractable uncertainties (Agustdinata, 2008; van Asselt, 2000). van Asselt (2000) classifies a problem as complex if it has the following three characteristics.

- Multi-problem. The problem is part of a tangled web of related problems rather than being a single well-isolated problem.
- Multi-dimensional. The problem is located across, or intersects several disciplines for instance by having economic, environmental, social, and political aspects.
- Multi-scale. The underlying processes interact over various scales, i.e., local, regional, national global, and at different temporal scales.

Problems of this kind are challenging for two reasons: first they tend to involve taking into consideration the perspectives of many different actors with conflicting goals and perspectives, and second the phenomena, e.g., transport, climate change or technical innovation, and their underlying processes, are not fully understood.

2.2 How can (deep) uncertainty be accounted for in model-based policy analysis?

2.2.1 The challenge of decision making under deep uncertainty

Making decisions for the future requires the anticipation of change. More specifically, it can be thought of as the challenge of making short-term decisions that may affect, or be affected by, long-term events. Lempert, Popper and Bankes (2003) introduced the concept of robust decision making as a new approach for long-term quantitative policy analysis (LTPA), or any decision making situation characterized by deep uncertainty. In this context, long-term policy making refers to when short-term policy options are affected by events that may happen 30 years or longer into the future. Lempert, Popper and Bankes (2003) claim that even though humans have for long times used various approaches for thinking about the long-term future and the consequences of their actions on it, these approaches suffer from fundamental shortcomings in dealing with deep uncertainty as outlined below.

- Narratives. Humans have used narratives about the future for many centuries and they provide powerful means for imagining how the future may look like. Narratives have been used both to explain the historical reasons for why the world is as it is, but also as a way to deal with anxiety about the future by crafting myths about future events that could help people prepare themselves before they happen. Often, narratives rely on learnings from history for motivating a prediction about the future. This could be done by drawing parallels between a specific period in history and the current or anticipated future settings[3]. Another approach is to identify grand designs, patterns or dynamics of history and then apply them as tools for a prediction about how the future will play out[4]. For LTPA, narratives can fill a function of confronting people with the long-term future by imagining how it may look like and linking it to near term societal choices. However, the obvious drawback of narratives is that they are often wrong about what will happen in the future. Narratives tend to discern the multiplicity of futures that are plausible and most often, the aim is to affect the present rather than providing a guide to the future.

- Group narratives such as Delphi, and Foresight. The Delphi method was developed by RAND in the 1950s to synthesize knowledge from experts from various knowledge areas and converge toward one or a set of paths for the future for the subject being under study. In this sense, Delphi is a method for seeking consensus among a group of diverse experts on a (set of) future scenarios. However, there is little reason for expecting these scenarios as reliable estimates of the future. Foresight is a similar method but with a focus on the deliberations when considering future developments rather than the outcome of the process, which is the focus of the Delphi method. Often, the focus is primarily on creating arenas for different stakeholders to form communication among each other and jointly envision what may lay ahead in the future. The authors stress that foresight struggle with the multiplicity of plausible futures and that foresight processes tend to lead to efforts to reduce the number of irreducible uncertainties to contain the complexity of foreseeing the future.
- Simulation modelling. Simulations models can fill an important role for LTPA since it helps systematically analyze how components in a system change over time as they interact. Typically, simulation models use a mathematical representation of processes of interactions between components in a system. The mathematical expressions can be designed by fitting them to historical data of such processes or through theoretical understandings of the system, or a combination of both. Simulation models thereby can combine historical information with assumptions about key causal relationships to study how a system may develop over time. However, the assumptions about the structure and dynamics of systems are a source of deep uncertainty and in order to provide value to LTPA, there is a need to utilize simulation models within a formal decision analysis process.
- Decision analysis. Decision analysis frameworks seeks to confront that humans' ability for reasoning about probabilities and making assessments about uncertain futures is limited and suffers from multiple forms of bias. Conventional decision theory is based on a "predict-then-act" framework. First, the decision options are outlined along with their expected outcomes expressed as the option's utility. In case of uncertainty about the consequences, the consequences are weighted by their likelihood and the option that maximizes the expected utility is chosen. In situations where the available options, their consequences and likelihood can be comprehensibly and accurately estimated, this framework is a logical consistent basis for making decisions. However, these key assumptions do not hold under conditions of deep uncertainty since it, by definition, means that it is not possible to enumerate all possible

[3] Lempert et al. (2003) gives the example of an analysis by Dewar (1998) which reasoned about the social effects of the internet by comparing it to the historical impacts of the printing press.

[4] Some of the examples on this use of history provided by Lempert et al. (2003) include Friedrich Hegel's concept of dialectics and the subsequent works by Karl Marx and Friedrich Engels outlining the dynamics of class struggle and the theory of historical materialism, Nikolai Kondratieff's ideas about long economic waves, and Herman Kahn's (Kahn et al., 1976) work with crafting a future scenario based on a combination of quantitative and qualitative arguments.

future or reliably assign a likelihood to each of them. Also, decision analysis seeks to identify one optimal choice which performs best against a given set of likelihoods, which is not necessarily a good criterion for making long-term policy decisions.

- Scenario-based planning. All the above approaches are limited by the challenge of multiplicity of futures. Scenario planning is intended to grapple with precisely that challenge. Scenarios can help understand that the future might be vastly different from the present and support decision makers to choose strategies that are beneficial for different futures. Instead of one narrative, multiple complementary but fundamentally different stories are constructed to span a wide range of futures. A small set, typically three or four, scenarios are crafted that should be plausible and logically self-consistent. These scenarios can be seen as more or less likely to occur, but no scenario should be impossible. Scenarios can help organizations to better understand risk in relation to decisions and what it takes to reach a certain objective in different futures. However, there are drawbacks also for this approach. First, crafting a small number of scenarios to span a highly complex future will ultimately be an arbitrary choice and scenario planning will by default miss many important futures. Therefore, the logic used for selecting and sorting scenario may bias conclusions drawn from them. For instance, humans tend to put more emphasis on scenarios driven by one drastic event instead of the slow compounding effects of many gradual changes even though the effects may be bigger for the latter type. Second, scenario planning offers limited support for the systematic of comparison of alternative policy choices across scenarios and the design of policies based on the scenarios.

Lempert, Popper and Bankes (2003) argue that the above mentioned approaches each have specific strengths that should be combined when developing new, better methods for LTPA. However, these methods all struggle with a similar challenge, namely the multiplicity of plausible futures. Therefore, better methods for LTPA must not only build on the strengths of these methods, but also find ways of managing the problem of the multiplicity of futures regardless of the subject matter and Robust Decision Making (RDM) can be seen as an effort to address this issue.

The need to adapt planning approaches to account for the multiplicity of futures is addressed also by Maier et al. (2016). They argue that in order to use model-based quantitative policy analysis in situations where deep uncertainty is present in the form that multiple futures are plausible, there are three main approaches that should be combined:

- Uncertainty should be described with the aid of scenarios that represent various distinct plausible futures that represent a joint trajectory rather than only as probability distributions of input parameters. Also, both global and local uncertainty should be accounted for, see Figure 4.
- System performance should be measured using metrics for insensitivity, i.e., robustness, of the performance to changes in future conditions rather than measures focused on the performance in a single forecast.
- When feasible, adaptive strategies that can be flexibly adjusted when the conditions change should be designed and implemented rather than relying on fixed strategies.

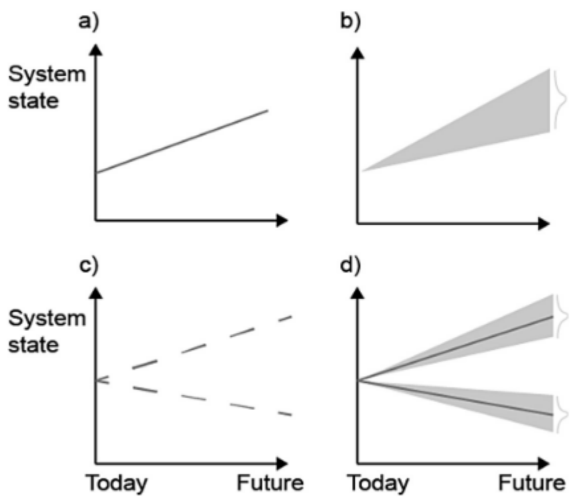


Figure 4 Different paradigms for estimating future system states. a) point prediction, b) point prediction with quantification of uncertainty, c) outlining multiple plausible futures, d) combining b and c to account for different types of uncertainty. Figure from Maier et al. (2016).

2.2.2 Introduction to Decision making under deep uncertainty (DMDU)

Decision Making Under Deep Uncertainty (DMDU) is a broad framework that aims to help decision-makers navigate complex and uncertain problems by identifying strategies that are robust and adaptive in the face of uncertainties that are difficult to quantify or predict (Marchau et al., 2019). DMDU is an alternative decision-making approach to the conventional “predict-then-act” approach, in which a single, or small set of, forecasts are used as a basis for policy design and analysis (Lempert et al., 2003). The DMDU approach is also distinct from probabilistic forecasting, which uses probability distributions to model which futures that are more likely than others to occur. In conditions of deep uncertainty, using specific probability distribution for modeling uncertain scenario or model parameters represents just another set of assumptions, but instead of parameter point-estimates as is the case for conventional forecasts, these are assumptions about the underlying probability distributions (Lempert et al., 2022). One way of describing DMDU in contrast to forecasting is that it focuses on the decision alternatives and how uncertainty affects their impacts:

> *Which assumptions would I need to believe will hold true to recommend one course of short-term actions over another? (Lempert et al., 2022, p. iv)*

DMDU is based on three key ideas: *exploratory modelling*, *adaptive planning* and *decision support* (Kwakkel & Haasnoot, 2019). Exploratory modelling is the use of computational scenario approaches to explore the consequences of various uncertainties and is used to support human reasoning and decision-making based on a comprehensive set of scenarios, allowing for the analysis of systematic regularities among subsets of the full set of experiments. The use of models is necessary because human reasoning with respect to complex uncertain systems is intrinsically insufficient, as mental models often ignore feedback, fail to account for time delays, and are insensitive to nonlinearity. If appropriate models are available, they can help decision makers to alleviate these shortcomings. Exploratory modelling uses computational experimentation to overcome the limitations of using computer models for decision support in situations characterized by deep uncertainty by analyzing how the system would behave under a large set of uncertain assumption about the system and its inputs. Adaptive planning means that plans are designed to be adaptable over time in response to how the future unfolds, with the flexibility of the plan being a key means of achieving decision robustness. Adaptive plans require exploring a wide variety of futures during the plan design, gaining insight into which actions are best suited to which futures, and monitoring signals from the unfolding future to ensure the timely implementation of appropriate actions. Unlike planned adaptation, which entails changes occurring at predetermined moments, adaptive planning involves a paradigm shift from planning in time to planning conditional on observed developments. Decision support involves stress testing candidate policy decisions over a wide range of uncertainties, characterizing the uncertainties by their effect on the decision, and enabling a constructive learning process among stakeholders and analysts. The intention is to support the decision process of multiple actors coming to an agreement through an iterative approach that facilitates learning across alternative framings of the problem, stakeholder preferences, and trade-offs (Kasprzyk et al., 2013; Singh et al., 2015).

The use of computer models is paramount for DMDU as it enables the exploration of different scenarios, evaluating policy options, and identifying robust and adaptive strategies. To understand the role of computer models in DMDU, the distinction between scientific models and policy models is an important aspect as it is typically policy models that are used for DMDU. Walker et al. (2013) describe the differences between them as follows. The purpose with scientific models is to achieve a better understanding of a clearly delimited and well-defined system. For these models, typically the model's "goodness" and validity are evaluated by its ability to closely match (measurements of) the real system. Policy models are used to provide insights to policymakers about future problem situations that can support decisions. A policy model is used to test and experiment with different policies and see how it may affect the system in different future scenarios without having to implement the policies in the real world. An important requirement for policy models is that they require rather short run-times and high flexibility so that multiple policy options can be evaluated against multiple future scenarios. When developing policy models, there is a need to balance model flexibility and run time with model completeness (including relevant mechanisms and policy components) and model credibility (level of detail and model validity). Also, policy models tend to require several different types of outcome indicators. One way to develop a policy model is to use meta-models, which is a model of a model, intended to replicate the behavior of large, complex models but with lower resolution. See Lemp et al. (2021) for an example from the transportation domain of how meta-models can be developed and applied for DMDU.

However, it is crucial to recognize the inherent limitations and potential drawbacks of using computer models for decision support in situations characterized by deep uncertainty. Lempert, Popper, and Bankes (2003) emphasize the challenge of defining the system structure in terms of the causal relationships between model variables that determines the system's behavior, a priori, in cases of presence of deep uncertainty. The World 3 model, used by Meadows and the Club of Rome (1972), is mentioned by Lempert, Popper, and Bankes (2003) as an example of a long-term simulation model that allegedly led to erroneous conclusions because of incorrect assumptions about the strength and structure of central causal relationships within the model. Lempert, Popper, and Bankes (2003) reason that agent-based models may offer a promising alternative, as they allow for emergent macroscopic behavior without a priori specification. This means that the model can endogenously simulate structural changes within a system due to interactions between agents, which the model developer might not have anticipated or considered. However, the rules governing the behavior of agents still need to be specified, and thus remain as a source of deep uncertainty. Also, agent-based models often require detailed representations of the environment the agents are interacting within.

This could in a transport context relate to the detailed road network design, signaling times etc. Lempert, Popper, and Bankes (2003) argue that for any model to be useful for decision-making under deep uncertainty, it must be employed within a formalized decision-making process that accounts for the many plausible model specifications in terms of causal relationships or the rules governing agents that deep uncertainty entails.

The literature on approaches for dealing with deep uncertainty in model-based policy analysis has developed substantially during the last decade. One important development is the emergence of DMDU as an umbrella term, and a distinct research field, combining existing and emerging DMDU approaches. This seems to have sparked research towards a broader and more general understanding of DMDU and how its various tools and approaches differ, when and how they are complementary and the appropriateness of different approaches for different types of policy problems and domains. DMDU approaches are particularly relevant to use when three conditions are met, according to (Marchau et al., 2019). The conditions for when DMDU is appropriate is illustrated in Figure 5. First, the problem should be characterized by deep uncertainty, in particular related to the external factors affecting the system. Second, there are many policy options, for instance due to that there are many policy levers that can be combined to design distinct policy options. And last, that the system complexity makes it hard for analysts to intuitively assess the impacts of policies to the outcomes of interest. When these conditions are not met, other approaches might be more appropriate. For instance, short-term policy analysis may be more effective in cases where the uncertainty is rather well characterized, and scenario planning in cases where the complexity is not too high.

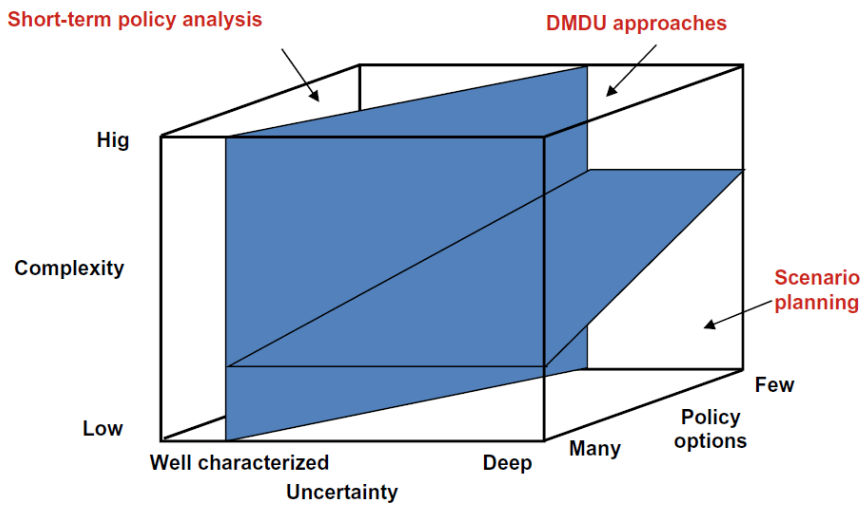


Figure 5 Figure by Marchau et al. (2019) illustrating for which situations DMDU approaches are relevant.

DMDU encompasses a variety of methods and approaches designed to address deep uncertainties in policy analysis and decision support. It is beyond the scope of this report to review and summarize all these methods. Instead, the interested reader is referred to (Kwakkel & Haasnoot, 2019) which summarizes a number of tools and approaches for supporting DMDU along with key references for each one of the following:

- Assumption-Based Planning
- Robust Decision Making (RDM)

- Many-Objective Robust Decision Making
- Dynamic Adaptive Planning
- Dynamic Adaptive Policy Pathways
- Info-Gap Decision Theory
- Engineering Options Analysis
- Decision Scaling
- Scenario Discovery
- Adaptation Tipping Points
- Many-Objective Robust Optimization

Several of these tools and approaches are complementary to each other and can be combined or integrated. Kwakkel and Haasnoot (2019) suggest to consider the nature of the problem at hand and choosing an appropriate combination of DMDU tools that fits the problem rather than choosing between distinct approaches (e.g. RDM vs DAP).
To better understand similarities and differences between the previously proposed DMDU tools and approaches, Kwakkel and Haasnoot (2019), proposes a taxonomy that covers five components of DMDU upon which the various DMDU approaches are mapped, see Table 1 for an overview of the components in the taxonomy.

Table 2 Taxonomy of components of approaches for DMDU used by Kwakkel and Haasnoot (2019).

Component	Examples of approach
Generation of policy alternatives	• Protective adaptivity: protect basic plan against contingencies • Dynamic adaptivity: sequencing alternatives conditional on observed future
Generation of scenarios	• Exploration: global or local sampling • Search: optimization • Pre-specified: expert opinion, standardized
Robustness metrics	• Regret: comparing alternatives • Satisficing: individual alternatives
Vulnerability analysis techniques	• Subspace partitioning: Scenario discovery • Sensitivity analysis: ranking of factors

There are several published case studies applying and discussing DMDU methods for various types of problems and domains in the scientific literature. A review of DMDU case studies published up until February 2020 by Stanton and Roelich (2021) identified 36 published studies. Most of these case studies dealt with water-related policy problems such as flood management and water supply issues, and six studies concerned transport problems. Their review showed that 80% of all case studies were prospective, meaning that they demonstrate how a DMDU method could be applied, while only 20% were cases that had been implemented or commissioned directly by policy makers. According to Stanton and Roelich (2021), this high share of prospective studies suggests that the DMDU literature so far has largely focused on developing better DMDU tools, with less focus on practical implementation. In addition, Stanton and Roelich (2021) propose that DMDU studies have so far not fully taken into account the decision making context on the institutional, organization and individual level. They further claim that many case studies do not clearly and explicitly argue why the specific

DMDU approach was more suitable to apply than a more conventional policy analysis method. There have been efforts to map when to apply DMDU-related methods, and in particular RDM, depending on the type of policy problem and decision context within the area of climate adaptation. Dittrich et al. (2016) review RDM, real options analysis, portfolio analysis, no/low regret options and measures for reduced decision-making time horizons. They conclude that deep uncertainty indeed creates a need for more robust planning methods, but also that they come with methodological challenges, for instance mapping out the scenario space, and may also be complex and require different know-how and data than conventional appraisal methods. RDM specifically is presented as a resource intensive method which is best suited to apply for large projects, where there is deep uncertainty and little flexibility in altering the decision once taken.

Finally, it is noted that the concept of applying DMDU to support policy analysis has clear conceptual links to the area of future studies which have similar, and partly overlapping, frameworks and tools for dealing with different levels of uncertainty for generating insight into future developments (Van Dorsser et al., 2020).

2.2.3 Exploratory Modelling and Analysis (EMA) and Robust decision making RDM

This section outlines two DMDU approaches that are in focus for the MUST project, namely Robust Decision Making (RDM) and Exploratory Modelling and Analysis (EMA). RDM and EMA are complementary approaches that fall under the umbrella of DMDU[5]. Both EMA and RDM share the common goal of helping decision-makers understand the potential consequences of different policy interventions under deep uncertainty and support the identification of robust and adaptive strategies.

RDM focuses on identifying decision strategies that perform well across a wide range of future conditions and are robust to uncertainty. It is an iterative, simulation-based approach that involves exploring the space of future uncertainties, evaluating the performance of decision options under different scenarios, and identifying robust strategies that meet specific performance criteria or objectives. This approach requires confronting a commonly held perspective, namely that predictions are necessary precursors to effective action (Lempert et al., 2003, p. 19). Or as put by Lempert et al. (2013), RDM is intended as a method to make *good decisions without predictions*. Typically, it involves the following four steps, which are intended to be performed in an iterative manner together with stakeholders and policy makers (Eker & Kwakkel, 2018; Kasprzyk et al., 2013).

1. Problem formulation. Typically the policy problem is formulated with the help of the XLMR framework (see Figure 6).
2. Generation of policy alternatives. In this step, a set of candidate policies, i.e. combinations of policy levers, are specified. The generation of policy alternatives can be done prior to the analysis, i.e. that there are pre-developed policies which robustness will be analyzed with RDM. Alternatively, policy alternatives can be generated within the RDM process by using optimizations to derive Pareto-optimal candidate policies based on the available policy levers. This optimization-based approach is further explained in the sub-section “Directed search” below.

[5] Note that EMA is not listed as a distinct DMDU approach or tool by Kwakkel and Hassnoot (2019). However, EMA can be understood as the use of various techniques for analysing uncertain systems which is a fundamental underlying approach within robust decision making and a number of other DMDU approaches.

3. Uncertainty analysis. The candidate policies' performance is evaluated over a large set of plausible scenarios. These scenarios are typically generated by systematic sampling of the uncertainty space spanned by the ranges of the X parameters. With use of a simulation model of the system, a model run is performed for each of the policy alternative in each of the scenarios. The robustness of candidate polices are evaluated using a robustness metrics (Kwakkel et al., 2016) and a small set of the candidate solutions with high robustness are chosen.
4. Scenario discovery. Although the policies selected in the previous step are robust according to the specified robustness metrics, there may still be certain types of scenarios where the policy fails to generate a desired outcome. The vulnerability analysis is used to identify scenario conditions under which the policy fails to meet a pre-specified performance criterion. Scenario discovery uses cluster analysis on the database of model runs generated in the previous step to identify certain combination of inputs in which the policy fails to meet the performance criterion. Often, the vulnerability analysis is done with the use of scenario discovery, for instance using the patient rule induction method (PRIM) (Bryant & Lempert, 2010; Friedman & Fisher, 1999). PRIM identifies hyper-rectangular subspaces of the input data.

Steps 3 and 4 of RDM, and step 2 in case optimization is used, requires the use of various forms of data analysis, modeling, or algorithms. There are different methods and tools that can be used for each of the step and choosing which one to use, and how to best apply them, requires careful considerations based on the specific nature of the policy problem, data and model (Kwakkel & Haasnoot, 2019). For instance, the uncertainty analysis requires carefully selecting what sampling strategy to use based on the analysts understanding of the various parameter uncertainties, and with regards to the computational complexity of the model. Also, robustness metrics must be carefully chosen (McPhail et al., 2018). Similarly, when applying these different tools and algorithms there is a need to carefully consider how to apply them to the specific problem and whether any modifications are required. For instance, when applying PRIM for step 4, preprocessing of the experiment database using orthogonal rotations (for instance using principal component analysis) might be required to more effectively identify vulnerabilities with PRIM's hyper-rectangular input subspaces (Dalal et al., 2013). There are also various extensions of PRIM, for instance to better manage heterogenous input parameters and multinomial outputs (instead of binary, as in the case of a Boolean indicating whether a performance target is met or not) (Kwakkel & Jaxa-Rozen, 2016). Applying optimization for step 2 also involves a number of sensitive choices related to specifying the optimization problem, choosing what type of optimization approach and specific algorithm or solver to use, and often also selection of so called hyperparameters, i.e. the parameters that govern the behavior of heuristic optimization algorithms (Kasprzyk et al., 2013).

The intended outcome of the RDM process is the identification of policy alternatives with high robustness and a clear understanding of the vulnerabilities of these robust policy alternatives. Also, it has been proposed that when RDM is performed iteratively along with relevant stakeholders, it can serve as a learning process that helps: refine the understanding of the policy problem and system under study; generate new and better performing policy alternatives; create a better understanding of various tradeoffs involved (Kasprzyk et al., 2013).

EMA is, compared to RDM, a more general approach that involves creating, exploring, and analyzing a large number of alternative policies, models or scenarios to understand the impact of uncertainties on system behavior and decision outcomes (Kwakkel & Pruyt, 2013). EMA utilizes several methods

and techniques, such as sampling techniques, sensitivity analysis, uncertainty analysis, scenario discovery, and (multi-objective) optimization, which can be applied to various types of system analysis and decision problems. The concept of exploratory modelling was proposed by Bankes (1993) who distinguished exploratory modelling from predictive (or consolidating) modelling. The goal of predictive modelling is to produce an accurate prediction of the system's behavior for a given set of inputs by incorporating known facts into a single unifying model of the system. In contrast, EMA is used to generate one or a set of plausible models that are consistent with available data and knowledge, scenarios, and policy options for the system of interest. The space spanned by scenarios, and policies is then searched through or evaluated using optimization algorithms and sampling techniques and inferences are made about how scenarios, policies and model formulation affect the outcomes of interest. In EMA, a single instance drawn from the set is not a prediction but rather a what-if experiment that reveals how the real-world system would behave if the specific assumptions about the various uncertainties encapsulated in the specific model and scenarios were correct.
EMA problems are often structured using the so called XLRM framework (Kwakkel, 2017), see Figure 6.

- X: external factors are uncertain factors that are uncontrollable for the considered actor. A specific parameter set of external factors constitute a *scenario*
- L: policy levers are the decision variables the considered actor has available to influence the system. A specific parameter set of policy levers constitute a *policy.*
- R: relationships in the system which collectively constitute a model of the system.
- M: performance metrics are the outcomes of interest for the system, i.e., the model outputs of interest.

A unique combination of a scenario and policy comprises an *experiment*.

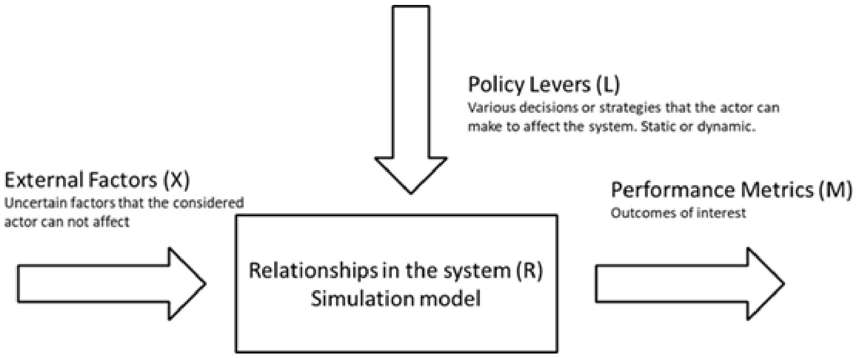


Figure 6 The XLMR framework (Lempert et al., 2003), figure based on Kwakkel (2017).

Within this framework, EMA can be understood as an approach for analyzing how regions of the uncertainty space spanned by X and R, and/or the decision space spanned by L map to the outcome space, spanned by M. In some cases, it is also of interest to study uncertain parameters within the system model (R). Then, the analysis includes an additional parameter set for the uncertain model parameters. Also, in cases when it is not clear what type of model is appropriate for representing the system, the analysis can be performed over an ensemble of models (a set of R's). Then, the same experiments are conducted for each of the model in the model ensemble.

In EMA, a distinction can be made between two types of applications: *open exploration* and *directed search*. Open exploration is when the uncertainty space, and/or the decision space is systematically sampled. Directed search is when the uncertainty space or decision space is searched using optimization techniques. These approaches are often complementary when performing policy analysis with DMDU. For instance, directed search might be used to identify promising candidate strategies and open exploration can be used to test how these strategies perform over a large set of scenarios. The two approaches, along with examples of specific tools and analysis methods for each of these are summarized in the subsequent sections.

Open exploration

Open exploration can be used for various purposes, some examples are:

- Span the outcome space. For uncertain systems, it is often useful to understand what ranges of outcomes are plausible given the plausible combinations of uncertain inputs, and policy options at hand. By sampling the model over the uncertainty space, for instance using Monte-Carlo or Latin hypercube sampling, and if relevant also over the decision space, the range of plausible outcomes can be estimated.
- Comparing candidate policies. In cases where there are pre-specified policies that needs to be evaluated, open exploration can be used to analyze how these policies perform over a large set of scenarios spanning an uncertain future.
- Sensitivity and uncertainty analysis. Open exploration can be used to understand the influence of the various uncertainties in the system. There are several techniques for doing this, for instance various types of feature scoring. Also, global sensitivity analysis can be performed, for instance through more advanced sampling methods, such as Sobol sampling which allows the influence of both direct- and interaction effects to be quantified (Pianosi et al., 2016).
- Vulnerability analysis. It is important to know under what circumstances a policy fails (or succeeds) in meeting its intended outcomes. This means to identify regions of the input space that are highly predictive of leading to the policy targets not being met (or the opposite, depending on how the analysis is set up. Methods for such analysis are called scenario discovery (Bryant & Lempert, 2010).
- Identifying policy-relevant scenarios. There is sometimes a need to use a smaller set of scenarios for communication purposes, for more in-depth analysis or when practical constraints in the policy analysis process limits the number of scenarios. Carlsen et al. (2016) propose a method to choose a small set of policy-relevant scenarios by combining a vulnerability-based approach with a diversity-based approach, i.e., scenarios that are highly predictive of a policy to fail and that are different to each other in terms of their inputs and/or outputs and therefore spans a large portion of the input and/or output space. Eker and Kwakkel (2018) propose a similar method and shows how it can be incorporated into the many objective robust decision making context

Directed search

Directed search is the use of mathematical optimization to search the decision space or the uncertainty space to identify sets of policies or scenarios. When the uncertainty space is searched, a typical application is to identify the scenario with worst-case (or best-case) performance of a given policy (Halim et al., 2016).

However, more commonly, directed search is applied to search the decision space to identify policies that perform well given a certain set of criteria and constraints. This use of directed search is applied in RDM when policy alternatives are identified by the help of optimization. Often, there are multiple criteria that are not combined into a joint objective function. This may for instance be due to uncertainty in valuation of outcomes (see 2.1.3). A mathematical formulation of an optimization problem with multiple objectives is outlined below, based on the formulation and notation provided in Kasprzyk et al. (2013).

$$\text{minimize } F(l) = \left(f_1, f_2, \dots f_p\right), \forall l \in \mathrm{L} \ (1)$$

Subject to:

$$c_i(l) = 0 \ \forall i \in [1, \mathrm{q}] \ (2)$$

$$d_j(l) \leq 0 \ \forall j \in [1, \mathrm{r}] \ (3)$$

The problem is to minimize the vector $F(l)$, where l is a vector of levers (i.e., decision variables) in the decision space, L (Equation 1). The levers can be represented as real-valued, integer or categorical variables. There could also be q equality constraints c_i (equation 2) and r inequality constraints d_j (equation 3). For a solution to be feasible, these constraints need to be met. By solving the optimization problem, the set of non-dominated solutions is identified. A non-dominated solution is a solution that cannot be outperformed by any other solution across all objectives, representing a balanced trade-off among these objectives. This concept is closely related to the concept of Pareto optimality. In a Pareto-optimal set, each solution represents a unique trade-off among the objectives, and no solution in the set can be improved upon without making at least one objective worse. The collection of non-dominated solutions forms the Pareto front, which represents the optimal trade-offs between the objectives. For a mathematically precise definition of non-dominated solutions, see Kasprzyk et al. (2013) or, for a broader background, Coello, Lamont, and Van Veldhuisen (2007).

Due to the complex search space and non-linearity of the problems and systems typically being studied using EMA, the approach for solving the multi-objective optimization[6] problem typically relies on multi-objective evolutionary algorithms (MOEA) (Eker & Kwakkel, 2018; Kasprzyk et al., 2013). A formal mathematical description of such algorithms is not provided in this report, but is for the interested reader available in Coello, Lamont, and Van Veldhuisen (2007). In short, such algorithms typically consist of the following steps.

1. Initialization: A population of candidate solutions, i.e., a feasible point in the search space, is randomly generated.
2. Evaluation: The fitness of each candidate solution is evaluated by calculating the values for each objective function and determining the dominance relationships among the solutions.
3. Selection: A subset of the solution population is chosen to create offspring for the next generation. Selection is typically based on the fitness of the solutions.
4. Variation: Offspring solutions are generated through so-called genetic operators, for instance by crossover (recombination) and mutation. The purpose of this step is to explore the search space and maintain diversity in the population.
5. Replacement: The offspring solutions are added to the population, and some of the existing solutions may be removed to maintain a fixed population size. The process of selecting which solutions to remove can be based on fitness, diversity, or a combination of

[6] Sometimes, the term many-objective optimization is used. To the understanding of the authors of this report, in the context of EMA many-objective optimization can be understood as an extension of multi-objective optimization for problems with more than a few objectives. For simplicty, the term multi-objective is used throughout this report although some of the references refer to many-objective.

both. Maintaining diversity along the Pareto front is crucial to ensure a good representation of the trade-offs among the objectives.

6. Termination: The algorithm iterates through steps 2-5 for a predefined number of generations or until a stopping criterion is met, such as reaching a certain level of convergence according to some specified convergence metric.

Many Objective Robust Decision Making (MORDM) and other RDM variants

A common use of directed search is within various forms of RDM applications (Kwakkel & Haasnoot, 2019). In its original conception, *RDM*, focused on evaluating the robustness and vulnerabilities of pre-generated policy alternatives (Lempert et al., 2003). Since then, multiple approaches for using directed search to generate policy alternatives within the RDM framework have been developed. Figure 7 provides an overview of these approaches with a focus on how the steps of Generating policy alternatives and Robustness analysis are performed. Kasprzyk et al. (2013) introduced Many Objective Robust Decision Making (*MORDM*) in which instead of using pre-specified policies, MOEA is used to generate a set of Pareto-optimal policies based on a reference scenario. These policies are then used as candidate solutions which then are subjected to robustness, uncertainty, and vulnerability analyses in the same way as conventional RDM. The intention with using MOEA for the generation of policy alternatives is to alleviate some of the challenges and potential biases that decision makers face in situations where there are many possible policy alternatives, multiple objects to consider simultaneously, and deep uncertainty about the future (Kasprzyk et al., 2013; Singh et al., 2015). However, a clear limitation of this specific approach is that the identified policy alternatives are scenario dependent as they are generated for a single reference scenario. Therefore, these policies are such that the perform Pareto-optimal in the reference scenario and the subsequent robustness and vulnerability analysis helps identify policies from this set that perform well over a large number of plausible scenarios relative to other identified alternatives. Naturally, this may limit the potential for identifying robust policies since deep uncertainty is disregarded when generating the policy alternatives (Eker & Kwakkel, 2018). To face this challenge, approaches where multiple scenarios are used during the generation of alternatives have been developed. These approaches are denoted as *Multi-scenario MORDM* in Figure 7.

Watson and Kasprzyk (2017) perform policy optimization on multiple scenarios that are identified through scenario discovery during the vulnerability analysis of the candidate policies identified for the reference scenario. This showed that the policy performance is highly dependent on what scenario are used to identify them using MOEA. Eker and Kwakkel (2018) proposed another method for selecting what scenarios to use for generating policy alternatives in multi-scenario MORDM. The idea is to select scenarios that are policy relevant and diverse. Policy relevance is defined as a problem-specific concept that relate to the decision makers concerns but is typically scenarios with poor performance of the outcome metrics. Diversity means that the set of scenarios are different in terms of their location in the uncertainty or outcome space. More specifically, the diversity metric proposed by Carlsen et al. (2016) is used where diversity is defined as a weighted sum of the minimum and mean pairwise average Manhattan distances for the scenarios in the scenario set. The scenario selection is done by first generating many scenarios using random sampling, then filter out a sub-set of these with policy relevance, and then for this filtered set select the set of *n* scenarios with maximum diversity (*n* is set by the analyst). Compared to conventional MORDM where the generation of policy alternatives is only done using a reference scenario, the approach by Eker and Kwakkel (2018) generate more decision options and more robust policies.

A variant of directed search is *multi-objective robust search (MORO)* (Hamarat et al. 2014; Kwakkel, Haasnoot, and Walker 2015). In MORO, a MOEA is run with an objective function comprised of a robustness metric for each of the objectives. This objective function is then evaluated over a large set of scenarios. MORO therefore ensures Pareto-optimal robustness in the solutions. This means that policies will not be designed to perform “optimally” in any given reference scenario, but instead yield a good performance over several scenarios according to the specified robustness metric. However, MORO is computationally expensive since for each step in the optimization, a large number of scenarios are evaluated. Also, the selection of robustness metrics can have a large impact on the obtained results and it may require extensive work to set appropriate metrics (Eker & Kwakkel, 2018; Kwakkel et al., 2016; Shavazipour et al., 2021). A study by Bartholomew and Kwakkel (2020) compared MORDM, multi-scenario MORDM and MORO applied to the lake problem (Carpenter et al., 1999), which is a common benchmark problem in the policy analysis literature . Focus is on how the three methods different extent of robustness consideration in the policy search phase affects the robustness of solutions, and computational cost. The analysis is made for three types of policy formulations: inter-temporal (static) policies, a direct adaptive policy search (closed loop) approach in which the policy lever values are updated every time step, and a planned adaptive approach, which is a variant of the direct policy search, but with policy levers updated only every *t* time step (*t*=5 is used in the study). The comparison concludes that the more adaptive policies demonstrate better robustness, regardless of what policy search method was used. MORO produces the most robust solutions for all three policy formulations. This result is unsurprising since MORO does to the largest extent consider robustness in the search phase. However, the computational cost for MORO is substantially higher, and when examining specific scenarios, MORO generated policies often perform worse than policies generated with MORDM methods (this effect is often denoted “the price of robustness”). The authors argue that in general, multi-scenario MORDM is a good pragmatic choice of method: it requires a minor increase in computation cost compared to MORDM, and MORO only offers a clear advantage when searching for static policies with a high focus on robustness.

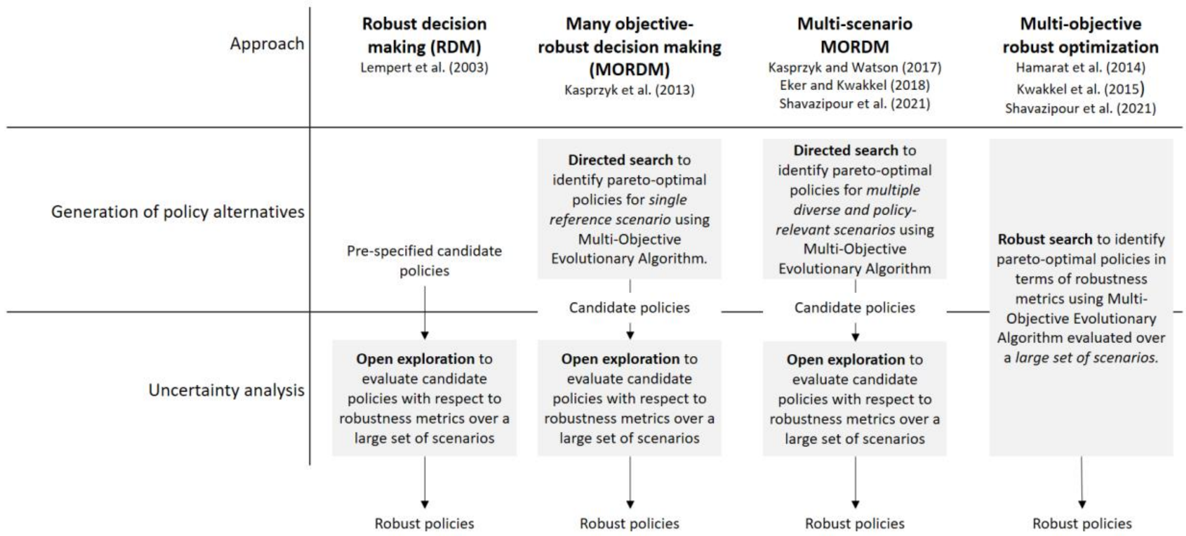


Figure 7 Overview of the Robust Decision-Making approach, and comparison to subsequent further developments thereof, with a focus on the steps Generation of policy alternatives, and Uncertainty analysis.

As previously noted, a key challenge for both MORDM-approaches and multi-objective robust search is how to specify relevant robustness metrics that measures the policy-relevant robustness features of the policies. Kwakkel, Eker and Pruyt (2016) discuss different types of robustness metrics within the framework of robust multi-objective optimization. Typically, robustness is understood as one of two views when it is operationalized within an optimization framework: (i) robustness is low uncertainty in the consequences of a policy, i.e., a robust policy has a small bandwidth of its consequences over all analyzed scenarios, or (ii) robustness in the form of minimization of undesirable outcomes, i.e., a robust policy will lead to desirable outcomes in a large share of scenarios. Furthermore, three types of metrics are distinguished.

- Regret-based metrics. These compare the outcome of a strategy option to some performance measure for the same scenario. For instance, comparing the strategy option to the best performing strategy option for each scenario and then seek to minimize the maximum regret across all scenarios.
- Satisficing metrics. These seek to maximize the number of scenarios that meet a pre-determined minimum-performance threshold. This is similar to robustness in the framework of info-gap decision theory. However, the introduction of a pre-determined performance criteria introduces a new source of uncertainty since the proper selection of the criteria might be uncertain or disputed.
- Statistical or density-based metrics. These asses the distributional characteristics of outcomes. Robustness is then characterized by either a “high-peaked” distribution (small bandwidth of policy consequences), or a more skewed distribution towards the region of desirable outcomes (desirable outcomes in a large share of scenarios).

Through a case study of the European energy system, Kwakkel, Eker and Pruyt (2016) showcase that different selections of robustness metrics will highlight various aspects of robustness. They therefore stress the importance of carefully selecting robustness metrics to the policy problem at hand, and that it is typically a good idea to use multiple complementing robustness metrics. An additional in-depth review of robustness metrics was performed by McPhail et al. (2018) which covers metrics for a broader set of applications. They categorize metrics using two dimensions: 1) whether the robustness calculation is based on relative or absolute values of system performance, and 2) whether the indication of system performance focuses on satisfactory performance or actual system performance. This results in four types of metrics:

- Metrics based on absolute system performance values measuring absolute system performance. These metrics directly measure the performance of the system without comparing it to other options or thresholds.
- Metrics based on relative system performance values measuring absolute system performance. These metrics compares the performance with other decision options or reference points, such as minimax regret, which compares the performance of different options in the same scenario.
- Metrics based on absolute system performance values measuring whether the system performance is satisfactory or not. These metrics determine if the system performance meets a predefined satisfactory level or threshold.
- Metrics based on relative system performance values measuring whether the system performance is satisfactory or not. These metrics compare the performance against a satisfactory level or threshold in a relative manner, considering how different options perform against the threshold for satisfactory performance.

2.3 How, and to what extent, have (deep) uncertainty been accounted for in transport planning?

2.3.1 Accounting for uncertainty in transport planning processes

Walker et al. (2013) conduct a literature review of general long-term planning approaches that acknowledge that plans need to be robust and adaptive to deal with an uncertain future. The authors stress that a sustainable plan should not only meet social, economic, and environmental goals, it should also be robust (perform good-enough for many different futures) and adaptive (able to cope with changing futures). In the review, Walker et al. describe five robust/adaptive planning approaches: assumption-based planning, robust decision making, adaptive policymaking, adaptation tipping points and adaptation pathways, and dynamic adaptive policy pathways. These approaches are assisted by several computational support tools for the design of robust/adaptive plans: fast and simple policy models, exploratory modelling and analysis methods, scenario discovery methods, robust optimization methods, and information gap methods.

Lyons, Cragg and Neil (2018) describe the process that started at Transport Scotland with accounting for uncertainty in national transport planning. The authors stress that handling uncertainty in transport planning is a wicked problem, i.e., a problem which does not have a single simple solution. Often when trying to solve a wicked problem, new problems arise because of complex interdependencies. A scenario planning method was used to develop plausible alternative future scenarios, instead of the traditional method to produce one most probable scenario. This method includes conducting workshops to decide upon key drivers that are most uncertain and most important to identify critical uncertainties. The eight key drivers identified were:

- Population,
- GDP / (disposable) income,
- energy supply capacity relative to demand,
- demand for personal travel,
- share of knowledge work within the economy,
- capabilities and affordability of digital technologies,
- change in share of manually controlled motor vehicles, and
- popularity of walking and cycling.

Lyons and Marsden (2021) discuss the concepts of opening out and closing down on uncertainty in transport planning. By opening out the authors mean embracing the uncertainty that is present. This can be done for example by a scenario planning approach where more scenarios are developed compared to the traditional approach with one most probable scenario. An example of application of such a scenario planning approach for the Baltimore-Washington DC region can be found in Knaap et al. (2020). Lyons and Marsden (2021) conclude that a lesson learnt from the experience with opening out is that communication to decision makers can be difficult due to an excess amount of information. By closing down on uncertainty, the authors mean the process of reducing complexity so that policy actions can be identified and communicated to decision-makers.

A Swedish study with the aim to broaden the future scenarios evaluated in municipal planning for commercial development and involve decision-makers in a participatory manner is Larsson et al. (2018). The authors developed a multicriteria decision analysis tool, with which several policy alternatives could be compared, and rank ordered. All involved stakeholders evaluate the same policy alternatives, but each stakeholder has their own set of criteria. For each criterion, the stakeholder needs to rank-order the policy alternatives in relation to the criterion. Furthermore, the stakeholder also needs to rank-order the criteria. It is acknowledged that these rank-orderings are uncertain and therefore an embedded sensitivity analysis is included in the tool. One of the main findings, when the tool was applied in case studies, was that it enabled the stakeholders to get more insight into and understanding of conflicting objectives. Thus, the nature of uncertainty mainly addressed in this work is ambiguity, i.e., uncertainty arising due to stakeholders interpreting data and results differently because of differences in frames and values.

During recent years, there has been an emerging interest of applying EMA and DMDU to transportation modeling to support transport planning and policy analysis. One example is the work on EMA and DMDU within the U.S. Federal Highway Administration's program TMIP (Transport Model Improvement Program). Within TMIP, various initiatives have been performed to develop tools for applying EMA and DMDU to transport planning (see Section 2.3.3) (Lemp et al., 2021), analyze how EMA and DMDU can bring value to transport planning, and assessments of the practical and organizational factors related to an introduction of EMA and DMDU (Lempert et al., 2022). A TMIP report by Lempert et al. (2022) suggest that DMDU approaches would "…turn traditional, predict-then-act analyses on its head" (Lempert et al., 2022, p. iii) in the sense that it would change the starting point of the process from generating the forecast, to the proposed long-term infrastructure and policy plan. This plan would then be evaluated against a large number of scenarios to illuminate the plans' strengths and weaknesses over varying scenario conditions. These results would then be used to guide improvements of the plan for making it more flexible or robust to these conditions. The same report stress that while the planning approach would differ, DMDU can often rely on existing transport models and other scenario and forecasting tools. Through interviews with planners and modelers at various U.S. transport planning agencies, Lempert et al. (2022) identifies several motivations, benefits and barriers to DMDU implementation and provide recommendations for how to support early-stage adoption of DMDU.

2.3.2 Uncertainty in relation to transport forecasting models and project appraisal

Uncertainty in traffic forecasts

de Jong et al. (2007) review attempts to quantify uncertainty in traffic forecasts. They divide these attempts into those who consider the effect of *uncertain input* on forecast output uncertainty and those who consider the effect of *model uncertainty* on forecast output uncertainty (some papers consider both types). They find two methods to investigate uncertain input data in the literature:

- Forming of several scenarios which try to sketch consistent futures. Advantage: the researchers try to take correlation between input variables into account, e.g., high income growth is correlated with high car ownership values. Disadvantage: There is no measure of the likelihood of the different scenarios under study, which makes it impossible to calculate uncertainty bands for outcome variables.

- Applying statistical distributions for each input variable that is considered uncertain and then making several runs with random draws from these distributions, i.e., a form of Monte Carlo simulation. Advantage: Uncertainty in outcome can be quantified from the variance in outcome when running the same model with different inputs drawn from the predefined distributions. Disadvantage: Correlation between input variables is seldom considered, rather random draws are typically made from independent distributions. However, correlation can be considered by making draws from multivariate distributions.

Regarding model uncertainty, the three main methods to quantify uncertainty are:

- Jack-knife/Bootstrap method to correct for model specification errors.

- Analytic calculation of the output standard error as a function of model parameter standard errors. Advantage: Exact calculation of output standard error due to estimation errors. Disadvantage: Requires a rather simple model.

- Forming of parameter distributions from parameter standard errors and drawing from these distributions to make several model simulations with different parameter values. This is similar to the Monte Carlo simulation of input uncertainty. Advantage: Can handle complex models. Disadvantage: Requires multivariate parameter distributions to take correlations into account.

The reviewed studies find a larger variance in link flows/area-wide demand due to input uncertainty (95% confidence intervals for demand between 18-33% around the mean) than due to model uncertainty (95% confidence intervals for demand between 5-14% around the mean). Also, in the application the authors conduct in the same paper using the national transport model for the Netherlands, effects of input uncertainty are found to be larger than effects of model uncertainty.

Input data uncertainty is found to have a large effect on forecast accuracy also in Andersson et al. (2017), who compare eight Swedish national reference forecasts between 1975 and 2009 to actual outcome statistics of vehicle kilometers travelled (VKT). From 1990 and onwards all reference forecasts overestimate car VKT when compared to actual outcomes. The overestimation is in the order of magnitude of 5-20%. The authors investigate both the differences between cross-sectional and time-series elasticities and the effect of uncertain input data. They find that cross-sectional and time-series elasticities are remarkably similar, whereas incorrect input data lead to significant deviations between the forecast and actual outcome. The input variables which were the largest sources of errors were fuel prices, car ownership and GDP (after 2005). Especially future fuel prices were largely underestimated. The authors conclude that input values will always be difficult to predict (deep uncertainty) and therefore sensitivity analysis is very important. For some of the reference forecasts between 1975 and 2009 sensitivity analyses were in fact conducted at the time of prediction (when actual outcome statistics were not available). However, these sensitivity analyses did not result in an outcome as low as the actual vehicle kilometers travelled for car traffic, which calls for testing larger intervals of input parameters, such as fuel prices, in sensitivity analyses.

A corresponding study was also conducted concerning freight transport forecasts between 1975 and 2009 (Vierth et al., 2016). Vierth et al. find that truck and sea transport forecasts have on average been close to actual outcomes, whereas rail transport forecasts have systematically been overestimated. The freight reference forecasts are developed in two steps: first demand for freight transport between different zones are calculated, second the demand is allocated on different modes using a cost-minimizing model. The first step of the process is not transparent but there have been indications of too high levels of overall freight transport demand. Vierth et al. therefore stress the need for sensitivity analyses regarding the growth of freight transport demand.

Cruz and Sarmento (2020) review literature concerning inaccuracy in traffic forecasts and calculate a deviation of actual traffic flow and forecast traffic flow for the reviewed studies. The average deviation, when allowing for compensation of over- and under-estimation, is and overestimation (forecast flows higher than actual flows) of 9.3% for road projects and 23.6% for rail projects. Cruz and Sarmento (2020) find seven main causes of inaccuracy in traffic forecasts, which they rank-order according to how common they are as explanators in the reviewed literature: 1) opportunistic behavior and optimism bias, 2) inadequacy in forecast models and data, 3) overall uncertainty (such as unexpected events and a constantly changing reality), 4) changes in demographics and land use patterns, 5) quality or construction delays, 6) competition and demand, and 7) economic cycle. The authors divide their conclusions into those that confirm insights from previous literature and those that are new insights. The confirmed conclusions are:

- Errors in traffic forecasts are not normally distributed, rather there is a bias towards over-optimistic forecasts.
- Accuracy of traffic forecasts has not increased over time even though forecasting models have been developed and are today much more complex.

The new conclusions are:

- Forecasts for rail projects are in general more optimistic compared to road projects.
- Inaccuracy of traffic forecasts tend to decrease over time since there often is a ramp-up effect, meaning that traffic on the new road/railway increases year by year during the first years of operation and thus reduces the gap towards the over-estimation in the forecast.

Cruz and Sarmento (2020) state that the main driving force behind the optimism bias is political bias, in the sense that planners often conduct CBAs of projects that politicians have already publicly committed to. Eliasson and Fosgerau (2013) show however that optimism bias need not be deliberate and deceptive – a bias is introduced already by selecting projects with low costs and high demand into a shortlist of projects to be evaluated using CBA, see also discussion below in the section “Uncertainty and cost-benefit analyses”.

Hoque et al. (2021) apply a data-driven method to quantify forecast uncertainty from the accuracy of previously conducted forecasts for road projects. In line with Cruz and Sarmento (2020), they find that overestimation of traffic on a road is more common in forecasts compared to underestimation. Considering all road projects, the median for actual traffic when the road is opened is 6% lower than the forecast. Several characteristics of the road projects have a significant effect on how much the forecast deviates from actual traffic counts: type of road (forecasts for arterials and local roads deviate more from actual traffic compared to freeways), type of project (forecasts for new roads deviate less from actual traffic compared to improvements on an existing road[7]), and forecast method (forecasts where transport models are used deviate less from actual traffic compared to

[7] The authors acknowledge that this result is counter-intuitive and call for more research on the topic. They suggest one possible explanation which is that forecasters are aware of the difficulty of predicting traffic on a new road and therefore treat the assignment with care.

trendlines/professional judgement). The authors end with three main recommendations for practitioners: 1) Present the results of a forecast as a range of expected outcomes, 2) Investigate the low and high ends of the range to see if these extreme values of traffic will change the overall investment decision, and 3) Measure traffic of new projects during their first year of operation and compare this to forecast values in order to monitor the accuracy of the forecast and to use these local measurements for estimation of uncertainty of future forecasts. Furthermore, the paper also includes a discussion about the relation between accuracy and uncertainty, which is summarized in Figure 8.

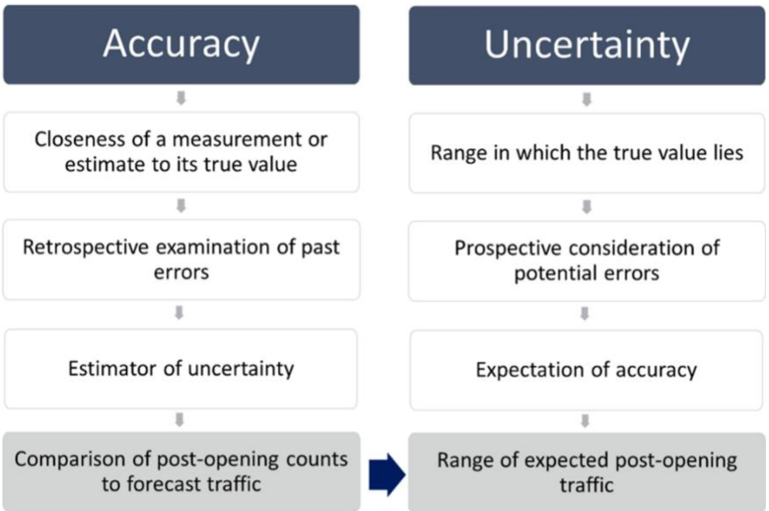


Figure 8 The relation between accuracy and uncertainty in traffic forecasts. Figure from Hoque et al. (2021).

Uncertainty and cost-benefit analyses

It is not only forecasts of traffic effects that suffer from uncertainty – the valuation of these effects may also be uncertain. Nocera and Tonin (2014) discuss uncertainty in the valuation of CO2 emissions. The recommended valuations for reduction of CO2 emissions e.g., when conducting cost benefit analyses (CBA) of transport projects, differ substantially in the scientific literature. This is related to the uncertainty regarding what impacts climate change will have on our economies and well-being in the future, and the uncertainty related to the non-linearity of these impacts, where additional CO2 emissions in a situation when the stock of CO2 emissions is already high is worse than when it is low. The authors suggest the use of a probability distribution for CO2 emission valuation to capture the uncertainty in marginal social cost of CO2.

Asplund and Eliasson (2016) discuss the broader question of how uncertainty impacts cost-benefit analyses (CBA). They investigate the impact of different types of uncertainty and conclude that CBA results are most affected by uncertainty in investment cost and forecast transport demand. However, the authors stress that CBA ranking of investments is surprisingly stable to the tested uncertainties, meaning that the CBA rank order of investments does not change much even in a situation with large uncertainty.

Flyvbjerg (2009) and Flyvbjerg and Bester (2021) show that costs are systematically underestimated and benefits systematically overestimated for infrastructure investments when ex-post evaluations of built projects are compared to ex-ante forecasts. Flyvbjerg (2009) argues that this bias comes from misleading forecasts. Fosgerau and Eliasson (2013) show however that the bias could just as well be due to a selection bias, where projects for which costs have been underestimated and demand overestimated are more likely to be selected and built. Thus, the bias found when comparing ex-post evaluations and ex-ante forecasts does not have to be deliberate. Rather it could be unbiased uncertainty in ex-ante forecasts which leads to bias in the projects selected for implementation. Furthermore, Fosgerau and Eliasson (2013) show that the average payoff of projects selected using the CBA method is higher compared to average payoff of randomly selected projects, even if forecasts are very uncertain.

2.3.3 The use of EMA and DMDU with transport models

Within the previously mentioned U.S. Travel Model Improvement Program (TMIP), the tool TMIP-EMAT has been developed to support EMA and DMDU applications for regional travel demand forecasts (Lemp et al., 2021). TMIP-EMAT is developed by extending the open source Python library EMA-Workbench[8] (Kwakkel, 2017) which provides a variety of tools for performing EMA and DMDU analyses. The purpose of TMIP-EMAT is to allow for more than a single point prediction by providing methods to systematically explore uncertainties in input and model parameters and provide a model forecast as a range of outcomes. Using a travel forecast model in an exploratory manner allows the analyst to investigate a range of different futures, rather than trying to predict only one future. Several uncertainty variables important for the forecast outcome need to be selected and assumptions need to be made regarding ranges and distributions for these uncertainty variables. Milkovits et al. (2019) state that defining a range is less restrictive compared to assuming a single point value, which is state-of-practice when not using EMA. Travel forecasting models usually take several hours just to run one scenario. Therefore, TMIP-EMAT includes tools for generating a meta-model of the travel forecasting model. The meta-model is a simplified representation of the original model which is much faster to run. The meta-model is automatically generated and includes a linear regression model to capture overall trends and linear relationships, as well as a Gaussian process regression model to capture non-linear effects Lemp et al (2021). A visualization tool within TMIP-EMAT facilitates for the analyst to investigate results for different values of the uncertainty variables. Validation of the original travel forecasting model is also facilitated. A proof-of-concept study has been performed for TMIP-EMAT in which it was applied for the Greater Buffalo-Niagara Region in the US (Lemp et al., 2021; Milkovits et al., 2019). Four uncertainty variables are included in the proof-of-concept study: Households and employment in the region, roadway capacity, valuation of car in-vehicle time, and alternative-specific constants for vehicle availability. The authors note however that the value of the approach needs to be further explored.

EMA has also been used together with a transport model in a fairly recent master thesis from the Netherlands (van Baarle, 2021). In the thesis, robust decision making is applied to bike and car policy analysis in the municipality of Groningen. The transport model used is a Visum model which is adapted to reduce run time. Run time is reduced by removing route assignment, removing indirect tours (tours including a secondary stop such as shopping on the way home from work, accounting for about 20% of the tours in the model), and running the model once instead of three times. The authors validate the changes to the model and find that removing the route assignment part does not affect the distance travelled by car in the municipality. They also find that the car share changes by less than 1% when only calculating mode and destination choice for direct tours, not indirect

[8] EMA-workbench is available at: https://github.com/quaquel/EMAworkbench

tours. All in all, model run time is reduced from about 22 hours to 12 minutes. The Visum model is connected to EMA using the built-in Visum python console. The script implementing this connection is available as open source on GitHub[9]. With the reduced run time the EMA calculations took about 1 week. Three policy levers are analyzed: fast bike lanes, car speed limit reduction, and extension of car parking fee area. The results show that the bike policy is most robust to uncertainties in e-bike use, car cost per km, public transport cost per km and reduction in tours due to working from home. The speed limit reduction policy shows a very small effect on car share in all scenarios.

Other, non EMA-based, DMDU approaches have been applied to various transport planning issues, for instance dynamic adaptive policy making has been applied to the implementation management of Mobility-as-a-service (Jittrapirom et al., 2018) and automated taxis (W. E. Walker & Marchau, 2017).

2.3.4 Implications of uncertainty for planning the future transport system

Lyons and Marsden (2021) argue that we currently face significant changes to the role of travel in society and that people are likely to travel less in the future due to among other things new digital solutions. This is in contrast with Eliasson (2022) who argues that historical transport and digital technological developments have not decreased travel in society and is not likely to do so as a consequence of the digital technology developments during the pandemic either. People seem to be willing to dedicate a surprisingly stable amount of time per day to travel. When travel speeds increase, due for example to an infrastructure investment, then we travel longer distances in similar travel times. On the same token, when online meetings are made possible, we add another meeting which was not possible to conduct previously. This way, accessibility to places and people has constantly increased in our society. However, there are other uncertainties, which may be very important for transport planning decisions, such as how fast the vehicle fleet will be electrified, as well as the development of fuel price (including price of electricity), population and GDP. Note also that changes in fuel prices, population and GDP also indirectly affect the total amount of vehicle kilometers travelled in a country.

Performing policy analyses of policies that have not previously been implemented or evaluated is another uncertainty related challenge. In such analyses, there might be a high degree of uncertainty about policy impacts, and how they will interact with other (Trosvik et al., 2023; Witzell, 2020). This ties in to the broader, ongoing debate on how different types of measures for reaching the climate targets (increasing the share of electric vehicles and more energy efficient vehicles; increasing the share of renewable fuels; and limiting or reducing future traffic volumes) should be combined and balanced, considering the costs, feasibility, trade-offs, and distributional effects various measures entail.

2.4 Summary and synthesis of literature review

The scientific understanding and its relationship with uncertainty have undergone significant evolution. Initially, during the Enlightenment, science was viewed as a pursuit of certainty, leading to the positivist view that understood uncertainty as unscientific. During the 20th century, this view evolved. Developments in physics and mathematics illuminated and conceptualized fundamental

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9 https://github.com/ilmovanbaarle/Thesis-Ilmo

uncertainties in nature. Within economics, ideas distinguishing between calculable risks and inherent uncertainties emerged. This era also saw the rise of post-modernism and social constructivism, emphasizing that science is not purely objective, and that more data and knowledge does not necessarily mean less uncertainty. Instead, more knowledge might reveal that a system is more uncertain than what was initially understood.

At its core, uncertainty is a limited knowledge of past, current, or future events. If an event's probability is not definite, it is uncertain. Uncertainty ranges from complete determinism, an ideal that cannot be achieved, to total ignorance. *Deep uncertainty* arises in situations where it is challenging to assign probabilities due to system complexity, scarce information, or inherent unpredictability of complex systems. Deep uncertainty leads to a need to consider a multiplicity of futures, which is typically challenging in decision-making situations. Other frameworks like VUCA and global/local uncertainty have also emerged, highlighting the importance of considering multiple potential futures.

To better describe and communicate uncertainty in relation to policy making, the literature has moved past the basic differentiation of risk and uncertainty types. The framework by Walker et al. (2003) was developed as an unifying typology to describe uncertainty in model-based policy analysis. This framework identifies the location, level, and nature of uncertainty and sought to help policy analysts prioritize and treat uncertainties in models, and to communicate uncertainty more clearly in their policy analyses with policy makers. This framework was later further developed by Kwakkel et al. (2010).

The role of uncertainty is central when applying scientific methods for policy analysis and the study of sociotechnical systems. Weinberg's concept of *trans-scientific questions* (Weinberg, 1972) illustrate that policy issues might be framed scientifically but lack definitive answers. Solutions to these problems cannot objectively be labelled as right or wrong but are rather deemed good or bad based on subjective judgments, and different stakeholders often have differing opinions. Adding to the challenges of policy-oriented science is the idea of *wicked problems* (Rittel & Webber, 1973). Contrary to clear-cut scientific issues, wicked problems are ambiguous and multifaceted. Their solutions are judged subjectively, often leading to varying stakeholder opinions. Modern societal systems' complexity further introduces uncertainties. As van Asselt (2000) described, modern policy problems tend to be interconnected, span multiple disciplines, and operate across vast scales. Addressing them is challenging because they demand diverse perspectives and have to account for not entirely understood phenomena, like climate change or emerging technologies.

Making decisions for the future involves anticipating long-term changes that can influence or be influenced by short-term actions. Lempert, Popper, and Bankes (2003) introduced robust decision-making (RDM) to address challenges associated with long-term policy analysis (LTPA) in situations of deep uncertainty. Historically, various methods have been used to think about the future, such as: narratives, group narratives like Delphi and Foresight, simulation modelling, decision analysis, and scenario-based planning. However, each approach has limitations, especially in addressing the multitude of plausible futures.

Maier et al (2016) highlight the importance of considering multiple futures in model-based quantitative policy analysis. They recommend describing uncertainty using distinct plausible scenarios, measuring system performance based on its robustness to future changes, and designing adaptive strategies that can be adjusted as conditions evolve.

Decision Making Under Deep Uncertainty (DMDU) is a collection of tools and methods used to identify strategies that are robust and adaptive in the face of deep uncertainty (Marchau et al., 2019). DMDU is based on three key ideas: exploratory modelling, adaptive planning, and decision support. When applying DMDU, quantitative policy models are used to simulate a range of scenarios and assessing policy alternatives. There are many different DMDU techniques and tools, of which many are complementary. An overview and classification of DMDU methods is provided by Kwakkel and Haasnoot (2019). For the MUST project, two of these methods are in focus: Robust Decision Making (RDM), and Exploratory Modeling and Analysis (EMA).

RDM focuses on identifying strategies that are robust against a wide variety of future conditions. It challenges the prevailing notion of basing policy analysis on a prediction of a system's future state, aiming instead to support decision-making in cases of deep uncertainty when definitive forecasts cannot be made. The RDM process is comprised of a four-step iterative procedure: i) problem formulation, ii) generation of policy alternatives, iii) uncertainty analysis, and iv) vulnerability analysis. The overarching goal of RDM is not just the identification of policies with a high degree of robustness, but also identifying potential vulnerabilities for these strategies. Moreover, if RDM is performed in collaboration with relevant stakeholders, it can enhance the understanding of the policy problem, generate additional policy alternatives, and provide deeper insights into the inherent trade-offs of policies.

EMA is a more general approach which involves creating, exploring, and analyzing many alternative policies, models, or scenarios to understand the impact of uncertainties on system behavior and decision outcomes (Kwakkel and Pruyt 2013). EMA utilizes several methods and techniques, such as sampling, sensitivity analysis, uncertainty analysis, scenario discovery, and (multi-objective) optimization. To structure EMA problems, the XLRM framework is often used to specify the external uncertainties (X), policy levers (L), relationships in the system (R), and outcomes of interest (M). EMA is essentially an analysis of how regions of uncertainty (X and R) and the decision space (L) relate to the outcome space (M).

EMA differentiates between two applications: open exploration and directed search. Open exploration systematically samples uncertainty or decision space, serving multiple purposes like quantifying feasible outcome ranges, comparing policies, analyzing sensitivity and uncertainty, vulnerability analysis, and selecting policy-relevant scenarios. Directed search uses mathematical optimization to search the decision or uncertainty space, aiming to identify policies or scenarios of interest. Often, EMA problems have multiple objectives involving trade-offs. In these cases, multi-objective optimization is performed, often using a multi-objective evolutionary algorithm (MOEA). Directed search can be used to generate candidate policies within RDM. One such approach is Many Objective Robust Decision Making (MORDM), where a MOEA is used to generate Pareto-optimal policies based on a reference scenario. Thereafter, the robustness and vulnerabilities of these candidate policies are evaluated using RDM. However, policies based on a single reference scenario might limit robustness, leading to the development of multi-scenario MORDM. Multi-objective robust search (MORO) is another variant that uses an objective function with a robustness metric for each objective, evaluated over several scenarios, to identify robust policies. Specifying relevant robustness metrics is crucial, with robustness understood either as low uncertainty or minimization of undesirable outcomes. Three metric types are distinguished: regret-based, satisficing, and statistical or density-based. Different robustness metrics emphasize various aspects of robustness, underscoring the need for careful selection tailored to the problem at hand and use of complementary metrics.

In the transport planning field, it has for several decades been common practice to make a transport forecast of a future year (typically around 20 years in the future) and to calculate costs and benefits of transport projects for the forecast of this forecast year. In some cases, sensitivity analyses have been made in which the planner tries a few changes to the input data such as changes to assumed population growth or assumed future fuel prices. The accuracy of these transport forecasts has been evaluated in several studies (Andersson et al., 2017; Cruz & Sarmento, 2020; Hoque et al., 2021) coming to the conclusion that transport forecasts are more often optimistic rather than pessimistic, over-estimating demand and under-estimating costs when compared to actual outcome statistics. Thus, the uncertainty in the forecast is not purely random, there is a systematic bias. In the reviewed studies, the over-estimation of forecast traffic flows/vehicle kilometers compared to actual outcome statistics is in the order of 5%-20%. It is also found that rail traffic forecasts in general deviate more from actual outcomes compared to road traffic forecasts.

Rather than conducting a handful of sensitivity analyses of selected input parameters, researchers and planners have in the latest years tried to deal with uncertainty in transport planning and transport forecasting in a more all-encompassing way, applying approaches from the DMDU field. This implies that policies/measures are tested against a large set of scenarios with varying input parameters within defined ranges, and that the policies/measures that are most robust across the different scenarios are selected. The prominent example of this is a U.S. model called TMIP-EMAT (Lemp et al., 2021; Milkovits et al., 2019). TMIP-EMAT applies EMA together with a travel forecasting model to give a range of outcomes given uncertainties in employment levels, values of travel time etcetera.

3 Workshop series

The purpose of the workshop series is to bring together experts within various areas of model-based analysis at Trafikverket with researchers from the project partners to identify, analyze and discuss deep uncertainty and the challenges it poses for Trafikverket's long-term planning and policy analysis processes, and methods for managing it. It is also intended as a primer to the concepts and methods explored within the project to achieve better transfer of knowledge to Trafikverket from the other work packages in the project. The objectives for the workshop series are:

- To gather empirical data on analysis needs and uncertainties of importance for Trafikverket's planning and policy analysis processes.
- To share knowledge about concepts and methods identified during the literature review to a selected group of stakeholders at Trafikverket and to researchers not involved in a day-to-day basis in MUST.
- To get guidance for scoping the modelling work and analysis in WP2 and WP3 and to put these modelling studies in a broader context.
- To generate ideas for (potential) future activities that Trafikverket can undertake to strengthen its ability to manage deep uncertainty.

The workshop series consists of two workshops, Workshop 1 (WS1) and Workshop 2 (WS2), which build on each other, see Table 2 for an overview. In WS1, focus is on the concept of deep uncertainty and to analyze how it relates to some of Trafikverket's analysis needs. During the workshop, a framework for classifying and communicating deep uncertainty in model-based foresight or policy analysis is introduced. Exercises are performed to identify and categorize Trafikverket's analysis needs, and to perform an analysis of uncertainty for one of the analysis needs, producing the reference forecast (basprognos) for the Swedish transport system, by applying the aforementioned framework. WS2 is focused on the concept of decision making under deep uncertainty and introduces a framework for uncertainty in the policy analysis process and an overview of exploratory modelling and analysis by presenting the case study in WP2. The exercises are centered on the case of identifying and analyzing policies for reaching the national climate targets for the transport system. WS2 is concluded by a brainstorming session on the implications for Trafikverket and to generate ideas of potential activities Trafikverket could undertake to improve its ability to manage deep uncertainty.

Table 3 Summary and overview of the two workshops

	Workshop 1	**Workshop 2**
Date and location	2022-06-09 at VTI's facilities in Stockholm	2023-02-21 at VTI's facilities in Stockholm
Aim	Identify and describe analysis needs in the transport sector which are characterized by (deep) uncertainty	Analyze uncertainty in the policy making process and how it can be managed
Scope	General analysis needs, uncertainties and forecasting processes Case: Reference forecast 2040 (basprognos)	Policy analysis process Case: Policies for reaching the climate targets for the transport system

Theoretical focus	Deep uncertainty: definitions, dimensions, and classification.	Decision making under deep uncertainty.
Tools and methods introduced	Framework for classifying and communicating uncertainty in model based policy analysis (Kwakkel et al., 2010; W. E. Walker et al., 2003)	Policy analysis framework (Marchau et al., 2019; W. E. Walker, 2000) Exploratory modelling and analysis (Bankes, 1993; Kwakkel & Pruyt, 2013)
Exercises	1.1 Identify and categorize analysis needs in the transport sector and the associated uncertainties. 2.1 Detailed analysis and classification of uncertainty regarding the 2040 reference forecast	2.1 Analysis of uncertainty in the policy analysis process for policies to reach the climate target for the transport system 2.2 Managing uncertainty using Decision making under deep uncertainty and exploratory modelling and analysis & activities to strengthen Trafikverket's ability to deal with deep uncertainty
Outputs	Mapping of key analysis needs for future freight and passenger transport and their associated uncertainties Uncertainty analysis for reference forecast in the form of uncertainty matrix	Uncertainty analysis for climate policy strategies and how DMDU and EMA can support the policy analysis and decision making. Reflections on EMA and other ideas to improve the ability to manage deep uncertainty in transport forecasting, planning and policy analysis.

Planning of the workshops, designing exercises and the identification and recruitment of participants is done together by KTH ITRL and VTI with assistance from Trafikverket's project leader.

3.1 Workshop 1

3.1.1 Aim

The aim of workshop 1 was to identify and describe analysis needs in the transport sector which are characterized by uncertainty. The workshop contributed to the research project both by collection of data and by testing how groups of experts can work systematically with uncertainty matrices for uncertainty analysis.

3.1.2 Exercises and set up

The workshop was carried out on site at VTI premises in Stockholm on June 9th, 2022. Ten experts participated during the workshop (see Appendix for a list of participants), which lasted for three hours. The workshop started with an introduction to the project and the workshop series and then continued with two exercises (coffee in-between) and reporting back to all at the end of each exercise. During the exercises, the participants were divided into two groups, one for passenger transport and one for freight transport, depending on their main area of expertise.

Exercise 1.1 – Identify and categorize analysis needs in the transport sector and the associated uncertainties

In this exercise, the experts were first asked to individually note analysis needs in the transport sector which they think are characterized by uncertainty. The analysis needs were written on template slips of paper, see Figure 9[10].

Analysis needs	
Which uncertainties are coupled to the analysis need?	

Figure 9 Template for paper slip used to document analysis needs during exercise 1.

The experts were then asked to sort the slips of paper into clusters of similar analysis needs. Then, the last part of Exercise 1 was for the experts to map the analysis needs in a matrix along the axes small - large uncertainty and less - more important topic, see Figure XX.

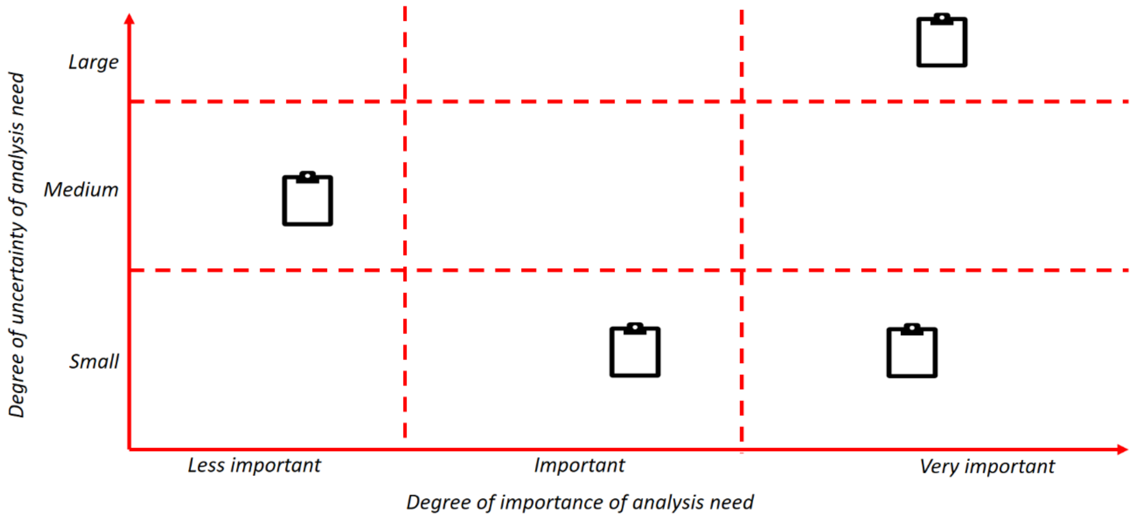

Figure 10 Template for mapping of analysis needs along two axes. Vertical: degree of uncertainty for the analysis need. Horizontal: degree of importance for the analysis needs for Trafikverket.

Exercise 1.2 – Detailed analysis and classification of uncertainty regarding the 2040 reference forecast

In Exercise 2, the experts were asked to focus on *one specific analysis need* – the 2040 reference forecast.
The experts were first introduced to the uncertainty framework developed by Walker et al. (2003) and further developed by Kwakkel et. al (2010). The aim of this framework, see Section 2.1.3, is to: 1) give a common terminology to communicate around uncertainty, 2) give a better understanding of different dimensions of uncertainty, and 3) facilitate finding suitable ways of handling uncertainty. The main dimensions in this uncertainty framework are: 1) *where* uncertainty is located, 2) to *what*

[10] The text on workshop material has in this report been translated from Swedish to English.

extent uncertainty exist, and 3) *which type* of uncertainty we are dealing with. The framework is applied in the form of a three-dimensional uncertainty matrix with categories for each dimension. The experts were then asked to individually write down uncertainties related to the 2040 reference forecast. Just as with the analysis needs in Exercise 1, the uncertainties were written on template slips of paper, see Figure 11.

Uncertainty	

Figure 11 Template for paper slip used to document uncertainties for exercise 2.

Then, a simplified version of the Kwakkel et. al (2010) uncertainty matrix was used, focusing on two of the dimensions: 1) *where* uncertainty is located (categories: system limits, model, implementation, calibration, input data) and 2) t*o what extent* uncertainty exist (categories: shallow or deep uncertainty), see Figure 12. For each of the uncertainties related to the 2040 reference forecast that the participants had previously document, the expert group the discussed where it should be placed in the uncertainty matrix.

		Level of uncertainty To what extent is there uncertainty?	
		Shallow uncertainty	Deep uncertainty
Location of uncertainty Where is the uncertainty?	System limits (What should be included)		
	Model (Design of the conceptual model)		
	Model implementation (Bugs/code errors)		
	Calibration (Access to data /validity)		
	Input data (Forecast/scenario prerequisites)		

Figure 12 Uncertainty matrix used in exercise 2. This is a simplified version of the uncertainty matrix by Kwakkel et al. (2010), see Figure 1.

3.1.3 Results Exercise 1.1

Many analysis needs in the transport sector characterized by uncertainty were identified by the experts both in the passenger and freight transport groups. These were clustered together by the expert groups.

The passenger transport group identified nine clusters of analysis needs. In the analysis work after the workshop these clusters of analysis needs originally written in Swedish were reviewed by the authors of this report and given a name in English:

1. Changes in travel behavior
2. Demand for rail travel and the effects of high-speed trains
3. Automation, electrification, and digitalization (AED) and conflicting goals
4. Travel demand effects of AED
5. Effects of AED on different traveler groups

6. Effects on accessibility
7. Development of reference forecast
8. Passenger valuations over time
9. Long-term development of GDP, income distributions, demography etc. and the effect on passenger transport

The passenger transport expert group placed the clusters according to the pattern shown in Figure 13. It is interesting to note that the analysis need cluster with the highest importance and largest uncertainty is the long-term development of GDP, income etc. These are traditionally input data to transport analyses and are forecast and supplied by external sources, i.e., uncertainties are inherited from a previous forecast.

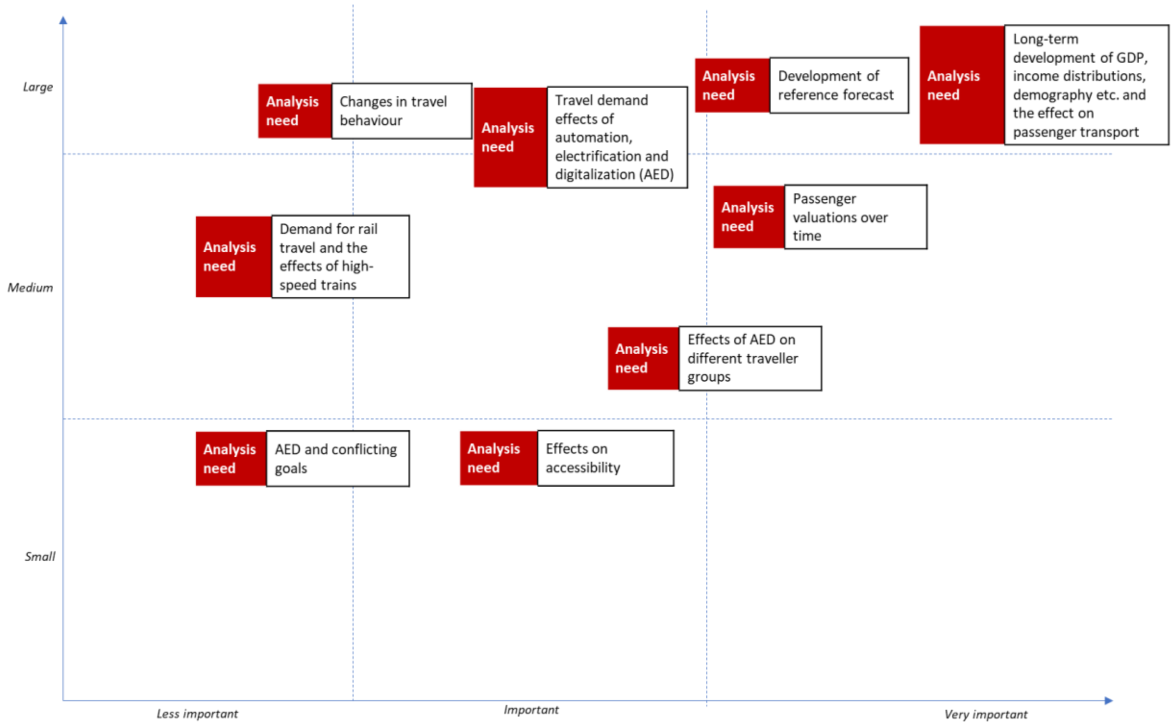

Figure 13 Summarized results for exercise 1, passenger transport.

The freight transport group did not manage to cluster all analysis needs within the time of the exercise. The non-clustered analysis needs are presented as-is in **Table 11** in the Appendix. Just as for passenger transport, the clusters of analysis needs originally written in Swedish were reviewed by the authors of this report and given a name in English:

1. Development of dynamic electricity prices and grid capacity
2. Effects of automated trucks
3. If, when and how automated trucks will be introduced
4. Mode choice and the effect of electrification/new technology
5. Future freight transport demand
6. Samgods model quality and correctness

The remaining analysis needs that were not clustered during the workshop where clustered by the report authors after the workshop as follows:

7. Analyzing the need (volume and location) for charging infrastructure
8. Analyzing the effects of potential policies which may not have previously been tested and therefore lack empirical evidence
9. Understanding the (future) relationship between road/rail/sea and how to achieve modal shifts
10. Estimating the future use and market shares of different fuel/energy sources.

The freight expert group placed the clusters 1-6 according to the pattern shown in Figure 14. There are two analysis need clusters which are identified as most important: the future freight transport demand and the Samgods model quality and correctness, out of these the future freight transport demand is assessed to be most uncertain.

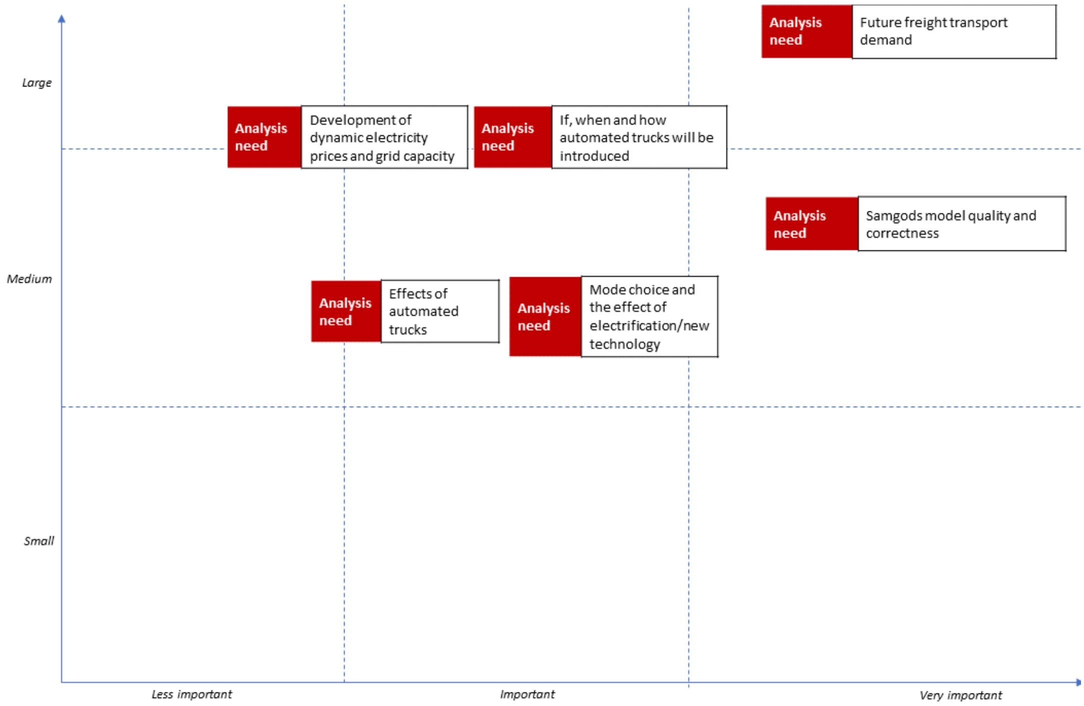

Figure 14 Summarized results for exercise 1, freight transport.

3.1.4 Results Exercise 1.2

As described above, the second exercise was centered on the 2040 passenger/freight transport reference forecasts. The passenger transport expert group identified 17 uncertainties related to the reference forecast. These were placed in the uncertainty matrix. The matrix cell where most uncertainties were placed was “input data/deep uncertainty”. Examples of uncertainties placed in this cell are: What will the economic development in Sweden look like until 2040? How will the cost for travel with different modes change over time? Where will people live and work 2040? There were also several uncertainties placed in the matrix cell “model design/deep uncertainty”, such as uncertainties related to: values of time, the driving cost as proxy when assessing policy effects, and changes in travel behavior over time. One uncertainty was placed in “system limits/Deep uncertainty” and this was related to digital accessibility and how it will affect travel demand in the future.

The categories “model implementation” and “model calibration” had almost no occurrences under “deep uncertainty” except for an uncertainty related to complex model systems leading to risk for errors which was placed in-between the shallow and deep uncertainty categories by the expert group. The freight group also had no occurrences of deep uncertainties regarding implementation or calibration. When the workshop participants presented their results from Exercise 2 it was discussed that this is to some extent a general characteristic of these categories – model implementation and model calibration are usually characterized by shallow uncertainty, not deep uncertainty. For example, model calibration is usually conducted against a recent year, and it can be difficult to find data from the recent year to calibrate against, but this is different from assumptions about input data for 2040 where there is no exact answer to be found, i.e., it is deeply uncertain. Similarly, code errors can occur during model implementation, but these are possible to find and remedy, i.e., they are also not deeply uncertain.
Several shallow uncertainties were identified in the passenger expert group. These were related to model design (e.g., network effects of investments in bicycle infrastructure), to calibration (ticket prices for air and train, cost matrices for car, data about passenger kilometers by mode and trip purpose, etc.), and to input data especially concerning the transport networks (correct infrastructure/timetable/public transport supply?).

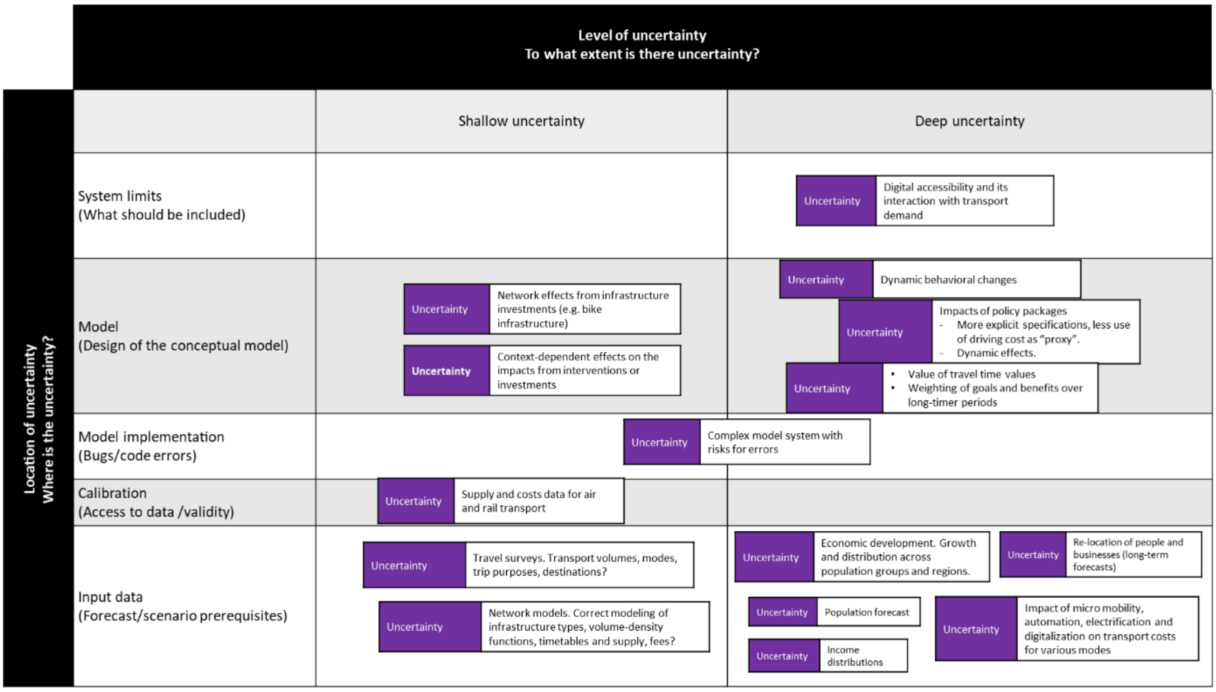

Figure 15 Summarized results from exercise 2, passenger transport.

The freight transport expert group identified 29 uncertainties related to the freight 2040 reference forecast and placed these within the uncertainty matrix. Just as for passenger transport, the cell where most uncertainties were placed was “input data/deep uncertainty”. Examples of uncertainties placed there were both similar to passenger transport such as general development of the economy, fuel price, and technical development of vehicles, but also uncertainties specific to the freight sector such as industry establishments in the north of Sweden and sourcing-strategies/trade patterns. A few deep uncertainties were also identified in the categories “system boundaries” and “model design”. No deep uncertainties were identified in the categories model implementation or calibration. Shallow uncertainties were identified for all location categories. Most shallow uncertainties were placed under “input data” (infrastructure changes, regional scenarios from national data, interpretation of climate goals, uncertainty in EU-policy, and uncertainty in rail capacity), followed by “model design”, “model calibration”, “model implementation”, and “system boundaries”.

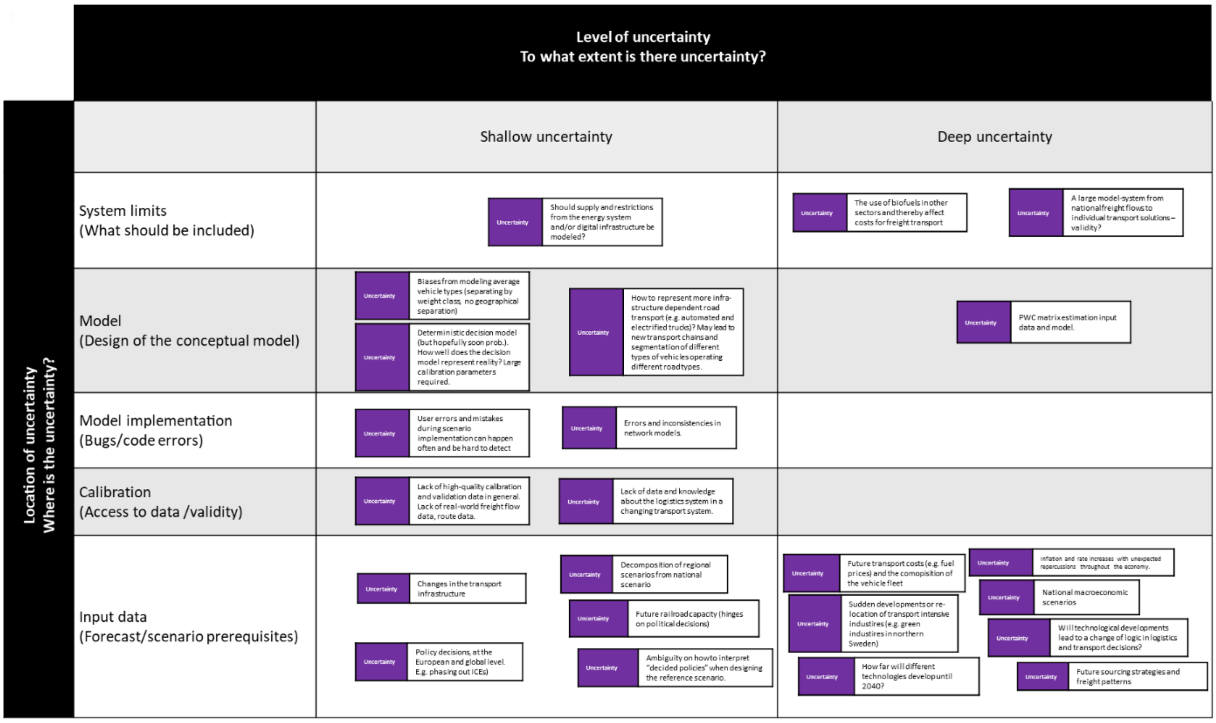

Figure 16 Summarized results from exercise 2, freight transport.

3.1.5 Discussion and takeaways

The following takeaways have been identified from Workshop 1:

- Forecasting the future transport demand, which in turn means forecasting of multiple factors affecting transport demand (economic growth and distribution thereof, population growth, location choices, etc.), was identified as a highly uncertain and important analysis needs.

- Analyzing the impacts of (potential) policies, and in particular, combinations of policies was identified as an uncertainty. Lack of empirical data, dynamic effects and network effects were both mentioned as factors making the analysis complex.

- Analysis needs related to emerging transport technologies such as automation, electrification and digitalization are repeatedly mentioned for both passenger and freight transport when discussing analysis needs characterized by uncertainty. These are associated with uncertainties both related to in what direction and how fast these trends will develop (scenario uncertainty) but also how they should be conceptually modelled and/or how they will affect model input parameters (structural uncertainty). These trends may also require adjusting the system boundaries for forecasting models, e.g. to incorporate how digital accessibility will interact with the transport system and affect transport demand, and how the energy (electricity) system may impose capacity restrictions for charging of electric vehicles.

- Uncertainties related to model implementation and model calibration are in general shallow uncertainties regarding data shortage and implementation errors.

- The complexity of the forecasting models was identified as an uncertainty by both the passenger (Sampers) and freight transport (Samgods) groups. This relate both to uncertainty in the model implementation and the risk for unidentified errors in the code or input data but also to the conceptual design of model systems

- For both passenger and freight transport, most of the identified deep uncertainties for the 2040 reference forecast are located in the “input data” category. Several of these uncertainties are in inherited from previous forecasts regarding economic and population development.

- Having a face-to-face meeting was important for achieving good discussions about such a complex topic as uncertainties in transport forecasting.

3.2 Workshop 2

3.2.1 Aim

The aim of the second workshop was to:

- Identify and discuss uncertainty for analyzing policies for reaching the climate targets for the national transportation sector.

- Introduce the concept of EMA and get inputs on its benefits, drawbacks, and potential applicability in Trafikverket.

- Get input on challenges for Trafikverket due to deep uncertainty and what could be done to address these.

3.2.2 Exercises and set up

The workshop was held at the 21 February 2023. Just as for workshop 1, the workshop was carried out on site at VTI premises in Stockholm. Eight experts participated during the workshop (see Appendix for a list of participants), of which four also participated in workshop 1.

The workshop started with an introduction to the project and the workshop series and then continued with two exercises. During the first exercise, the participants were divided into two groups, one for passenger transport and one for freight transport, depending on their main area of expertise. Before the second exercise, an introduction to Exploratory Modeling and Analysis (EMA) and a demonstration showcasing some of the ongoing work using EMA in WP2 was given. In total, the workshop lasted for three hours.

Exercise 2.1 – Uncertainty in the policy analysis process for policies to reach the national climate targets for the transport sector.
In the first exercise, an uncertainty analysis of the policy analysis process for policies for reaching the national targets for the transport sector was performed. As a basis for the exercise, a framework based on Marchau et al. (2019), see Figure 17, was used. The framework describes the various elements in the policy analysis process and distinguishes different types of uncertainties (illustrated by red boxes in Figure 17). First, an introduction to the exercise and framework was given followed by an introduction to previous a policy analysis made by Trafikverket (Trafikverket, 2020d) which was used as a case for the exercise.

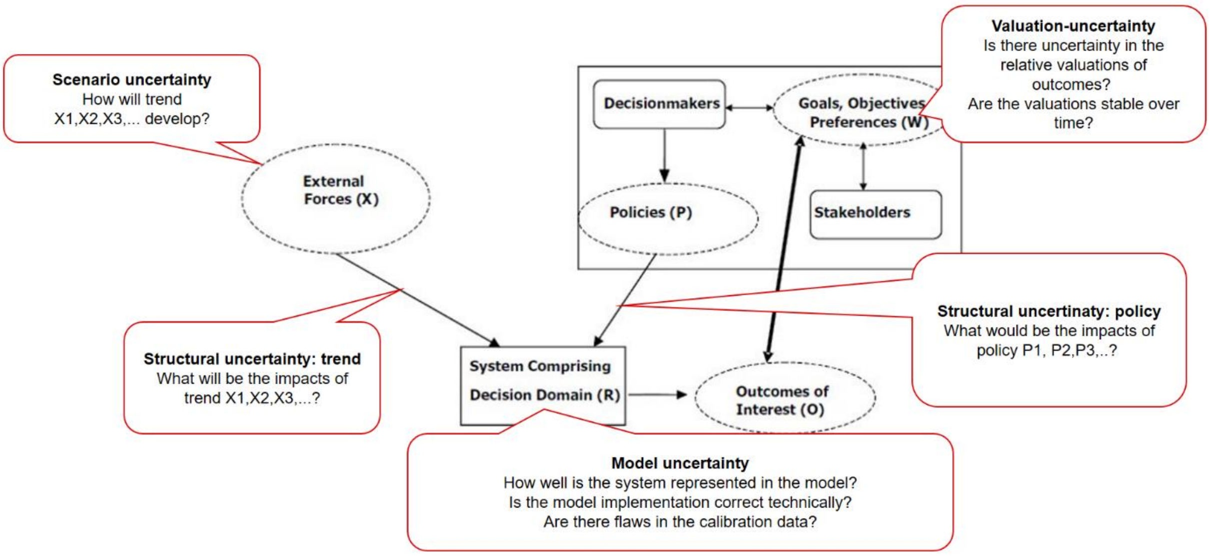

Figure 17 Analysis framework for categorisation of different types of uncertainties in the policy analysis process for exercise 1. Author's adaptation based on Marchau et al. (2019).

The participants were split into two smaller groups, one for passenger transport and one for freight transport. Each participant was asked to think of what uncertainties the policy analysis process entails and write each uncertainty on a post-it note. The participants in the two group then jointly clustered and categorized their uncertainties and mapped them onto a canvas separated according to the different uncertainty categories of the framework, see Figure 18. The final task was that each participant voted for which three uncertainties they deemed as most important to consider for the policy analysis work in WP2 in MUST.

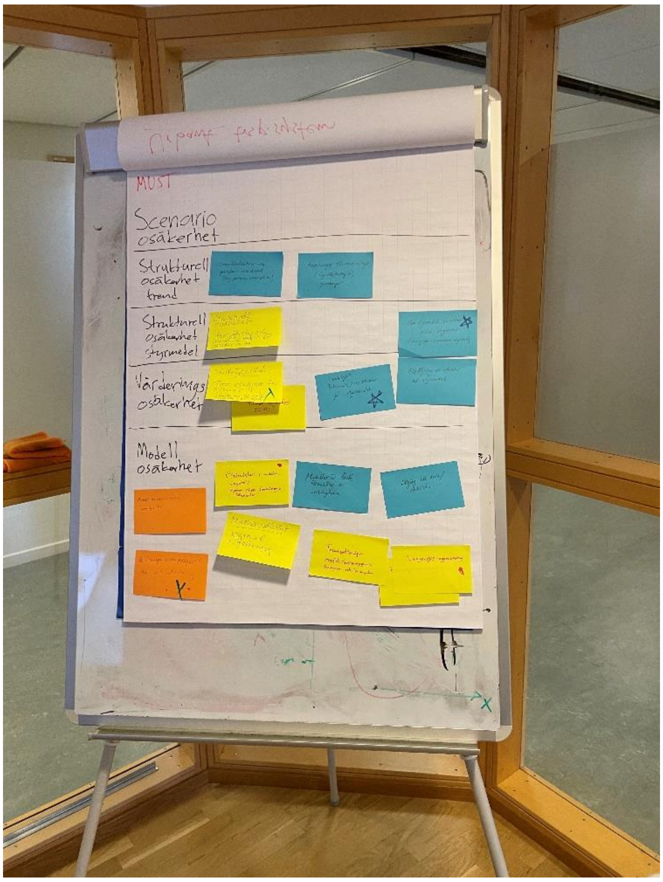

Figure 18 Example of an uncertainty canvas from exercise 2.1.

Exercise 2.2 – What can Trafikverket do to enhance its ability to deal with deep uncertainty?
The second exercise was designed as a brainstorming session intending to open up for general reflections on deep uncertainty in transport planning, if and how EMA can be applied to better manage it and ideas for how Trafikverket can enhance its ability to deal with deep uncertainty. The exercise was intended to be performed mainly through a pre-prepared online template which the workshop participants got access to. This document consisted of a set of headings and questions to guide the participants' and the participants were supposed to fill in their thoughts and comments (see Appendix). However, during the workshop, the introduction to EMA and the demo of work done with EMA in WP2 which proceeded Exercise 2, sparked a long discussion in the workshop group which touched upon many of the topics intended to be covered during Exercise 2. This discussion was not cut short, and notes were taken by the workshop organizers. Only a short amount of time was allocated to work with filling in the document prepared for the exercise.

3.2.3 Results Exercise 2.1

The freight transport group identified in total 34 distinct uncertainties, of which the majority (20) are Scenario uncertainties, see Table 4 for a complete list. The passenger transport group identified 40 uncertainties which were more evenly distributed across the different types, see Table 5 for a complete list. The remainder of this section provides a summary of the identified uncertainties.

Uncertainty from international and global events

One identified type of scenario uncertainty is large-scale societal crises such as pandemics or wars, which was identified by both groups. These uncertainties have been highlighted by recent and ongoing crises such as the COVID-19 pandemic and Russia's illegal war against Ukraine. Such crises are not only highly difficult to predict, but they also tend to generate many hard-to-foresee events on various levels, for example: disruptions to supply chains, destabilization of regional and global markets, politically imposed interventions (e.g. lockdowns or sanctions), and behavioral change. Such events can have direct impacts on the transport system or the demand for transport but also wider effects due to shifting preferences among individuals and firms, changing long-term trade flows, sourcing strategies, etc. For instance, the rise of telecommuting and e-commerce following COVID-19 or the diminished trade with Russia, coupled with an increased focus on geopolitical factors in supply chain decisions post Russia's war. Even if these events could be predicted, it is hard predicting whether they will be short-term shocks, which once the crisis is averted will subside, or if they will constitute fundamental shifts that alters the long-term development trajectory. Also, in the freight transport group, it was suggested that Russia's war in Ukraine might lead to a shift in risk perception among policymakers and the with a greater emphasis on national security, and less focus on other pressing issues which previously were in focus, such as the climate crisis. This is an example of a valuation uncertainty.

Uncertainty from societal and behavioral development and change

Both groups highlighted many uncertainties that relate to the broader societal development. These included the demographical and economic development of Sweden, international trade-patterns, and the influence of shifting geopolitics on these. Also more general preferences and cultural factors that affect people's need for mobility and demand for products and services was highlighted as highly uncertain. These factors all affect demand for transport, which was stressed as a key uncertainty by both groups. Several uncertain factors that affect the electrification of the transport system were mentioned such as. This included the development of the energy system in terms of production capacity and transmission capacity, and to what extent they will limit the electrification pace. Also the supply of raw materials, and production capacity, for electric vehicle batteries was identified. Similarly there is uncertainty in the availability and costs of other types of fuels and energy carriers, such as biofuels and hydrogen, and to what extent they will be produced sustainably. Also, more transport sector specific uncertainties were highlighted, for instance how the European truck driver labor market will develop and to what extent foreign drivers and vehicles will be used for transport missions within Sweden.

Policy landscape uncertainty

The developments of policies within other sectors and decision domains introduce a different set of uncertainties. Examples of such uncertainties that were identified during the workshop are: how the climate packages by the EU (e.g. Fit for 55) will play out in terms of actual investments, directives or legislation, and the development of Sweden's non-transport-related policies. This can be seen as a form of scenario uncertainty. There is also uncertainty from political uncertainty about what investments in transportation infrastructure that will be made (e.g. high-speed rails) as well as what types of policies, in particular for climate policies, that will be politically acceptable.
Furthermore, multiple examples of structural policy uncertainty were mentioned. For instance: potential for unexpected effects from policy instruments, a general lack of knowledge about the efficacy and impact of policy tools on different groups of citizens, as well as different types of industries and transport buyers, and the uncertainty in how priorities of different benefits and costs (climate, accessibility, particle emissions, noise, safety, robustness, etc.) will develop among policy

maker and the general public. Also, the uncertainties in predicating the effects of policies, or packages of policies, that have previously not been implemented on large-scale was highlighted.

Technological uncertainty

Technological advancements as well as the adoption rates of emerging and future technologies were identified as significant uncertainties in both groups. This covered many technology areas such as maritime fuels development, the future of battery technology, the advent of self-driving vehicles, the trajectory of electrification, the balance between static and dynamic charging infrastructures, and the general development of vehicle technology. The ability to forecast these changes accurately is a considerable challenge but are important for policymakers as they can substantially affect the supply side of the transport system (and therefore indirectly will also affect the demand), as well as the impacts in terms of various societal costs and benefits.

Data and modeling-related uncertainty

Both groups highlighted multiple general challenges related to how to account for uncertain and emerging technologies and phenomena within transport models as well as more specific shortcomings of conventional transport models (such as the aggregation of travelers, commodities, and vehicle types). The freight group also stressed the uncertainty of the current state of the system in terms of the official traffic statistics. For instance, the data of actual traffic and transport work by trucks has significant uncertainty, as well as to what share these are being performed by foreign trucks and drivers. Also, the data on actual freight demand (e.g. in terms of cargo volumes between various geographical

Prioritized uncertainties based on workshop participants' votes

During the workshop, participants were given the opportunity to vote on uncertainties they perceived to be of the highest importance or relevance to consider in the analysis performed in WP2. Freight Transport Uncertainties with Votes:

- Transport demand (now and future development) received the highest votes at 4, indicating a shared concern about accurately predicting current and future transport needs.
- Other uncertainties with a single vote included EU policies in the transport sector, trade patterns (geopolitics and economic structure), technology and availability of batteries, the advent and cost implications of self-driving vehicles, and real behaviors and reactions to policy instruments.

Passenger Transport Uncertainties with Votes:

- Demography was recognized as a significant uncertainty, garnering 3 votes. This illustrates the emphasis on understanding and predicting the impact of population trends on passenger transport.
- Economic development, how the EU governance will evolve, the ability to comply with policy instruments, the potential for planning and decision-making to support trends, the interpretation and implications of the net-zero target, and the evolution of elasticities over time each received 2 votes.
- Uncertainties with a single vote include the unpredictability of another pandemic, the influence of EU governance on national policies, and the limitation of current models reflecting only the existing system.

The voting suggests that there is a shared concern about predicting transport demand and the underlying factors of it, such as trade, demographic shifts, and the economic development. Additionally, uncertainties around technological developments, policies (both domestic and international), and the impact of large-scale global events (like pandemics) are collectively seen as pivotal areas of focus.

Table 4 Freight transport: all uncertainties identified during exercise 2.1

Type	Uncertainty	Votes
Scenario	Maritime fuels and development	
Scenario	EU policies in the transport sector and other areas. Which EU directives do we need to comply with? What technologies is the EU investing in (e.g., H2)?	1
Scenario	Trade patterns (geopolitics and economic structure)	1
Scenario	Crisis and war	
Scenario	How much space will there be on the railway? (how many passenger trains, how many people travel by train today?)	
Scenario	Transport demand (now and development)	4
Scenario	Electric grid capacity	
Scenario	Batteries: technology development and availability (raw materials)	1
Scenario	When will self-driving vehicles arrive, and what is the cost of the technology? Technology, legislation, acceptance	1
Scenario	Development of automated transshipment	
Scenario	Sweden's policies in areas other than transport, e.g., regional policy	
Scenario	How will the market-driven development of charging infrastructure look (different types of static, vs dynamic)?	
Scenario	Cost structures (transport cost components)	
Scenario	Economic development (including foreign trade)	
Scenario	What is happening in the world? China's development?	
Scenario	Immigration	
Scenario	How large a share of domestic/foreign drivers	
Scenario	Vehicle sizes	
Scenario	Distribution between energy carriers	
Scenario	Development of vehicle fleet	
Scenario	"Performance" in vehicles	
Structural: trend	External factors affecting the market (war, pandemic, climate impact)	
Structural: trend	Adaptations to the external situation (logistics strategies, priorities)	
Structural: policy	How companies and households react to taxes, etc.	
Structural: policy	What policy instruments are available for a transport-efficient society, and how effective are they?	
Structural: policy	Monitoring the effects of policy instruments	
Structural: policy	"Real" behavior/reactions to policy instruments	1
Structural: policy	How policy instruments affect different segments (commodity types, industries, regions)	1
Valuation	Peace more important than climate - values not static over time	1
Model	Elasticities in the model (scenario tool), assumed linear, are they stable for large changes?	1
Model	Model limitations in Samgods	
Model	Access to data and statistics	
Model	Models are simplifications of reality	
Model	Commodity type aggregation (in the scenario tool)	1
Model	Vehicle type aggregation (in the scenario tool)	

Table 5 Passenger transport: all uncertainties identified during exercise 2.1

Type	Uncertainty	Votes

Scenario	Black swans	
Scenario	Demography	3
Scenario	Economic development	1
Scenario	Cost and availability of electricity	
Scenario	Cost and availability of biofuels	
Scenario	Cultural differences	
Scenario	Another pandemic?	
Scenario	Are there enough natural resources for all the batteries needed?	
Scenario	Electrification, will it happen and how much?	
Scenario	War, crisis. Shortage of raw materials, globalization	
Structural: trend	Definitions and system boundaries, e.g., "accessibility"	
Structural: trend	Long-term effects of COVID-19	
Structural: trend	Sharing	
Structural: trend	Digitalization - reduced transport needs	
Structural: trend	Variations in effects due to context, combinations of measures, network/scale effects	
Structural: policy	How will EU governance develop and how will national governance be influenced by the EU?	2
Structural: policy	Many stakeholders	
Structural: policy	Unexpected effects of instruments	
Structural: policy	Uncertainty in the effect of electrification policy, such as bonus-malus	
Structural: policy	System boundaries, LCA and assumptions about sustainability/effect (e.g., biofuels)	
Structural: policy	Legitimacy and feasibility of measures	
Structural: policy	Ability to comply with instruments (policing)	1
Structural: policy	Potential for planning and decision-making to support trends and behaviors	1
Valuation	Uncertainty in the view of the climate target, vision, or established policy?	
Valuation	What does the net-zero target mean? Uncertainty in the actual goal formulation	1
Valuation	New goals; biodiversity, cultural effects, etc.	
Valuation	Valuation and benefit of (travel) time and other abstract valuations	
Valuation	Relative valuations of "apples and pears" in models	
Valuation	Environmental thinking, political development	
Valuation	Sensitive when authorities "invent" economic instruments that are not on the political agenda	
Valuation	Political acceptance	
Model	Complex system	
Model	Complex models	
Model	Lacking data/understanding	
Model	Structural uncertainty, linear, step, exponential	
Model	Non-quantifiable values	
Model	How will (average) elasticities develop over time	2
Model	Model can only reflect the current system	1
Model	Models cannot capture heterogeneity	
Model	Uncertainty in model elasticities, applies to driving cost elasticity from Sampers in such major changes?	

3.2.4 Results Exercise 2.2

The results from the discussions and written comments generated during Exercise 2.2 are presented using the main headings in the pre-prepared workshop document: Areas in the Swedish Transport Administration's (planning) activities characterized by deep uncertainty for passenger transport, Exploratory Modeling and Analysis (EMA), ideas for other measures or initiatives to handle uncertainty, other thoughts.

Areas in the Swedish Transport Administration's (planning) activities characterized by deep uncertainty for passenger transport

The freight transport group highlighted that several key inputs for transport forecast rely on forecasts or scenarios developed by other agencies. One example is the long-term scenarios for the economic development in Sweden by the Ministry of Finance which are central deriving various transport forecast inputs related to transport demand. Any uncertainties, and the way such are managed (or not) in these other studies are therefore “inherited” to the forecasts by the STA. The freight group also highlighted the uncertainties of the technological development within vehicles and alternative fuels such as electrification, hydrogen, and automation.

The passenger group reasoned around broad topics such as the need to accept and incorporate that there are deeply uncertain factors that cannot be predicted with a high degree of confidence, and the need to consider alternative societal and paradigm in the planning process. However, other participants questioned to what extent STA should really spend effort on *deep* uncertainties and suggested that focus should rather be on “medium” and shallow uncertainty. Several points were raised related to how the concept of accessibility, and its relation to the need for physical mobility would develop going forward.

For instance, potential changes to the valuation of travel time from a broader view of accessibility which does not only consider mobility. It was also discussed to what extent a more transport efficient society can be developed and how the impacts of a combination of physical planning (e.g. location of workplaces) and other policies could interact to affect travel behaviors. It was also discussed how climate policies will relate to other goals related to the transport sector. Another topic was to what extent the development of electrified vehicles and the use of biofuels would significantly affect what infrastructure investments are included in the investment plan or not, i.e. does uncertainty in these factors have a big impact on the STAs role in planning infrastructure.

Exploratory Modeling and Analysis (EMA)

Some participants saw EMA (and similar approaches) as useful for “opening up” the planning process and to highlight that there are many plausible futures that are legitimate to consider, not just the future that is reflected in the STA base forecast. It was seemed as beneficial to have tools that allow “the whole” outcome space to be considered in various planning and decision analyses, and not just only a single scenario. It was reasoned that the methods for robust decision making mainly are useful for irreversible decisions (such as physical infrastructure) while many other measures, for instance economic policy instruments, are more flexible, and can be better used for managing uncertainty with more dynamic planning methods. It was also mentioned that EMA in combination with more simplified models (compared to the conventional national forecasting models) might be useful to identify interesting scenarios that can then be studied in detail with the conventional models. Also, it was mentioned that EMA in combination with simplified models might be useful to study timing effects of policies and investments, as a compliment to current analysis which are mainly done for a single forecast year.

Several challenges for practical use of EMA were mentioned. Participants noted that interpreting results can be challenging, and there may be too much information for decision-makers. Some also expressed concerns about the ability of EMA to handle large trends with great uncertainty and questioned how trends would be identified or incorporated. One participant stressed that uncertainty/sensitivity analysis are already performed in various phases of the planning process for transport infrastructure. However, there is still a need to base the impact assessments on a single joint main forecast since it is not feasible to make impact assessment of several hundred of investment objects of thousands of scenarios.

Ideas for other measures or initiatives to handle uncertainty

Several ideas for managing uncertainty were brought up:

- Put more effort on gathering knowledge and experiences from other countries' forecasting efforts. This relate both to their methodologies and approaches, but also to more empirical issues, such as identified societal and technology trends and the expected developments of these.
- Broader exploratory analyses and scenarios in the early stages based on a comprehensive definition of accessibility; regionalized scenarios in collaboration with other planning levels and relevant agencies - leverage regional expertise!
- A structured approach to testing, evaluating, and learning from interventions - overcoming the "catch 22" in knowledge building.
- Use model results and scenarios as communication tools, i.e., as a basis for discussions, rather than as final outputs.
- Conduct sensitivity analyses that reveal actual effects on various objectives (e.g., effects on actual carbon dioxide emissions, rather than being translated to the uncertain cost valuation of carbon dioxide, where effects due to model assumptions are usually considered minor compared to time savings).
- Work more qualitatively with uncertainty and potential futures.
- Engage more in backcasting.
- Improve impact assessments of control measures/actions within a transport-efficient society.
- The STA needs to be more agile and use our expertise on traffic work development in a broader manner than just the base forecast.

Other thoughts

Under this heading, there are two main categories: general thoughts and reflections about uncertainty in transport planning, and thoughts relating to the case study in WP2 and for the remainder of the MUST project.

The general thoughts were:

- This workshop series mainly separated the work into freight and passenger groups. This separation might not be beneficial since many uncertainties and issues are common for both passenger and freight transport.
- There is an excessive reliance on quantitative tools: only aspects that can be quantified are included.
- Generally, decision-makers and many others prefer "simple" scenarios with just one or two options. They do not "like" uncertainty but rather things that are easily communicated.
- EU policy is crucial and will likely overshadow national objectives and control measures relatively soon (it has already in some cases). This leads to a more complex world to analyze.

- It is important to not just consider robustness, but also adaptivity in policy analyses. Many policy measures can be understood (and modelled as) dynamically changeable and potentially temporary - even international measures are renegotiated, refined, and withdrawn. Allow for risk diversification!

Thoughts that primarily related to the case study in WP2, and other forthcoming work in the project.

- It is important to remember the responsibility of the Swedish Transport Administration (STA): to plan transport infrastructure. What matters for this work? For the STA, biofuels and electricity are factors outside of their control; what the STA can influence is the infrastructure (and the transport system through support such as urban environment agreements, perhaps financing of so called “stage 1 and 2”, co-financing, etc.). Uncertainties relating to planning for a transport-efficient society, are more crucial for the STA than uncertainties in biofuels and electricity.
- It would be beneficial to more clearly consider how these tools (EMA and DMDU methods) relate to the STA’s core task: planning of physical transport infrastructure.
- It would be a good idea to collaborate with organization with a detailed understanding about transport policy design.
- It is important with realistic input distributions in EMA analyses.
- It was questioned the chosen case (climate policy needs) really characterized by *deep* uncertainty.

4 Trafikverket's Scenario Tool: description and applicability

One task in work package 2 is to assess the Scenario tool (version 1.0)[11] (Trafikverket, 2020a) and the application of it to generate policy scenarios for reaching the climate targets as part of the governmental task to develop alternative scenarios for the transport system (Trafikverket, 2020d). This assessment mainly aims to provide an understanding of how the Scenario tool can be used as a case study in work package 2. In this chapter, there is also a brief summary of the modifications of the Scenario tool that have been performed as part of the case study in work package 2. Note that the majority of work package 2 is delivered in other deliverables than this report, see Table 1.

The assessment of the Scenario tool was conducted in two steps. First, during Q1 2022, a read through of the scenario tool documentation (Trafikverket 2020a) and previous scenario analysis (Trafikverket, 2020d) was done. In parallel, the scenario tool was explored to get a feeling for its features and behavior. Also, the analyses from the previous scenario analysis were recreated to see whether the same results were achieved and if the model behaved as expected. The second step consisted of further developing the scenario tool to include effects of driverless vehicles and to utilize it as a case study in the robustness analysis of climate policies. This hands-on work gained additional insights about the tool.

4.1 Description of The Scenario tool

Trafikverket releases a new base forecast for the development of the Swedish passenger and freight transport system every fourth year, with minor updates every second year. The latest base forecast was released in June 2020 with a base forecast for the years 2040 and 2065 (a new forecast with minor updates was released in 2022). A major change in how the 2020 base forecast was developed compared to previous base forecasts, is that it assumed that the domestic transport-sector's climate target of reducing annual direct territorial CO_2 emissions by 70% in 2030 compared to 2010 levels, and the national target of reaching net-zero emissions by 2045 will be achieved, and that corresponding policy measures will be taken. An overarching principle for the base forecasts is that they should reflect decided policy. Since 2017, the climate goals are part of a Climate Act for Sweden and therefore the base forecast needs to align with these climate goals. In their governmental instructions for 2020, Trafikverket was given a task to provide alternative forecast scenarios for the transport sector and how they relate to the political goals for the transport area, including the climate targets (Trafikverket, 2020d). This in turn triggered the development of the Scenario tool.

The Scenario tool (Trafikverket, 2020a) is an Excel-based tool that is intended to support the analysis of whether various climate strategies (combinations of policy measures) lead to a future which meets the climate goals or not. The Scenario tool covers domestic[12] road transport including light vehicles

[11] The review has been done for version 1.0 which is available through this link https://bransch.trafikverket.se/tjanster/system-och-verktyg/Prognos--och-analysverktyg/scenarioverktyget-for-styrmedelsanalyser/ (accessed by the authors 2023-02-07)

[12] Traffic activity performed at swedish territory

(cars and light trucks[13]), heavy trucks and, partly, bus traffic. The scenario tool is developed to study climate strategies that include three types of policy measures 1) an increased share of electric vehicles and more fuel-efficient vehicles, 2) an increased share of renewable fuels, 3) reduced road traffic activity. More specifically, the Scenario tool allows the user to evaluate measures regarding

- blending of sustainable biofuels[14]
- fuel tax
- kilometer tax
- share of electric vehicles (only a choice between two levels – decided or ambitious politics)
- energy efficiency
- external reduction of vehicle kilometers travelled from e.g., transport planning and parking policy measures and
- energy use from buses

The Scenario tool is intended to mimic how the conventional transport models used for producing national forecasts in Sweden, *Sampers* (for passenger transport) (Beser & Algers, 2002), *Samgods* (for freight transport) (Bergquist et al., 2020; de Jong & Baak, 2020) and *Bilparksmodellen* (for car fleet modelling) (Beser Hugosson et al., 2016) reacts on changes in driving costs (including both variable and fixed costs for passenger cars but only variable costs for trucks) at an aggregate level. Using the Scenario tool, alternative forecast scenarios can be made for the years 2030 and 2040[15].

The starting point for the Scenario tool is a default reference scenario based on the base forecast from year 2018 using Sampers and Samgods for passenger cars and trucks respectively, which contains assumptions on population growth and car ownership for the Swedish population for the years 2030 and 2040. From this starting point, the scenario tool calculates changes based on the policy measures the user enters the tool. This calculation of changes is done in three steps: 1) calculation of changes in driving costs, 2) calculation of changes in vehicle kilometers travelled and 3) calculation of updated effects (CO2 emissions, energy use and tax revenues). Elasticities intended to mimic the behavior of the national models are used in step 1) and step 2) as described above. The elasticities are summarized in Table 6. Driving costs for vehicles using different types of fuels or propulsion technology are first calculated separately in step 1. However, for the subsequent steps, the driving cost is expressed as a weighted sum of different vehicle types based on their share of total VKT.

Table 6 Default elasticities used in the Scenario tool.

Elasticity	**2030**	**2040**	**Used in step**
Passenger cars changing to electric in response to fuel price	0.07	0.19	1
Fuel consumption in response to fuel price for diesel and petrol passenger cars	-0.05	-0.05	1
Fuel consumption in response to fuel price for diesel trucks	0.00	0.00	1

[13] With maximum permissable weight less than 3.5 tonnes

[14] Swe: "reduktionsplikt"

[15] Year 2040 has been used instead of 2045, since 2040 is the forecast year in the national base forecast.

Car ownership for passenger cars in response to driving cost	-0.10	-0.10	2
Vehicle kilometers travelled for passenger cars in response to driving cost (excluding the effect of car ownership)	-0.20	-0.20	2
Vehicle kilometers travelled for trucks in response to driving cost	-0.22	-0.22	2

4.2 Previous work by Trafikverket for identifying climate strategies using the Scenario tool

Trafikverket have, using the Scenario tool, identified eight climate strategies that manage to reach the climate target for the base scenario, which vary in the combination of policies applied to reach the goal (Trafikverket, 2020d). In other words, these climate strategies are by design goal fulfilling and illustrate different ways of reaching the climate targets, assuming the development of other factors in line with the reference scenario. All eight climate strategies apply ambitious politics (in the choice between decided and ambitious politics) for the share of electric vehicles in the fleet, i.e., it is assumed that national Bonus-Malus measures are added to the already decided EU-requirements for vehicle manufacturers regarding vehicle emission levels with a corresponding resulting electrification rate of the vehicle fleet. The eight climate strategies are summarized in Table 5. Details on policy parameter settings and results are available in (Trafikverket, 2020a).

Table 7 Climate strategies (scenarios) developed by Trafikverket using the scenario tool (Trafikverket, 2020d).

Climate policy strategy	**Description**
B	Biofuel scenario
C1	High fuel tax, biofuel use limited to 20 TWh in 2030
C2	Fuel and kilometer tax, biofuel use limited to 20 TWh in 2030
C3	High fuel and kilometer tax, biofuel use limited to 13 TWh in 2030
C4	High fuel tax, biofuel use limited to 13 TWh in 2030
D1	External reduction of VKT, fuel and kilometer tax, biofuel use limited to 20 TWh in 2030
D2	External reduction of VKT, high fuel and kilometer tax, biofuel use limited to 13 TWh in 2030
D3	Large external reduction of VKT, high fuel and kilometer tax, biofuel use limited to 13 TWh in 2030

Two of the policy strategies identified using the Scenario tool, namely: B and C2 were thereafter analyzed more in-depth, see Trafikverket (2020e) for details. This analysis was made using the national forecasting models Sampers and Samgods in which the corresponding policy strategies were represented. Policy C2 includes fuel- and kilometer-taxes that will substantially increase driving costs for trucks and cars. These taxes were estimated to increase the average driving cost for cars by about 50%, and for trucks by around 75%, compared to a reference policy strategy based on the previously decided policy at the time of the analysis[16]. This increase in transport costs could negatively affect accessibility and therefore also the economic activity as well as production volumes and trade

[16] The reference policy strategy was forecasted to reduce direct CO2 emissions by roughly 45% until 2030 and 60% until 2040, both compared to 2010.

patterns of different commodities. Since Samgods relies on an exogenous, fixed, matrix of freight volumes between each model zone, a new freight demand input matrix for the Samgods model was calculated to account for the increase in driving cost. Based on the model results from Sampers and Samgods, an assessment of the two policy strategies in terms of monetized societal costs and benefits over a 40-year analysis horizon was made. This assessment was made using cost-benefit appraisal covering: producer surplus, budget effects, consumer surplus, external effects (excluding CO2 emissions since a specific reduction is a prerequisite of the analysis), maintenance and re-investments, and welfare effects from changes in economic activity due to changed transport costs. The societal benefits and costs for each of the two policy scenarios were compared to the reference policy strategy based. The analysis by Trafikverket (2020e) estimated that both policy strategy B and C2 would generate a net loss in terms of societal costs and benefits (total costs are higher than total benefits). However, the estimated loss is substantially greater for strategy C2: - 2 240 billion SEK for C2 compared to -70 billion SEK for B. Following this analysis, policy strategy B has been adopted as the presumed transport climate policy in subsequent base forecasts up until currently (Trafikverket, 2020c).

4.3 Applicability and limitations of the Scenario tool

The main aim of the Scenario tool is according to Trafikverket (2020a, p. 6) to *simplify analyses of the road transport sector's CO2 emissions*. Furthermore, it is stated that the conventional forecast models that produce more disaggregate and detailed forecasts (Sampers and Samgods) are complex, require a large and broad set of input and are time- and resource intensive to run. Therefore, they are practically unsuited to use for identifying goal-fulfilling scenarios by iterating over parameter space of policy lever combinations. The Scenario tool can therefore be used to on an overarching level quickly test many policy combinations to identify a set of policy candidates. It is highlighted that the Scenario tool is suited for high-level analysis on the national level, primarily due to its aggregated representation of vehicles and transport demand, and simple representation of complex causal relationships (e.g. between driving costs and transport demand, and changes in the vehicle fleet composition). To summarize, Trafikverket describes the Scenario tool as an option to quickly perform rough, aggregate analyses of climate policies iteratively and exploratory.

The Scenario tool can be used in a sequential process in conjuncture with the conventional forecasting models in which the Scenario tool is first used to identify policy candidates based on their estimated impacts. The Scenario tool provides an approximation of the corresponding input data for representing these policies in Sampers or Samgods. The candidate polies can therefore then be analyzed more in detail with these models to provide data for more comprehensive decision support (e.g. analysis of societal costs and benefits, distribution effects, etc.). In the analysis by Trafikverket (Trafikverket, 2020d), this process with a detailed analysis in Sampers and Samgods, was applied to two of the eight policies identified with the Scenario tool. The reason why only these two scenarios were analyzed in with Sampers and Samgods is not clear from the reports, but it can be assumed that the resource demanding implementation and analysis of results as well as conceptual challenges with representing measures for transport efficient planning (which are considered in policy strategies D) contributed. This situation highlights how a less detailed, but also more flexible and faster model, such as the Scenario tool, and more detailed, but less flexible and more resource demanding models, such as Sampers and Samgods, can complement each other. Firstly, the less detailed model can be used to generate policy options which are then analyzed more thoroughly with the more detailed model. Secondly, the less detailed model can sometimes be used to generate a first-order estimation of impacts of scenarios or policies which are challenging to represent from a conceptual or resource perspective within the more detailed model. In this sense, simpler models might enable a broader exploration of scenarios or policies. In addition, the simpler model can enable more systematic and extensive sensitivity- and uncertainty analysis, or optimization-based analyses, which typically requires evaluation of a large number of model instances. Therefore, less detailed models might be more appropriate to use for various DMDU applications.

In the case study in work package 2, it is explored how the Scenario tool can be further leveraged by DMDU. More specifically, MORDM (see Section 2.2.3) is applied to assess to what extent it may allow a broader set of policy options to be explored, and how it can provide a better understanding of the robustness and vulnerabilities of different types of policies. This analysis will be published as a separate research paper[17]. The remainder of this section will present an assessment of the Scenario tool, followed by a brief summary of modifications to the Scenario tool which have been done within the aforementioned case study. The modified Scenario tool, and all code used for the MORDM case study will be published in a public code repository.

The assessment of the Scenario tool identified limitations and weaknesses of the tool. Some of these are already mentioned in Trafikverket's documentation of the tool (Trafikverket, 2020a). The findings of the assessment are summarized in Table 8. Please note that the assessment is not exhaustive and that it contains remarks of different nature. Some remarks relate to conceptual issues about system boundaries, model design choices and assumptions, while others concern the technical implementation, and the user friendliness of the tool. Furthermore, this assessment is not intended as a critique of how the tool was designed and applied for its original purpose. Some of the things pointed out are design choices that are well-suited for the analysis the Scenario tool was initially developed for. Furthermore, for the assessment of the Scenario tool was used for, some of the limitations were remedied by that a selection of scenarios identified through the scenario tool where also analyzed in Sampers and Samgods, which allowed some of the simplified relationships in the scenario tool to be studied more in detail, and to study various effects that are not covered by the Scenario tool, for instance accessibility impacts. The purpose of this assessment is rather to describe what type of problems the tool is more or less suitable to be applied for and provide a basis for further development for other applications.

[17] If the paper is not published when you are reading this report, contact Albin Engholm: aengholm@kth.se for more information.

Table 8 Identified limitations and simplifications in the Scenario tool.

Type	Issue	Addressed in MUST WP2 case study?
Design and assumptions	The validity and quality of the various elasticities used in the tool can be questioned. All elasticities are assumed linear. Some of the elasticities derived from Samgods/Sampers/bilparksmodellen are based on old analyses on similar, but not identical, scenarios and cost changes as the ones studied with the scenario tools. Other elasticities are based on (undisclosed) expert judgement or international research literature. Some scenarios studied using the Scenario tool result in substantial changes in driving costs (+100% for private cars and +300% for heavy trucks). It is not clear whether the elasticities are valid, and linear, for such large changes in cost.	Model elasticities which are considered uncertain are included as uncertain parameters when performing robustness analysis
Design and assumptions	The Scenario tool is highly aggregate in several dimensions: vehicle types (e.g. aggregated to one type of powertrain), geography (all calculations are on national level), trip-purposes (no separation), commodity types (no separation) and cost components (no separation into e.g. fixed, time-dependent, distance dependent) when calculating changes in driving costs and the resulting impacts on demand. This level of aggregation be argued to be too extensive even for a highly simplified model as the Scenario tool.	No
Design and assumptions	The distribution of truck traffic between different truck weight classes or powertrains is static. The choice not to account for shifts to battery electric trucks as a result from increases in driving costs for diesel trucks (which in some of the studied scenarios is in the order of several hundred percent) is motivated by a lack of foundational data for including this effect (Trafikverket, 2020a, p. 12).	Partly. A shift to electric trucks due to increased driving costs is included as an uncertainty when performing robustness analysis.
Design and assumptions	The modeling of electrification policy is highly limited with only two levels of electrification to choose between. All evaluated climate policy strategies assume the higher level.	Yes. Electrification rate is modeled as an external factor in the case study and the extent of it is varied in the robustness analysis.

Design and assumptions	No direct possibility to evaluate impacts of scenarios with different economic developments.	No
Design and assumptions	Fuel and energy costs are modeled as independent to fuel demand. This might be important for biofuels for which there might be supply shortages.	No
Design and assumptions	No dynamics, such as time delays, or other time dependent effects in system response to policies.	No
Implementation and bugs	In general, there is a lack of “reality checks” and handling of infeasible results. For instance, negative demand can occur in the model if demand elasticities are assumed larger than the default values and/or driving costs are increasing substantially.	No
Implementation and bugs	A few minor bugs have been identified and corrected: • Error in calculation of changes in fuel consumption due to fuel prices for heavy trucks. • Error in calculation of traffic volumes. Both the 2030 and 2040 calculations were based on the demand elasticity for 2030. This has not affected the previous analyses since by default, both elasticities are the same. • Error in calculation of fuel tax for diesel for which the gasoline fuel tax change input parameter was used. This has not affected the previous analyses since the same fuel tax change rate was applied to both diesel and gasoline in all scenarios.	Yes, corrected.
Scope and metrics	Only emissions from road transport are included which means that the definition of climate target fulfilling policies is not fully aligned with the climate target definitions (which cover all domestic emissions from transport).	No
Scope and metrics	Only direct emissions, i.e. tank-to-wheel are considered. There are no metrics for life-cycle emissions of fuels, electricity, or vehicles. Considering emission impacts on other non-transport sectors might be one relevant factor to consider for crafting robust transport climate policies, in addition to the direct emissions covered by the transport sector’s climate target.	No
Scope and metrics	Electric cars and trucks are the only technology innovation considered. Other potential developments such as automated driving and digitalization of the transport system are not considered	Yes. Automated vehicles are considered and modeled in the case study.

Scope and metrics	No metrics for accessibility losses. This might be particularly important for car users outside cities.	No
Scenarios and uncertainty	Only nine policy strategies are evaluated (one reference policy and eight goal-fulfilling policy strategies). It is not fully clear how these strategies were designed and to what extent they span the plausible decision space.	Yes. A large set of Pareto optimal policies are generated using optimization in the case study.
Scenarios and uncertainty	All policy strategies are only evaluated against a single reference scenario (corresponding to the base forecast). This scenario contains many uncertainties such as future fuel and energy prices, economic development, trade patterns, etc. These developments of these factors affect the policy needs for reaching the climate target climate policies, and different policies might perform better or worse in different types of scenarios.	Yes. An extensive uncertainty and robustness analysis is performed in the case study.

As shown above, there are many possible development areas for the scenario tool. In the case study in WP2 a few of them are addressed which are important for enabling the intended analysis. For the case study, the following modifications to the scenario tool have been made.

- The identified bugs were corrected.
- The reference Scenario was updated. Since the Scenario tool was developed, new base forecasts (the 2020 and 2023[18] editions) have been published. The input data and reference scenario has been updated to align with the base forecasts of 2023[19] which primarily consisted of a minor adjustment of forecasted transport demand and updating the assumptions about electrification rate and biofuel shares in line with Table 9[20].
- A module to enable a crude analysis of potential impacts of automated driving technology (driverless vehicles) was added. Driverless vehicles are assumed to impact driving costs and energy efficiency, see the orange box in Figure 19. To facilitate this, also non-fuel/energy related costs for trucks are included (derived from ASEK 7), and, the elasticity for truck traffic in response to changes in driving costs has been adjusted accordingly. More details on the modeling of driverless vehicles are provided in the research paper.
- To reduce the number of decision variables when applying optimization to identify policies, a single lever has been introduced to denote the total volumetric admixture of biofuels for diesel and gasoline, respectively. This lever can be used to override the individual levers for different types of biofuels from the original version. The new mechanism prioritizes FAME and Ethanol over HVO since they are generally cheaper, up to a threshold at which the chemical quality of the fuel is affected, assumed at 7% for FAME and 10% for Ethanol (Trafikverket, 2020b), beyond which HVO is used.
- In the case study, the Scenario tool is not used via its Excel interface. Instead, it is set up and run via Python, using the open-source library EMA-workbench (Kwakkel, 2017). A new sheet in which all inputs are specified, and all outputs are read from, is added to streamline the communication between the Scenario tool and Python.

Table 9 Assumptions for electrification rate and degree of admixture of biofuels used for the 2020 and 2023 base forecasts. These values are, in the base forecasts, assumed to be consistent with reaching the Swedish climate targets for 2030 and 2045.

Assumption	**Value used for 2040 in base forecasts 2020 and 2023**
Electrification rate, share of VKT [%]	Cars: 68% Truck <3.5t: 68% Truck <16t: 85% Truck <24t: 85% Truck <40t: 36% Truck <60t: 19%
Biofuel shares of gasoline fuel volume [%]	Ethanol: 10% HVO: 63%

[18] The 2023 edition is a revision of the 2020 forecast to account for changes in planned infrastructure investments. All other key assumptions and inputs are equal to the 2020 forecast.

[19] Only the values for 2040 have been updated, since this is the year studied in the case study.

Biofuel shares of diesel fuel volume [%]	FAME: 7% HVO: 63%

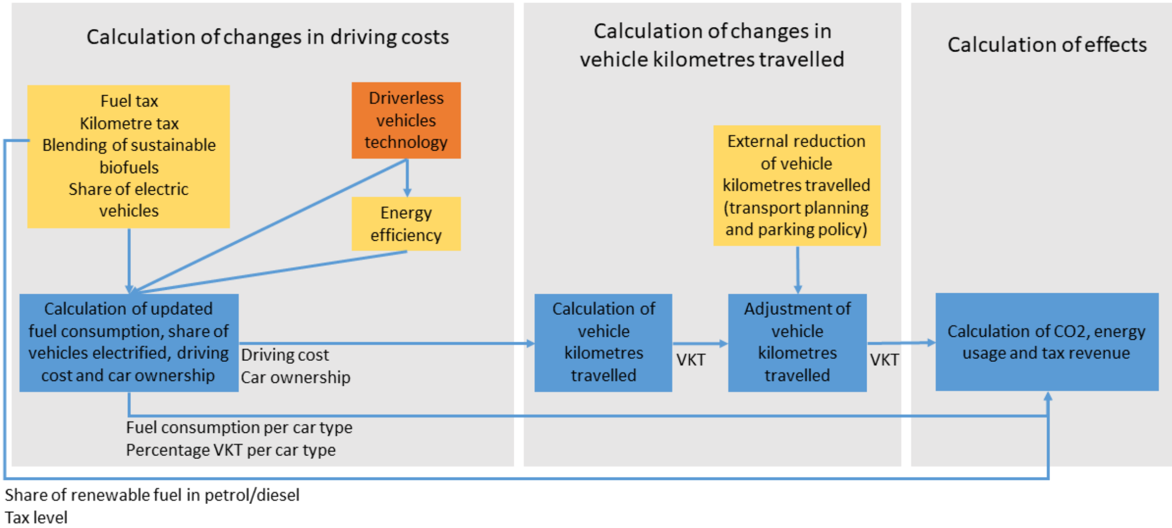

Figure 19 Overview of the calculation steps within the Scenario tool and an indication of how driverless vehicles technology is included.

5 Concluding discussion

Phase 1 of the MUST project covered three main activities: a literature review and workshop series (work package 1), and a case study in which MORDM was applied to Trafikverket's scenario tool aiming to improve transport climate policy making under deep uncertainty (work package 2). The remainder of this section summarizes overarching conclusions and reflections that have emerged throughout this work.

At its core, uncertainty is a limited knowledge of past, current, or future events. *Deep uncertainty* refers to situations where it is challenging to assign probabilities due to system complexity, scarce information, or inherent unpredictability of complex systems. Deep uncertainty leads to a need to consider a multiplicity of futures, which is typically challenging in conventional model-based planning or policy analyses, since they tend to rely on a "predict-then-act" framework in which forecasts generated with (relatively) computationally demanding transport models are used as the underlying basis for policy analysis. Both the literature and workshop results suggest that uncertainty is widely acknowledged as being present in many stages of planning and policy analyses processes. There is thus a need to more systematically account for it in the planning and policy analysis practice. Current Swedish transport planning practices and policy analyses in general, and the planning of national infrastructure, are in several central aspects characterized by standardized point estimates of uncertain, ambiguous, or complex variables. For instance, the use of a joint single reference scenario (the base forecast) and associated input assumptions for impact assessment of investments, policies, or other measures; and the use of standardized weighting of objectives (i.e. impact valuation and other parameter assumptions for calculation of societal costs and benefits for performing cost-benefit analyses). This standardization has solid motivation, for instance to ensure comparability between analyses of different objects (e.g. comparison between different investment options), and to enable easy-to-interpret metrics for decision support (e.g. a single metric of cost-benefit ratio for a single scenario). However, this standardization also means that a set of specific assumptions about the future, and valuation of outcomes, gets "locked in" as a central planning prerequisite. This prerequisite can be expected to limit to what extent analysts put emphasis on uncertainty, how sensitivity analyses are constructed and to what extent policy makers consider it.

The results from the literature review and workshop series both suggest that the deep uncertainty in model-based analysis in the transportation domain often relates to specifying model inputs, so called *scenario uncertainty.* For instance, this was a key result of the uncertainty analysis of the base forecast process performed during workshop 2 which identified many deep scenario uncertainties both for passenger and freight transport (see Section 3.2). Scenario uncertainty is not alleviated by developing "better" models (in the sense of the model making more accurate predictions for a given set of inputs). Instead, managing scenario uncertainty either requires improving the prediction of model inputs, which might be costly to achieve, or even infeasible due to ontological uncertainty, or that the decision analysis process is adapted to account for scenario uncertainty. The ubiquitous presence of (deep) scenario uncertainty in many transportation planning and policy making applications is a key motivation for why Exploratory Modelling and Analysis (EMA) and Decision

Making Under Deep uncertainty (DMDU) can be beneficial approaches for improving model-based transport planning and policy analysis, since they offer concrete tools for managing such uncertainty. While it is important to continuously improve transport models, e.g. in terms of the modeling of key decisions of different actors in the system, the level of resolution and detail, and the representation of current and emerging technology, behaviors, and preferences, it is also important to systematically improve how to use and apply these models to generate relevant and appropriate decision support in the presence of (deep) scenario uncertainty. An overarching insight from the literature review and workshop series, is that in the transport modeling practice, for applications related to planning and policy analysis, this is an area with potential for improvements.

Another important area of uncertainty relates to the modelling of policies, or combinations thereof, which have previously not been implemented or properly evaluated. This may imply a high degree of uncertainty about the policy impacts, efficiency, and costs, and that it is not clear how to appropriately represent the policy in the transport model. Examples could be policies to support large-scale electrification of cars and trucks, or measures for achieving a higher degree of transport efficiency. On a conceptual level, DMDU is capable of accounting for such uncertainty through exploratory modeling. Using the XLRM framework (Figure 6), uncertain policy impacts can be represented as parametric uncertainty and accounted for in uncertainty or robustness analysis. Similarly, uncertainty about policy representation could be managed by using alternative model formulations. However, it is noted that DMDU does not support how policies could be represented in various model specifications, which might in practice be a more challenging issue than accounting for this uncertainty once alternative model formulations are specified and implemented.

The literature on approaches for dealing with deep uncertainty in model-based policy analysis has developed substantially during the last decade. One important development is the emergence of DMDU as an umbrella term, and a distinct research field, combining existing and emerging DMDU approaches. This seems to have sparked research towards a broader and more general understanding of DMDU and how its various tools and approaches differ, when and how they are complementary and the appropriateness of different approaches for different types of policy problems and domains. There is also a growing number of case studies applying different DMDU methods to various problems. Furthermore, the field has benefitted from the development of well-maintained open-source software supporting DMDU, such as the general-purpose EMA-Workbench[21] (Kwakkel, 2017), and the transportation modeling focused TMIP-EMAT (Lemp et al., 2021). The availability of these tools has lowered the barrier for experimenting and implementing DMDU for researchers and practitioners. It is also noted that there is an active DMDU research community (DMDU Society[22]) which, among other activities, has held annual meetings since 2013. However, as noted by Stanton and Roelich (2021), the DMDU literature has to a large extent so far been focused on method development and prospective case studies with limited effort on the policy making context and how DMDU can be successfully applied for real-world policy making.

[21] EMA-workbench is available at: https://github.com/quaquel/EMAworkbench
[22] https://www.deepuncertainty.org/, latest accessed by the authors 2024-01-11.

An overarching insight from MUST phase 1 is that DMDU has potential to improve transport planning and policy analysis, since it offers systematic approaches for accounting for scenario uncertainty and policy impact uncertainty. Given the increasing maturity of the DMDU research field, and availability of tools, it is tractable to seriously explore and assess the practical usefulness of various DMDU approaches for different planning and policy issues and in various phases thereof. The purpose of the case study in work package 2 and of MUST phase 2 is to make initial work on such an exploration in a Swedish transport context by using real-world policy problems and models used by the Swedish Transport Administration. For specific, stand-alone, infrastructure investment analyses or policy analyses, these approaches may be relatively straightforward to implement without significantly additional effort. For instance, many methods for robust decision making are simple to apply in cases where there are predefined planning or policy options, given that the system model can be used to represent the deep uncertainties of interest.

It is, however, presumably a fairly long way to go for DMDU to become a core approach within the standard national transport infrastructure planning practice. Although there is a broad trend for transport planning in general to develop more into scenario-based approaches (Lyons et al., 2021) the current practice follows a clearly defined, but complicated and resource demanding, process which has its roots in a “predict-then-act” paradigm (Lempert et al., 2003). Also, this process is to a large extent bounded by politically decided regulations. A central issue is to consider and assess to what extent DMDU can and should be used during different stages of the planning process. Also, it needs to be analyzed to what extent DMDU can and should constitute a complement to existing practices or whether it would be required to more fundamentally adjust certain parts of the planning process. Applying DMDU to existing national transport models (Sampers and Samgods) requires a non-negligible amount of work to adapt the models and their infrastructure to enable EMA or DMDU. It requires the development of tools that supports to automatically generate, implement, run, and store relevant results from hundreds or thousands of scenarios. The EMA model infrastructure developed in MUST phase 1 is primarily designed for (semi-) manual scenario handling, and the scenario data consists of GBs of data. Furthermore, the rather long computation time of these models is an issue that needs to be accounted for and managed. In phase 2 of MUST, EMA is applied to the Samgods model and some of these issues will be explored. Another broader concern relates to how an increased use of DMDU approaches could affect transparency, and complexity of the decision support both for policy makers and citizens more generally.

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Appendix

Workshop series

Table 10 Participants in Workshop 1.

Name	Organization
Ida Kristoffersson	VTI
Sabrina Brunner	VTI
Albin Engholm	KTH ITRL
Anna Pernestål	KTH ITRL
Jacob Witzell	VTI
Rune Karlsson	VTI
Johanna Takman	VTI
Stefan Kurki	Trafikverket
Marcus Sundberg	Trafikverket
Peter Almström	Trafikverket

Table 11 Analysis needs from Exercise 1.1 that the freight transport group did not have time to map

Analysis need	Assosciated uncertainty
Validation of the Samgods model	Difficult to validate – data is lacking. Detailed validation is challenging due to unclear definitions (e.g. vehicle types). Deficiencies in ASEK values.
Understand impacts on freight transport demand due to increasing fuel prices	Modal distribution? New routes? Increased cargo consolidation?
Understand impact on choice of transport mode due to automation of freight transport (trucks)	Will there be a modal shift? Impact on driving times, routes, costs, emissions?
Impacts of changes fees and taxes	
Need for maintenance and new road infrastructure	
Where should charging infrastructure be built	Where is charging demand? Where is electricity supply?
Potential for measures for “transport efficient society”	How to model this? Data needs? Effect measures of interventions
Corridor-analyses (e.g. central Sweden to northern Germany)	
Efficient policies for reaching the climate targets	System boundaries. Scenario assumptions. Emission calculations
How will road transport volumes be affected by electrified trucks?	Electrification rate

Will 5G have any impact on transport (volumes, locations, speeds)?	
Contact surface road/rail/sea. How achieve modal shift from road to sea and rail in general?	
How will the split between different types of fuels and energy sources look like? Electricity, H2, bio-diesel, etc.?	What affects this distribution? Energy prices, battery prices, charging availability, etc.
Share of electro mobility in truck fleet. Which freight companies will electrify their transports?	Battery development (technology uptake). Availability of charging infra who/when/where. How will business models for freight companies change due to new technologies? Chicken-egg problem: electric trucks <-> charging infrastructure.
How will different policy measures affect transport flows?	
Policies and the policies for the future?	

Table 12 Participants in Workshop 2.

Name	Organization
Ida Kristoffersson	VTI
Albin Engholm	KTH ITRL
Erik Almlöf	KTH ITRL
Jacob Witzell	VTI
Inge Vierth	VTI
Helen Lindblom	Trafikverket
Disa Asplund	Trafikverket
Jenny Karlsson	Trafikverket

Områden i Trafikverkets (planerings)verksamhet som präglas av djup osäkerhet

Vilka frågor/områden som karaktäriseras av djup osäkerhet är av särskilt stor betydelse för Trafikverket? Hur stort är problemet?

EMA

Hur kan EMA bidra till att förbättra hanteringen av osäkerhet? Vilka problem kan adresseras? Vilka praktiska problem kan uppstå vid implementering? Vilken påverkan skulle detta ha på planeringsprocessen?

Idéer på andra åtgärder eller initiativ för att hantera osäkerhet

Vilka andra typer av åtgärder kan stärka Trafikverkets förmåga att hantera djup osäkerhet. T.ex. inom

- *Organisation och kompetens*
- *Anpassning av prognos- och planeringsprocesser, eller dess förutsättningar, T.ex. behov av att hantera fler scenarier, mer data, etc.*
- *Prognosmodeller (t.ex. Sampers/Samgods)*
- *Beslutstöd, analysverktyg, etc.*

Andra tankar

Figure 20 Headings and supporting questions used as a basis for the discussion in Exercise 2.2