TRANSPORTATION PLANNING FOR UNCERTAIN TIMES

A Practical Guide to Decision Making Under Deep Uncertainty for MPOs

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<tr><td colspan="3">16. Abstract
Transportation agencies must pursue ambitious goals in the face of intense, large-scale, and increasingly fast-paced change. They are also mandated to produce regular planning documents. But those documents have diminishing credence in the face of rapid and uncertain change, and the means used to produce them have difficulty in supporting more far-reaching strategic deliberation. Traditional planning methods, designed to use simulation models to provide future reliable demand forecasts, may often prove less sufficient than in the past. Such "predict-then-act" analyses can foster over-confidence and so limit consideration of strategic alternatives or the range of plausible future conditions. Planners and modelers might arrive at myopic decisions because they underestimate the uncertainty. Predict-then-act analyses can lead to gridlock when stakeholders contest the assumptions used to justify a proposed plan rather than work together to identify a plan that performs well over a wide range of scenarios.

MPOs now have available emerging methods and tools for decision making under conditions of deep uncertainty (DMDU). DMDU approaches can help planners and modelers augment their current modeling capabilities to identify and evaluate strategies that can help their agencies meet goals in the face of today's fast-paced change. DMDU methods use simulation models not as prediction engines but as exploratory tools. DMDU methods may therefore run an MPO's simulation models or their surrogates over a range of plausible futures to stress-test proposed plans and then use the results of those stress-tests to identify strategies that are low-regret, flexible in their ability to adjust over time, and shape the future along pathways consistent with desirable policy outcomes.

DMDU use in MPOs has to date been limited, in part owing to both analytic and organizational challenges. Based on experiences interacting with MPO planning and modeling staffs, this report summarizes DMDU analytics, stakeholder processes supported by DMDU, and offers guidance for agencies interested in bringing such methods into their organization.</td></tr>
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The report first introduces the DMDU concept which embraces a range of quantitative and qualitative methods. In particular, the report discusses in detail robust decision making (RDM), a specific model-based DMDU method that recommends itself as being potentially consonant with model-based analysis currently practiced in MPOs and other transportation agencies. The report reviews the methods and quantitative tools available to support MPOs in using RDM including the participatory processes with stakeholders supported by the analyses and the software packages available to facilitate RDM analyses. The report describes case studies of RDM and other quantitative and qualitative DMDU applications which have been employed by MPOs.

The report concludes with an organizational perspective of MPOs and their transportation planning functions. It lays out a value proposition for enhanced strategic foresight capabilities – the goal that DMDU methods seek to achieve, lays out several of the obstacles that might retard or prevent movement in that direction, suggests incremental steps toward implementation, and finally provides a guide that may be used by agencies as a whole or their modeling or planning staffs to gauge progress toward achieving a greater facility for accounting for and managing future uncertainties as part of their regular process.

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Summary

Transportation agencies are mandated to produce a series of regular planning documents. Despite being updated every 4-5 years, the pace and scale of today's change renders this planning output increasingly less useful for strategic guidance. A growing problem is that traditional methods and tools used by MPOs are based on predicting future values for important transportation trends and outcomes. Both the pace and scale of today's change means forecasts have become increasingly unreliable. The result is that the planning process produces documents that might receive diminishing credence from the public and fail to serve the needs for strategic guidance to the agencies themselves. New tools that have been developed and applied in other areas -- decision making under deep uncertainty (DMDU) methods -- are now beginning to be adopted by MPOs to address perceived shortcomings in transportation planning.

The preliminary uses are not to supplant large travel demand models that lie at the heart of most MPOs. Rather, DMDU tools have been used to shed greater light and support a strategic perspective within the agency that is difficult to achieve solely with long run-time demand models. Traditional planning methods, designed to use travel demand models to provide reliable future demand forecasts in "predict-then-act" optimization can foster over-confidence or limit consideration of strategic alternatives or the effects of a wider set of plausible future conditions. Planners and modelers might arrive at myopic decisions because they underestimate the uncertainty. Predict-then-act analyses can lead to gridlock when stakeholders contest the assumptions used to justify a proposed plan rather than work together to identify a plan that performs well over a wide range of scenarios.

Moving away from prediction may sound daunting, but DMDU methods help MPOs operate more effectively in the face of hard-to-predict deep uncertainty. This includes systematic discovery and testing of strategies broadly characterized as having low regret across many plausible futures, designing strategies to flexibly evolve over time in response to new information, and identifying hedging and shaping actions (based on pre-identified signpost indicators to give early warning of how the future is unfolding) to minimize potential loss or help make desired futures more likely.

These new DMDU approaches turn traditional, predict-then-act analyses on its head. Rather than begin with predictions, DMDU methods begin with a proposed MPO plan, stress test that plan over hundreds to thousands of plausible futures, use these stress tests to generate policy-relevant scenarios that illuminate the strengths and weaknesses of proposed plans, and then use this information to make robust and flexible strategies the perform better over

a wide range of futures. Often these plans are designed to adaptive over time in response to new information.

Rather than starting afresh, DMDU methods can build on the best of MPOs' current scenario planning and probabilistic forecasting models. Such models, however, are used in a different manner. Rather than generate predictive scenarios to ask, "What will happen in the future?", DMDU uses exploratory scenarios to ask, "What might happen by varying model assumptions?" --and normative scenarios to ask, "How can we best reach our goals despite the prevailing uncertainties?"

MPOs sometimes employ probabilistic forecasts to suggest which futures are more likely than others. But under deep uncertainty, such forecasts represent yet another assumption, this time regarding the unknown underlying probability distribution. Instead of characterizing uncertainties in such terms (with probabilities being difficult to convey to broad audiences under even the most favorable conditions), DMDU methods instead characterize uncertainties in terms of the specific problem itself: "Which assumptions would I need to believe will hold true to recommend one course of short-term actions over another?" This is most valuable when such probabilistic forecasts are unreliable. As such, DMDU is also designed to support a participatory process called "deliberation with analysis" which can help MPOs implement the types of stakeholder engagement they need to improve their plans, build legitimacy, gain buy in with their publics, and satisfy Federal requirements for stakeholder participation.

Several software packages are available to support MPOs using DMDU, including TMIP-EMAT and VisionEval, both of which have been supported by FHWA. The report provides a brief guideline to these tools and points to resources for gaining greater knowledge.

Based on MPOs' growing experience with DMDU methods, and workshops and interviews with MPO staff, it is possible to identify some key benefits of DMDU and some of the barriers slowing its uptake. Some of the latter derive from external expectations, particularly in the form of various government reporting mandates. Resource constraints may play a role as do various aspects of MPO internal organization and culture as detailed in the report.

Several approaches could ease introduction of DMDU into MPOs:

- Identify, cultivate, and empower ***local champions*** for the change within the MPO.
- Engage with and **work for *buy in*** from those asked to carry out the strategic foresight efforts and the analyses that will support them.
- ***Reconceptualize the work process*** to either elicit the newly looked-for capability or prevent an early rejection reaction.
- ***Communicate the nature of intended change*** to all along the value creation process.
- Think through in advance where ***potential turf issues*** might lie.

- Explore how DMDU may play a role similar to that ***a smaller, ranging telescope*** fixed to the side of the main instrument -- in this case, the large-scale transportation demand model.
- Apply DMDU methods ***at the beginning of the planning process*** itself. It could be used as a way to bring modelers, analysts, planners, managers, and decision makers on board at the beginning to frame a conversation and use of shared vocabulary that may persist during the cycle even if the DMDU outputs do not form a formal deliverable as part of the planning documents produced.
- Consider early joint exposure to DMDU methods and tools between MPO planning and government regulatory agency staffs to expand awareness of what might be possible and the potential utility of the type of output that MPOs could produce.
- Seek ***support from (or at least acceptance by) other partners outside the MPO***, including federal, state, and local government bodies.

In addition to these general points, there are several questions that can be addressed with reference to the specific MPO in which the agency or team within the agency wishes to explore the use of DMDU tools. These are presented in Table S.1.

Table S.1. Checklist of questions for MPO considering employing DMDU methods

1. *What application areas can provide early and convincing 'wins'?*
2. *What methods and tools can be most useful for early adoption?*
3. *What would constitute a good learning path for staff and units looking to innovate?*
4. *What can be done to develop external and internal allies?*
5. *What assistance would be helpful to receive from outside?*

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Chapter 1. From Forecast to Foresight

Planning during Changing Times

That we live during a time of intense and increasing change is by now no longer news. Less well recognized are several factors that make the challenge to transportation agencies[1] especially acute.

As institutions of both planning and operations intended to achieve a variety of public mission goals (safety, mobility, equity, sustainability, preservation of infrastructure, etc.) as well as attain organizational balance (budget, workforce, tort liability, etc.) their role is both visible and precarious. Transportation, after all, is quite literally the act of connecting all sectors of both society and economy to all others. Changes in individual sectors reverberate through to other sectors along the modes and services of transportation that themselves are undergoing change. And finally, while some mission agencies, such as the Department of Defense, can achieve a measure of control through the authority they have been given to dominate in their area of responsibility, transportation agencies must operate within a web of other authorities, agencies, constituencies, and levels of government. For a transportation agency, however, the hallmark of success will depend on how well it catalyzes the regional collaboration that is necessary for effective planning and implementation.

To achieve the mission goals that society has set for them, transportation agencies need to make use of tools and methods that will allow them to continue doing so under circumstances for which many long-standing rules of thumb no longer apply. Transportation agencies would benefit from greater capacities for strategic level planning under conditions unfavorable to attaining any level of assurance in predictions. The need, therefore, is for strategic approaches allowing short-term, operational, and longer-term investment decisions to be considered within a perspective that lays out long-term goals and alternative means for achieving them across a turbulent future.

Developing a capacity for foresightful strategic analysis to the level today's challenges call for what would be a large ask for any organization. It is all the more challenging for transportation agencies that are at the same time required to produce planning products that must satisfy federal and local requirements and established norms. At times, the one seems to limit scope and means for achieving the other.

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[1] We use this term to mean primarily U.S. state departments of transportation (DOTs) and Metropolitan Planning Organizations (MPOs) that themselves may also be regional councils of governments. The use of "transportation agencies", however, is intended to be broadly applicable to other public bodies concerned with transportation and regional planning.

This report provides guidance for transportation agencies seeking new means to meet new challenges. It will, in particular, explore recent methodological advances to enhance the support that analysts may provide to planners confronted with the challenge of decision making under deep uncertainty (DMDU). We discuss the concept of deep uncertainty in the next chapter, but for the present it is sufficient to say that it is a state in which even the best simulation models will have difficulty in predicting the future with any confidence. Rules of thumb that served well during prior conditions become questionable when underlying conditions are undergoing change – especially if the direction and extent of that change is unclear. Of similar consequence for agency analysts and planners, the same dynamic can render many if not most tools for risk management difficult and perhaps inappropriate to apply.

Transportation Agencies are Mission Organizations

Change of this magnitude can bring the entire enterprise of analysis that uses model-based prediction into question. That strikes close to the heart of most activities carried out in MPOs and other agencies. Dedicated and creative designers have over several decades developed sophisticated travel demand models and other modeling infrastructure used to generate analyses that, in turn, inform the activities and outputs of the agency planning staffs. We will speak later about the nature of these models and their ability to address contemporary policy analytic challenges. But first, we should examine the nature of the analytical enterprise in which they are used.

If we can forecast with some accuracy, we have the analytical means to conduct planning that will optimize for, and ensure a high likelihood of meeting, the goals set by policy – barring unforeseen circumstances not accounted for in the models. Of course, given likely divergences from any such forecast and given the complexity of the transportation system itself as well as that of the other systems it connects, there is a need to explore sensitivities and allow for certain tolerances. But what if even this level of forecasting accuracy becomes difficult to attain? It threatens the entire superstructure of analytical tooling designed to support transportation planning. In such situations, it would be useful to step back from the long-range planning that is usually conducted and instead gain a degree of strategic foresight into what the uncertainties might mean for the agency and the goals for which it is the steward. What short-term actions would be consistent with long-term agency objectives across different potential futures, futures that are difficult to predict based on current knowledge.

New analytical machinery may inform agency-level regional planning when the pace of change makes it clear that accurate forecasts will be neither feasible nor credible. These analytical approaches are intended to develop means of foresight when forecasting is not possible – a situation that applies widely across many MPO missions and activities owing to rapid changes in technology, economic structure and relationships, and policy and societal goals

But the existence of such analytical machinery is not necessarily sufficient. In particular, any effort at change in tools or technology must be cognizant of the setting in which the change is introduced. Therefore, in what follows the discussion will be attuned not only to what technical changes a transportation agency could undertake in its planning processes but also how such change could be affected within these agencies as organizations operating in complex environments and directed toward achieving specific goals.

Models and their Purposes

It is one thing to speak of MPOs and other transportation agencies as organizations, but they are made up of individuals. In particular, this report focuses in its next chapters on the professionals who conduct model-based analyses and the planners who make use of their outputs. In the last part of this chapter, we focus on the models that connect them and the different uses of models in the analytical support of planning.

Models in the physical sciences or engineering are usually deemed valid to the extent that they can be predictive and in the social science to the extent that they can be retrodictive, that is generate output that accords with historical time series. This presumes implicitly that the primary use for models depends upon their ability to predict.

But myriad models can do no such thing. Witness the massive combat simulation models that have been built and added to in earnest since at least the 1970s (with their roots several decades before the advent of mass computing.) Sponsors who support development of such models have not often found that these creations were, indeed, reliable predictive engines. If that is so, does it mean these models are no good or a waste of resources, effort, and time? On the contrary, they are superb human artifacts encapsulating a great deal of understanding about a range of causal relationships as well as encompassing decades and more of data. So, what is going on?

The answer is that we actually use models for things other than serving as consolidative prediction engines. Indeed, perhaps in many circumstances to which such models are put this is an inappropriate -- or at the very least, misleading -- purpose. But if the models are great consolidators of not only what is known but also of what is unknown (or even unknowable,) then there are several purposes to which they can be put.

One of these uses is as exploratory devices: not what will happen but rather what would need to be consistent to see one outcome versus another. How might various assumptions affect our thinking of which alternative strategies might be worth pursuing compared to others and what would need to be true for successful or unsuccessful outcomes to ensue? Another is to serve as handy descriptions of how we think particular systems operate and how the factors within those systems relate to each other. There are even further purposes, such as educational tools.

Many of the issues facing transportation analysts and planners in MPOs are inherently uncertain. That has always been the case. But today the rate of change and therefore the increasingly shorter durations of any plateaus that would afford the time and experience to learn the latest rules of thumb to be applied to considerations of the future makes the uncertainty dimension that much worse. It is not a lack of due diligence on the part of MPO staff that leads to poor performance in predicting outcomes. Rather, it derives from an external milieu increasingly characterized by large uncertainties. It used to be possible to employ certain rules of thumb in operating not just our transportation modes and corridors but also our economies, finances, foreign policy, education policy, etc. But we now seem to have entered a period wherein the dynamics of change no longer leave us with the occasional plateau during which we can deduce the new rules of thumb. Under such circumstances, the use of models, even those once designed to be predictive engines, should be reviewed for how they can contribute to the present dilemma; they may well take on an entirely different meaning for decision making under conditions of deep uncertainty.[2]

This report is based on experiences interacting with transportation agency planning staffs in several different venues, most recently as part of a FHWA project explicitly exploring DMDU approaches within transportation agencies. The next three chapters address the problems and opportunities faced by modelers and planners at the working level as they seek to shift from more traditional "predict-then-act" analyses to those more aligned with conditions of deep uncertainty. In Chapter 2, we introduce the concept of decision making under deep uncertainty which embraces a range of quantitative and qualitative methods. The chapter discusses in detail robust decision making (RDM), a specific model-based DMDU method that recommends itself as being potentially more consonant with model-based analysis current practiced in MPOs and other transportation agencies. Chapter 3 offers several examples of RDM and other applications that have been employed by innovating MPOs and will also refer the reader to examples of non-model-based, more qualitative examples of use to address challenges in transportation planning. Chapter 4 reviews the methods and quantitative tools available to support MPOs in using DMDU, including the participatory processes with stakeholders supported by DMDU analyses and the software packages available to facilitate DMDU analyses. The final chapter once more provides an organizational perspective of MPOs and their transportation planning functions. It lays out a value proposition for enhanced strategic foresight capabilities – the goal that DMDU methods seek to achieve, lays out several of the obstacles that might retard or prevent movement in that direction, suggests incremental steps toward implementation, and finally provides a guide that may be used by agencies as a whole

[2] See https://www.deepuncertainty.org

or their modeling or planning staffs to gauge progress toward achieving a greater facility for accounting for and managing future uncertainties as part of their regular process.[3]

[3] A note on attribution. This report will include statements for which no direct citation is provided. In these instances, the most frequent source will be from conversations with MPO staff, either individually or in a workshop setting, and with other transportation professionals such as those serving in federal agencies, state DOTs, or professional associations such as AASHTO or TRB. Care has been taken by the authors to restrict their views solely to their discussion of DMDU methods and the prospects for those methods within MPO workflows. Statements regarding MPOs as organizations or their responsibilities will first have been heard from the lips of professionals. Of course, the prevalence of such views among them and their colleagues is not something that the authors of this report are able to assess.

Chapter 2. Robust Decision Making and DMDU

In this and Chapters 3 and 4, we discuss the working level of modeling and planning in MPOs and other transportation agencies. Simply put, planners require quantitative information to make good decisions. How best to provide that information and organize it in a way that planners and their audiences find useful?

A vast body of analytic methods and tools exist to address this question. Most are organized around the concept of making predictions of the future. Planners often use these methods and tools directly. The framework underlying these prediction-based methods and tools also infuse many of planners' more heuristic approaches.

While there are many variations, it is useful to understand such methods by beginning with the fundamental structure of classical decision and risk analysis (Morgan and Henrion 1990), which are organized around several key elements. These classical methods assume a known set of possible future states of the world, a known set of alternative decision options, and a means to calculate the outcome for each possible combination of decision option and future state of the world. To characterize uncertainty, such methods also assume a known joint probability distribution over these future states of the world. Finally, these methods assume known preferences that allow an unambiguous ranking of outcomes from best to worst. Given these elements, one can calculate the optimum decision option, that is, the one expected to give the most preferred results.

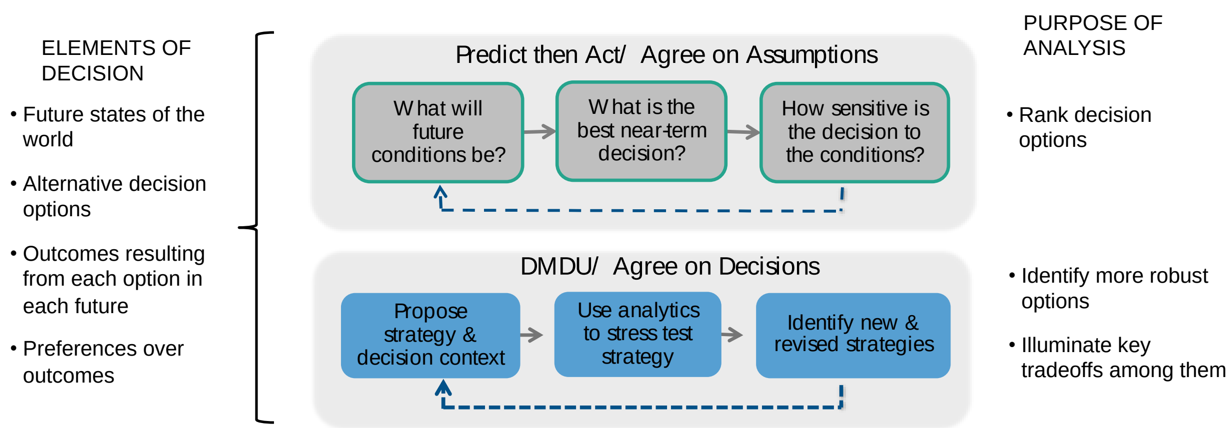
As an archetypal example, consider a chance-based game based on the roll of a die. The integers one through six represent the possible states of the world, each with a probability of 1/6. The game might give the player two options, let's call them A and B. The game's rules (which we can regard as a very simple simulation model) determine the consequences that result from each option in each future. For instance, with option A the decision maker might earn $30 if she rolls a 6 and nothing otherwise. With Option B, the decision maker might earn $1 if she rolls a 1, $2 if she rolls a 2, etc. We can calculate the statistical properties of the two options. For instance, the expected return is $5 for the first option and $3.50 for the second, while the variance for the two options is $12 and $2, respectively. We can then use such information to choose a strategy.

The upper panel of Figure 2.1 depicts the key steps in such "predict-then-act" analyses. They begin by generating a consensus and high confidence understanding of possible future conditions. In some cases, this understanding focuses on a single best-estimate forecast. More properly, this understanding involves a set of plausible future states of the world and a single, best-estimate probability distribution over those states. The analysis can then rank decision options based on this understanding of future conditions and an understanding of how alternative options perform in each future. Finally, the analysis might conduct a sensitivity analysis to explore how sensitive this ranking is to various assumptions.

As noted in Chapter 1, planners and modelers seeking to inform transportation decisions generally organize their quantitative methods with a predict-then-act framework. Sometimes these approaches follow all three steps. Sometimes they focus mainly on the first step – generating predictions of the future.

When the decision challenge has all the necessary attributes -- that is, when we have high confidence probability estimates over known states of the world, a comprehensive set of decision options, and well-known relationships between actions and consequences – predict-then-act analysis is a powerful and appropriate approach.

Figure 2.1. Predict-then-act vs. DMDU analyses



Source: RAND, adapted from Kalra, N., S. Hallegatte, R. Lempert, C. Brown, A. Fozzard, S. Gill and A. Shah (2014)

But predict-then-act can prove problematic when the situation does not match the method. Predict-then-act analysis can foster over-confidence, encouraging planners and modelers to under-estimate the extent of uncertainty. If the uncertainty is seen as too large, predict-then-act analyses break down. Sensitivity analysis can suggest that many strategies might be best, thus rendering any recommendations from the analysis meaningless. When multiple stakeholders are involved, predict-then-act analyses can also lead to gridlock. Parties to the decision well-recognize that the assumptions that structure the analysis determine the results. They will therefore contest the assumptions and exploit the uncertainty to undercut any policy recommendations that flow from the analysis. Finally, predict-then-act can lead to misallocation of resources, encouraging analysis to spend the bulk of their efforts on reducing uncertainty rather than on identifying strategies that work well irrespective of the uncertainties.

Managing under deep uncertainty

Today's planners increasingly face "deep uncertainty", the condition in which parties to a decision do not know or agree on the likelihood of alternative futures or on the models that link actions to consequences (Lempert et al. 2003). As noted in Chapter 1, many of today's most pressing challenges, in particular those faced by transportation managers are characterized by deep uncertainty.

Deep uncertainty may seem daunting. Transportation agencies may recoil from the suggestion that they face such conditions or else focus on reducing uncertainty as a precursor to any action. But there are in fact many ways to act confidently under conditions of deep uncertainty. These include strategies broadly characterized as low regrets, that is near-term actions that work well over a wide range of futures; flexible strategies designed to evolve over time in response to new information; and shaping strategies designed to make desirable futures more likely and less desirable futures less likely.

But most traditional risk and decision analysis tools can make it hard to identify such strategies (Gong et al. 2017). A number of approaches exist to address deep uncertainty, which are gathered under the label decision making under deep uncertainty (DMDU) (Marchau et al. 2019). DMDU includes many types of qualitative *scenario planning* (Schwartz 1991, Twaddell et al. 2016); approaches that focus on plans on engineering designs that adjust over time, such as *dynamic adaptive policy pathways* (Haasnoot et al. 2019) and *engineering options analysis* (de Neufville and Smet 2019); and *robust decision making* (RDM) (Lempert et al. 2003) which runs simulation models over many futures to stress test proposed strategies, identify scenarios that illuminate their vulnerabilities, and use this information to identify more robust strategies. While most of its examples are drawn from work with RDM, many of the insights this report offers are relevant over a wide of DMDU methods. Traditional scenario methods and dynamic adaptive policy pathways are also both discussed in more detail below.

In general, DMDU methods reverse the order of steps of a predict-then-act analysis, as shown in lower panel of Figure 2.1. Rather than beginning with projections of the future, the first, decision framing step of DMDU begins with one or more strategies or action plans, such as an agency's proposed transportation and land use plan. In practice, the initial plans can derive from a variety of sources, including one or more specific strategies drawn from the public debate or from a predict-then-act analysis that suggests a strategy based on best-estimate projections of the future.

In the second, stress testing step, a DMDU analysis then employs data and simulation models to evaluate the proposed strategy or strategies in each of many plausible paths into the future. This generates a large database of simulation model results. The analysis can now use visualization and data analytics to ask questions of this database such as "what combinations of a small number of uncertainties best distinguish between those futures in which the proposed plan meets and misses its goals?" Or the analysis can ask "under what future conditions might a policy maker prefer policy A to policy B, and vice versa?" In a world of deep uncertainty, such questions can often be answered with high confidence. Analysts may not know what the future brings, but they can understand the types of futures in which a policy will succeed and fail.

In the third, new options step, a DMDU analysis uses the results of the stress test to identify and evaluate new or revised strategies that prove more robust, that is, which reduce the vulnerabilities identified in the stress test and which perform well over a wider range of futures. In some cases, more robust strategies include policies or actions that are valuable no matter what the future holds. In other cases, such strategies emphasize flexibility, an ability to monitor and adjust over time in response to new information (Lempert et al. 1996, Walker et al. 2001, de Neufville and Smet 2019, Haasnoot et al. 2019). For instance, switching from a gas tax to a VMT fee might prove valuable for an MPO in every future it considers, while incentives for new mobility options might perform best as an adaptive decision strategy which increase or terminate depending on how technology and ridership evolve over time.

As shown by the recursive dotted line in Figure 2.1, a DMDU analysis is iterative. Once it identifies a new, potentially more robust strategy, the analysis can stress test this option over a wide range of futures to determine and address any remaining vulnerabilities or discover means to enhance its robustness further.

How DMDU has been used by MPOs

MPOs have long used traditional scenario planning methods, but not always as a DMDU approach, as discussed in more detail below. In addition, quantitative, model-based DMDU has begun to be used by MPOs. For instance, Sacramento Area Council of Governments (SACOG) used RDM to stress test its 2016 Metropolitan Transportation Plan/Sustainable Community Strategy (MTP/SCS) against a wide range of futures to determine the conditions under which the plan would meet and miss its climate, mobility, and equity goals. [See SACOG case study in Chapter 3.] Using then state-of-art approaches, the agency had developed its MTP/SCS based on a single, best-estimate forecast of the future in 2036. RDM helped the agency to understand the sensitivity of its plan to previously unexplored assumptions and to begin to develop hedging strategies against some of the plan's vulnerabilities (Lempert et al. 2020). Relatedly, TransLink, the transportation authority of Metro Vancouver, utilized the TMIP-EMAT (see Chapter 4) RDM-based application to help it and regional authorities understand alternative paths forward after fare- and fee-based services, the principal revenue source for regional transit, dropped 60 percent as a result of COVID-19 [See TransLink and Metro Vancouver case study in Chapter .]

To date, the most extensive applications of quantitative DMDU have been outside the transportation sector, particularly in water and coastal management. For instance, RDM helped the City of Los Angeles to identify an adaptive pathway approach to make its water quality implementation plans more robust to uncertainties regarding future climate change and the success of implementing land use policies aimed at making the city surface more permeable to water (Tariq et al. 2017). [See water quality case study in Chapter 3.] Non-quantitative DMDU approaches might also serve as entry points for gaining strategic foresight on transportation issues. Culver City in Southern California used such methods to address a contentious three-sided debate between a neighborhood's residents, adjoining businesses and neighbors, and city surface traffic engineers and develop an adaptive implementation plan to which all parties agreed [See Culver City case study in Chapter 3].

When to Use DMDU analysis

As shown in Table 2.1, the characteristics of deep uncertainty contrasts with those of well-characterized uncertainty. While the latter has known and single representations of all the key elements, deep uncertainty has multiple representations of states of the world, probabilities, or system models. In addition, deeply uncertain challenges often have contested weightings over objectives and assume many potential decision options are unknown at the start of the analysis. Following the uncertainty taxonomy of Walker et al. (2003), (also see Kwakkel et al. 2010), Table 2.1 also includes the category "Ignorance" which is similar to deep uncertainty but is often best addressed with qualitative rather than quantitative, model-based methods.

Many similar terms appear in the scholarly and practitioner literature. For instance, deep versus well-characterized uncertainty is related to historic division between risk and uncertainty first articulated by Knight (1921) and Keynes. Today, organizations such as the International Standards Organization defines risk broadly, as the effect of uncertainty on objectives (ISO 2009), a definition inclusive of both well-characterized and deep uncertainty.

Table 2.1. Types of uncertainty, key characteristics, and best analytic methods for each

Elements of decision	Well-characterized Uncertainty	Deep Uncertainty	Ignorance
States of the world	Known	All or many known	Mostly unknown
Probability distributions over states of the world	Single	Imprecise or unknown	Unknown
Decision options	Known	Some but not all initially known	
System model relating options to consequences	Single	Multiple	Unknown

Objectives	Single or multiple with consensus weighting	Contested weighting over multiple objectives
Best method of analysis	Predict then act/ Agree on Assumptions	DMDU/ Agree on Decisions Largely model-based search for solutions → Model-based and qualitative insight

Comparison to Current MPO Approaches

DMDU methods share important similarities with current approaches used by MPOs but build on and go beyond these current approaches. Here we discuss how DMDU methods employ scenarios, probabilities, and address learning over time.

Scenarios

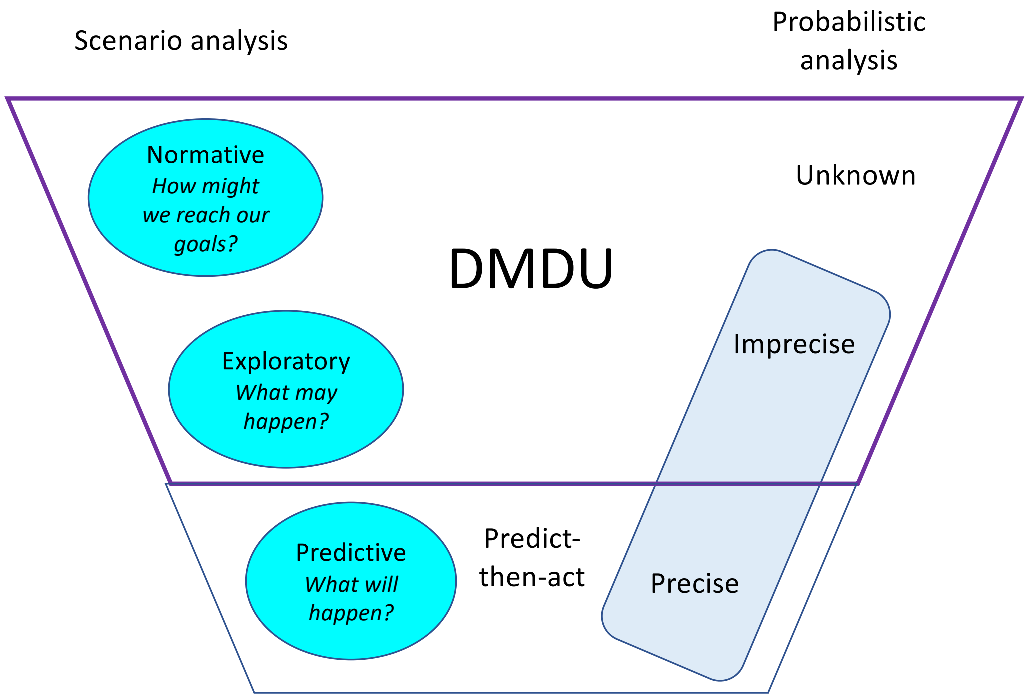
As noted above, DMDU methods include many types of scenario analysis. MPOs routinely use scenarios (Hopkins 2007). But there is a difference between how DMDU constructs and uses scenarios and the way MPOs traditionally do so. There exist three types of scenarios: 1) *predictive*, which ask, “What will happen?”; 2) *explorative*, which ask, “What might happen?”; and 3) *normative*, which ask, “How might we reach our goals?” (Borjeson et al. 2006).

Predictive scenarios lie at the heart of most transportation agencies’ plans and are predicated on best-estimate forecasts of economic growth, transportation technology, regulatory environments, and other factors (Lempert et al. 2020). Transportation agencies also increasingly use normative scenarios to consider how alternative combinations of land development and transportation investments would achieve desired goals (see the SACOG case study in Chapter 3). These normative scenarios are generally evaluated, however, using best-estimate forecasts of future conditions. Current planning practice manages uncertainty with techniques such as sensitivity testing that assess a limited number of changes in one or two assumptions (Lempert et al. 2020).

Transportation planners have made less use of exploratory scenarios to explicitly assess the inherent uncertainties among key policies and exogenous variables. Exploratory scenarios can be used to stress test proposed polices and planned investments, identify factors that support or conflict with achievement of the agency’s goals, and help craft responses. But employing scenarios as exploratory tools requires MPOs to adopt different approaches, mindsets, and analytic approaches with which most transportation planners remain unfamiliar (Avin and Goodspeed 2020).

As shown in Figure 2.2, DMDU analyses generate scenarios that combine both normative (How might we get what we want?) and exploratory (Under what conditions do we get what we want?) characteristics.

Figure 2.2. Relationship among DMDU, scenario analysis, and probabilistic forecasts



Source: RAND

Probabilistic forecasts

MPOs also employ probabilistic forecasts to generate explicit likelihoods for one or more future states of the world. As one example of a probabilistic forecast, an MPO might estimate the likelihood of each of several predictive scenarios. More formally, an MPO might estimate a joint probability distribution over all possible values for some set of important parameters such as the price of gasoline or the demand for transit. When such probability distributions can be estimated with high confidence, probabilistic forecasting provides an unparalleled input to decision making (Morgan and Henrion 1990).

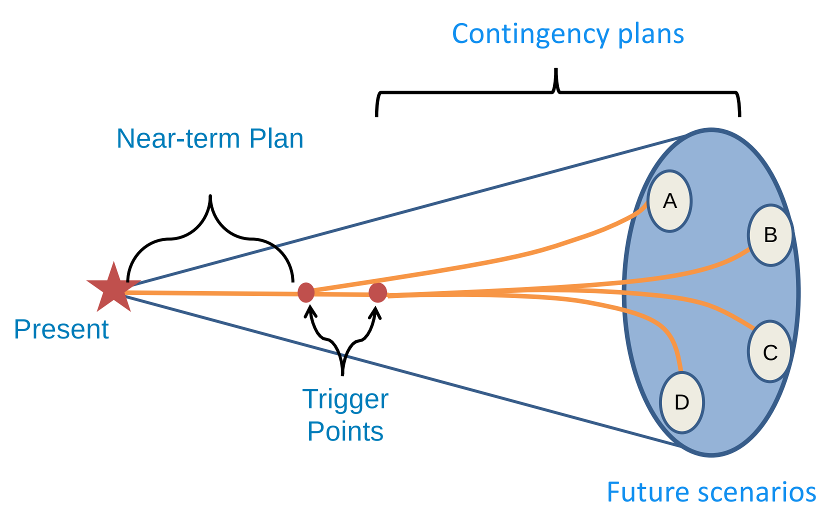
DMDU methods are most useful when probabilistic forecasts are unavailable or when there is low confidence in or significant disagreement regarding any such estimates. Some DMDU applications avoid the use of probabilities altogether, seeking to identify strategies with low regret over a wide range of futures. Other DMDU applications treat probability distributions as among the uncertainties and identify a probability threshold, that is, how likely some scenario would have to be to justify choosing one strategy over another. In more formal language, such DMDU applications treat probabilities as imprecise (Walley 1991). As shown in Table 2.1, when DMDU methods employ probabilities, one or more of the distributions are considered as imprecise. As suggested by Figure 2.2, any analysis that employs only predictive scenarios and/or precise probabilistic forecasts is a predict-then-act analysis.

Learning and adaptation pathways

Learning over time is one important approach for managing uncertainty. Many types of learning exist. These range from unplanned learning,[4] to more structured approaches such as the deliberation with analysis process discussed in Chapter 4. MPOs clearly engage in learning processes. MPOs all develop multi-decadal plans extending approximately thirty years into the future and periodically update these plans, every four or five years depending on the region's air quality nonattainment or maintenance area status. Each iteration of the planning cycle draws on prior experience. But much of this learning is unplanned in the sense that MPOs in each planning cycle do not explicitly anticipate what might be learned in the future, what near-term steps might be taken to enhance that learning, and how best to configure current actions in anticipation of future adjustments due to learning.

Learning is an important theme in DMDU and RDM analyses if for no other reason than one important means for achieving robust strategies is to design them to adjust over time in response to new information (Walker et al. 2001, Lempert et al. 2003). Figure 2.3 shows the basic structure of an adaptive decision strategy designed to evolve over time in response to new information (Moss et al. 2014, Fig 26.6). The strategy begins with a set of near-term actions, those intended to be taken over the next months or few years. These actions might include the operations of existing infrastructure and systems, plans for financing and revenues, regulatory or land use plans and policies, and decisions to invest in new infrastructure.

Figure 2.3. Adaptive decision strategies designed to evolve over time in response to new information



Source: RAND, adapted from Kaatz, L. (2015).

[4] The National Research Council (2009) defines unplanned learning as a situation in which "actions are undertaken without any explicit consideration of learning, and any change that occurs is unplanned and often unbidden."

Near-term actions also explicitly include activities to monitor key trends and evolving knowledge that might suggest the need to modify or update these near-term actions. An MPO might launch activities to monitor patterns of downtown office use and related travel as well as keep up to date on emerging empirical literature as their region responds to the pandemic. This monitoring would be designed to give warning that the future appears to be evolving along one of several alternative scenarios identified in the planning process. The NCHRP foresight series identifies such signals as "signposts" (Lorenz et al. 2014). The plan could also include contingency actions that might be taken if and when it becomes clearer what path the future is taking among the alternative scenarios. Each set of contingency actions may be associated with specific values for observed trends or resolution in the literature of particular debates (e.g. an observed, stable, new pattern of office use) that signals that the moment is ripe for particular contingency actions. These are often called tipping points, trigger points, or thresholds.

DMDU includes a variety of approaches for developing and evaluating such adaptive decision strategies. Dynamic adaptive policy pathways (DAPP) (Haasnoot et al. 2013, Haasnoot et al. 2019) has emerged as one of the most popular. DAPP and its precursors have informed the design of major infrastructure including the Thames River Barrier (Ranger et al. 2013) and provide the foundation for several national (New Zealand Government 2018) and state (State of California 2018) sea level rise guidance documents.

As a DMDU approach, DAPP begins with an initial strategy or system, several scenarios that may impede the ability of the strategy or system to achieve desired performance levels, and alternative decision options that might improve performance in each of these scenarios. The analysis then identifies the level for each trend at which alternative decision would no longer provide adequate performance. For instance, for each alternative design of a coastal road there would be some amount of sea level rise at which the road would no longer meet its reliability and other goals. These levels are called adaptation tipping points. The analysis then identifies a range of scenarios for the trend and identifies the point in time at which the adaptation tipping point might be reached in each scenario. The method traces alternative options for how one would step through the sequence of options in each scenario, paying particular attention to which options can work together to improve performance and which options might be conflicting. Finally, the analysis identifies a set of alternative pathways through the scenarios, evaluates these pathways according to multi-objective metrics, and presents this information to decision makers to help them choose which near-term pathways on which they wish to embark. An example of such an analysis is presented in the case study describing the Los Angeles water quality example in Chapter 3.

The DMDU literature contains many approaches for developing such adaptive decision strategies, including those associated with RDM (Lempert et al. 2003, Groves et al. 2019); those that explicitly consider adaptive strategies as interlocked financial, operational, and infrastructure investment strategies using a control theory framework (Zeff et al. 2016, Hamilton et al. 2021); and those focused on the flexible design of infrastructure using an engineering options analysis framework (de Neufville and Smet 2019).

Today, MPO transportation and land use plans are often static in the sense of laying out a series of specific steps into the future even though many of these steps will be revisited in future plans. Such static plans also shed little insight into the positive and negative effects of path dependence. With a few exceptions (see Wall et al. (2015) and Culver City case study), there are not yet many examples in the transportation sector of DMDU-supported adaptive planning, However, DMDU approaches may in the future help agencies make their plans more explicitly designed to evolve over time to changing conditions, likely to prove a more successful strategy under conditions of deep uncertainty.

Path dependence

The standard formats for transportation and land use plans also have difficulties addressing the challenges and opportunities generated by path dependence. Path dependence is the condition by which past events or decisions shape or constrain future events and decisions. An approach solely focused on normative assessment of a future equilibrium compared with the present misses the fact that often the actual dynamic path between the two states will determine the character of the later one. This process plays an important role in shaping current and future land use and transportation decisions. Choices made decades (or centuries) ago about where to build roads and what buildings to construct in which locations influence today’s land use and transportation options. The choices MPOs make today will strongly influence tomorrow’s choices.

Explicitly considering path dependence can help MPOs identify opportunities in which near-term actions help to open up future options, make desirable futures more likely, and close off pathways towards less desirable futures. In many cases, current transportation and land use plans are not well-designed to identify such shaping strategies. In contrast, DMDU analyses, which can explicitly model how alternative adaptive strategies evolve over time, are often well-suited to include the effects of such path dependence.

Potential Misconceptions and False Comparisons

Since DMDU is relatively new, there exist frequently held misconceptions about what DMDU entails and frequently made mistakes in conducting such analyses.[5] These include:

[5] Chapter 5 will present a list of commonly made mistakes with DMDU. Here we select a few and expand them because of their thematic relevance in a discussion of DMDU versus contemporary transportation agency planning processes.

RDM is not a model. People sometimes use the phrase “RDM model”. But RDM is not a simulation model. Rather, it is a set of concepts, methods, and tools for using simulation models in new ways. In some cases, an RDM analysis employs an existing model, generally one which was built to support predict-then-act analyses. For instance, in the Metro Vancouver work described below, the agency employed its existing travel-demand model, not as a tool for making forecasts but one for generating a wide range of scenarios. In other cases, an RDM analysis employs a model custom-built for generating many scenarios. For instance, the SACOG work described below developed a simple cohort-based model that would be inappropriate for forecasting but proved helpful for scenario generation. These two examples use different models, but employ similar methods for using the models.

RDM is not the same as running a model many times. RDM analyses generally involve running a simulation model many times – over hundreds, thousands, or even millions of cases – to create large databases of simulation results. While conducting many model runs is an important part of RDM, running a model many times is not the same an RDM analysis. An RDM analysis runs a model many times to address particular types of policy-relevant questions.

For instance, imagine a database constructed using a large, probabilistic Monte Carlo sample of model runs. An analysis might use this database to calculate the expected values of alternative policy choices and then use those expected values to rank the policies. Even though many model runs were involved, this would represent a predict-then-act analysis, not RDM, because it regards the probabilities used to construct the sample as a precise, high-confidence representation of the real world and asks “what is the optimum policy?” In contrast, an analysis might use the same database and ask questions such as “how far off do the probability estimates need to be before a different policy becomes optimum?” and “is there a policy choice that has low regret even if the probability estimates are significantly wrong?” An analysis asking such questions would represent RDM.

Insufficient exploration of a wide range of assumptions. Describing the U.S. government’s “stupendous unreadiness” in December 1941, Thomas Schelling wrote “it is not true that we were caught napping at the time of Pearl Harbor. Rarely has a government been more expectant. We just expected wrong.” (in Schelling's forward to Wohlstetter 1962) Scenario exercises often explore only a narrow range of futures and miss the what turn out to be the most saliant surprise (EEA 2009). Probability estimates are often overconfident. Bad decisions frequently flow from a failure to consider a sufficiently wide range of futures. By encouraging analysts to explore conditions under which their plans would not meet their goals, by providing means to conduct such explorations, and by providing a framework to usefully respond to the results, DMDU methods help decision makers avoid expecting wrong.

Too early aggregation of expectations and values*:* Many decision-analytic approaches commonly used by MPOs seek to aggregate expectations about the future and weightings over preferences into single values early on in the analysis. *Predict then act* approaches often require such aggregation. For instance, an MPO might use some type of forecasting or expert elicitation approach to obtain a single joint probability distribution over future states of the world in order to estimate the likelihood of alternative scenarios. An MPO might use some type of revealed preference approach to obtain a single set of weights over different stakeholder objectives in order to have a well-defined preference function they can use to rank alternative strategies.

As an explicitly multi-objective, multi-scenario approach, DMDU avoid such aggregation of expectations and preferences or defer them until late in the analysis. Stakeholder communities for most MPOs will be characterized by a heterogeneity of preferences and expectations about the future. Any attempt at early aggregation will tend to privilege some views over others, reduce transparency regarding whose views are favored and whose are neglected (see, for instance, discussion in Lempert 2021), and increases the potential for significant mistakes if the future turns out differently than that for which the plan is designed. More colloquially, DMDU regards premature aggregation as the root of all evil in decision support.[6]

Seeking certainty in forecasts, not in decisions: At a meeting of his agency's stakeholders, the director of the planning staff of a large California water district was asked whether he trusted the climate models he is using to inform their integrated resources plan (IRP). The planning director replied that his agency did not necessarily trust the climate models, but once their IRP analysis was complete, they would have confidence in their contingency plans (Lempert and Groves 2010). This story illustrates a central challenge and goal of DMDU methods. Decision makers turn to experts and policy analysis to increase their confidence. Often this information transfer is organized around predictions of the future, with the assumptions that decision makers can feel more confident if their decisions are based on an accurate picture of future events. In contrast, DMDU places the locus of confidence in the plan. DMDU emphasizes that the future will bring the unexpected but offers confidence that a robust and flexible plan will perform well no matter what the future brings.

[6] Personal communication with Dr. Jan Kwakkel, Delft Technical University.

Chapter 3. DMDU Applications in Transportation Planning

This chapter presents several practical applications of DMDU-based methods for exploration of future transportation system dynamics and strategic responses. The major methods highlighted in these vignettes will be discussed in more detail in Chapter 4.

Sacramento Area Council of Governments

The Sacramento Area Council of Governments (SACOG) used RDM to identify potential vulnerabilities in its 2016 Metropolitan Transportation Plan/Sustainable Community Strategy (MTP/SCS). Like many MPOs, SACOG faces a significant challenge in seeking to meet mobility, equity, and aggressive greenhouse gas emission reduction goals in the face of deep uncertainties

Development of SACOG's 2016 MTP/SCS

To create its 2016 MTP/SCS, SACOG engaged in a multiyear, state-of-the-art planning process informed by predictive and normative scenarios.[7] The agency used the Sacramento Regional Activity-Based Simulation Model (SACSIM; Bradley, Bowman, & Griesenbeck, 2010; SACOG, 2015), a regional activity-based travel simulation model, to inform the development of these scenarios and to evaluate the performance of its MTP/ SCS.

The planning process began with SACOG staff producing predictive scenarios that forecast how much growth (in terms of jobs, housing, and population) would occur in the region during the course of the plan. SACOG also conducts a revenue forecast to estimate regional transportation revenue over the same planning horizon.

For its 2016 MTP/SCS, SACOG created three normative scenarios for the year 2036. Each scenario had the same level of projected population growth and infrastructure expenditures but differed in the development patterns and transportation investments to serve that growth. Using SACSIM, SACOG analysts generated for each normative scenario a set of land use, transportation, equity, environmental, and other performance measures, reflecting the tradeoffs and effects of different development patterns and transportation investments. Drawing on member and partner agency input, stakeholder outreach, and public workshops, the SACOG board endorsed one of the scenarios -- one with a relatively high share of new compact housing, as well as more growth in high-frequency transit areas and fewer developed acres -- as meeting its broad policy goals. This preferred scenario and its associated land use forecast, collection of

[7] This text derived almost verbatim from Lempert et. al. (2020)

transportation projects and programs, policy direction, and performance outcomes ultimately became the adopted 2016 MTP/SCS.

RDM stress test

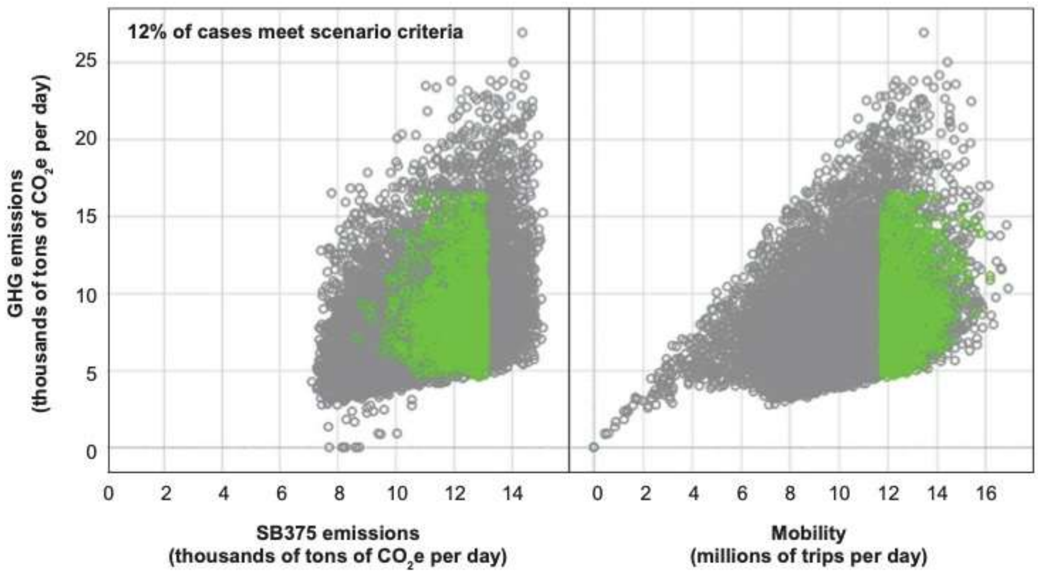
As part of SACOG's preparations for its 2020 planning cycle, the agency partnered with RAND Corporation to conduct an RDM analysis of their 2016 MTP/SCS (Lempert et al. 2020). The analysis focused on stress testing the MTP/SCS over a wide range of uncertainties that the agency judged were insufficiently explored when developing the 2016 plan. The SACSIM model's run times were too long to conduct the multiple runs needed. The study thus created a much simpler model designed to interpolate and extrapolate among SACSIM runs. This simple model tracked 450 cohorts, stratified by age, household income, residential density, and proximity to transit. Each cohort was characterized by VMT, trips per capita, and the number of people in the cohort. This cohort model was calibrated against the SACSIM projections for 2036 (a single predictive scenario) and used to estimate how overall outcomes of interest to SACOG might vary based on the effects of various uncertainties and policy choices.

The analysis focused on seven uncertainties in 2036: external parameters (gas prices, average fuel efficiency of internal combustion automobiles, employment growth in the region); technology adoption (percentage of ZEV/plug-in hybrids); and behavior (sensitivity of VMT to cost of driving, sensitivity of VMT to employment growth, and the extent to which today's millennials retain their current driving behavior or adopt the driving behavior of today's forty-somethings). Drawing on the range of estimates in the literature, the study chose high and low values for each uncertainty.

The analysis focused on four performance measures: total greenhouse gas emission from passenger vehicles, called *total GHG emissions*; a subset of total GHG reductions calculated according to California regulations requiring MPOs to reduce VMT, called *SB 375 emissions* after Senate Bill 375 which requires these reductions; overall *mobility* as measured by person-trips by all cohorts; and *equity* as measured by person-trips from low- and middle-income cohorts. Success for each metric was defined as meeting or exceeding the baseline numeric value projected in SACOG's original MTP/SCS analysis.

The analysis then ran the cohort model over 10,000 futures, each representing a different combination of the seven uncertainties. This generated a large database of runs, with one database record for each of the 10,000 futures. Each record had eleven entries: seven recording the value of the uncertainties and four recording the resulting total GHG emissions, SB 375 emissions, mobility, and equity in that future.

Figure 3.1. Futures in which SACOG meets its climate, mobility, and equity goals



Source: Lempert, R., J. Syme, G. Mazur, D. Knopman, G. Ballard-Rosa, K. Lizon and I. Edochie (2020).

Figure 3.1 shows the results of this stress test. Each dot shows the GHG emissions, SB 375 emissions, and mobility for each of the 10,000 futures. Solid (green) dots show futures in which SACOG meets all four of its goals in 2036. Open (gray) circles show futures in which SACOG misses at least one of its four goals. The panel on the right shows the tradeoffs between total GHG emissions against mobility. Many futures with low GHG emissions nonetheless fail to meet SACOG's goals because mobility is too low. Some futures with high mobility fail because emissions are too high. The panel on the left shows the tradeoffs between total GHG emissions and emissions calculated according to the rules of SB 375. Actual emission can be higher or lower than those calculated under SB 375 depending on how emissions per VMT varies across scenarios. The equity results are strongly correlated in this analysis with overall mobility and are not plotted independently here.

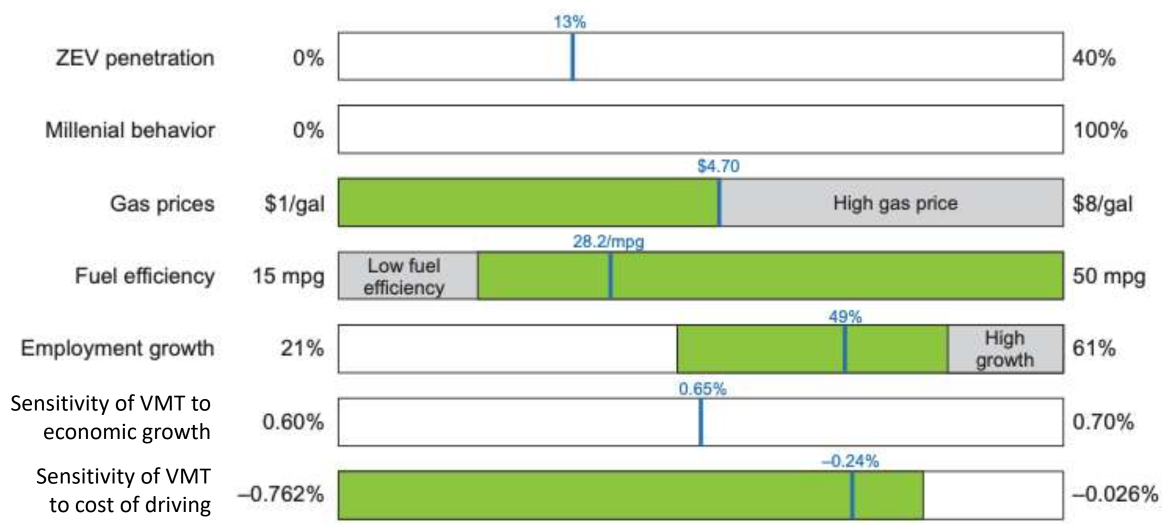
Scenarios that Illuminate Potential Vulnerabilities of SACG's Plan

The patterns of futures in Figure 3.1 raise the question – what future factors are most important in determining whether SACOG's MTP/SCS meets or misses its climate, mobility, and equity goals? To address this question, the study employed "scenario discovery" classification algorithms (Lempert et al. 2006, Bryant and Lempert 2010) to the database of model results to identify those combinations of uncertainties that best distinguish between the solid (green) and open (gray) circles in Figure 3.1.

Figure 3.2 shows results of this analysis. The bars show each of the range of values for each seven uncertainties considered in the analysis along with the best-estimate value used by

SACOG to evaluate the MTP/SCS. For instance, the bar showing uncertainty about 2036 gas prices ranges from $1/gal to $8/gal and shows SACOG's best-estimate of $4.70/gal. Four bars – gas prices, fuel efficiency of internal combustion vehicles, employment growth, and the sensitivity of VMT to the cost of driving – have dark (green) shading over a portion of their range, showing the results of the scenario discovery analysis. For SACOG's MTP/SCS to meet its 2036 climate, mobility, and equity goals each of these uncertainties needs to lie within the highlighted range. If any one or more of these conditions is not met, SACOG's plan is unlikely to meet all its climate, mobility, and equity goals. The three uncertainties without any dark (green) shading are significantly less important in determining whether or not the MTP/SCS meets its goals.

Figure 3.2. Settings of key drivers under which SACOG meets its goals



Source: Lempert, R., J. Syme, G. Mazur, D. Knopman, G. Ballard-Rosa, K. Lizon and I. Edochie (2020).

The study labeled these future conditions shown in Figure 3.2 as the "Meet All Goals" scenario. This scenario has four key driving forces, which must satisfy the following conditions in 2036: gas prices must be less than $4.70/gal, fuel efficiency greater than 22 mpg, sensitivity of VMT less than –0.17%, and employment in the SACOG region between 40% and 55% larger than it had been in 2016. Note that this scenario represents both normative (what do we want?) and exploratory (under what conditions do we get it?) concepts.

Figure 3.2 also indicates three scenario representing potential vulnerabilities of the MTP/SCS. In each of these vulnerable scenarios, the MTP/SCS fails to meet one or more of its goals. The first scenario, labeled "High gas price," is any future in which 2036 gas prices exceed $4.70/gal, which makes it difficult to meet SACOG's mobility goal. The second, labeled "Low fuel efficiency," is any future in which the average 2036 fuel efficiency of internal combustion automobiles is less than 22 mpg, which threatens the emissions goal. The third, “High growth” is any future in which total regional employment is more than 55% larger than in 2016, which also threatens the emissions goal.

SACOG used these scenarios to understand the vulnerabilities of its 2016 plan and to examine policy responses that might reduce these vulnerabilities.

Overall, the study suggested that SACOG’s ability to meet the mobility, equity, SB 375 emissions and total GHG emissions goals in its 2016 MTP/SCS is very sensitive to many exogenous uncertainties and that simultaneously achieving each of these goals is difficult. The study also explored several policy options for adjusting the plan to meet its goals in several of the vulnerable scenarios.

Decision Framing Used in this Study

DMDU analyses often used the XLRM framework to structure stakeholder engagements and decision framing discussions (Lempert et al. 2003) as well as provide information needed for the analysis steps. As shown in Table 3.1, performance measures, the M’s, represent the goals decision makers aim to achieve. Policy levers, the L’s, represent actions decision makers might take to achieve their goals. Uncertainties, the X’s, represent factors outside decision makers’ control that affect their ability to pursue their goals. Relationships, the R’s, among the measures, levers, and uncertainties are often represented by computer simulation models.

Table 3.1. XLRM factors employed in DMDU analyses

X: Uncertainties	L: Policy Levers
What uncertain factors outside decision makers’ control affect their ability to pursue their goals?	What actions might decision makers take to pursue their goals?
R: Relationships	M: Performance measures
How might policy levers (L) and uncertainties (X) be related to decision makers’ goals (M)?	What are decision makers trying to achieve?

Table 3.2 displays the XLRM factors used in this SACOG study. These factors were developed from consideration of SACOG’s official planning documents and from discussions with SACOG staff in response to the question “under what conditions will SACOG’s 2016 MTP/SCS meet its climate, mobility, and equity goals?”

Table 3.2. Main problem elements examined in SACOG RDM analysis ('XLRM' framework)

Uncertainties (X)	**Policy Levers (L)**

• Gas prices
• ZEV market share
• Fleet fuel economy
• Economic growth
• Millennial behavior
• VMT elasticity to cost of driving
• VMT elasticity to economic growth
	• Base case policy
	  - *2016 MTP/SCS*
	• Response options
	  - VMT fee
	  - Alternative land use scenarios
	• Adaptive pathways?

Relationships (R)	**Performance Metrics (M)**
• Cohort model	• Total GHG emissions • SB375 GHG emissions • Mobility • Equity

TransLink and Metro Vancouver

TransLink is the transportation authority within Metro Vancouver and also the statutory authority for a multi-modal regional system including fee-based transit services such as buses, heavy and light rail (Elgar and Bindra 2021).[8] Revenues from these services traditionally account for 60 percent of all revenues. The pandemic ridership drop was large and two years later still presents several uncertainties for operations and future planning, principally over questions of post-COVID travel behavior. Before the arrival or proven efficacy of vaccines, the agency envisioned three possible scenarios to which they could not attach meaningful likelihoods: “High Demand” in which the success of vaccination swiftly returned ridership to close to prior levels, “Medium Demand” in which there are delays in vaccine deployment and also in achieving levels of immunity that would let ridership rise above half of its prior levels in the medium term, and “Low Demand” in which less successful vaccination results combined with other factors such as new pandemic waves and behavioral shifts make it difficult to regain prior levels for several years.

Figure 3.3. Experimental design used by TransLink in RDM analysis of transit ridership

Factors of Uncertainty	Without Vaccine			With Vaccine		
	Ranges			Ranges		
	Max	Min	Peak	Max	Min	Peak
Employment	PC	80% PC	0.95	PC	80% PC	0.95
Propensity for Auto Ownership	115% PC	85% PC	1	115% PC	85% PC	1
Propensity to Share Rides	PC	60% ~~PC~~	~~0.9~~	~~PC~~	85% PC	1
Telecommuting/Remote Learning	55% ~~PC trips~~	~~PC trips~~	~~0.9~~	75% PC trips	PC trips	0.95
Discretionary Trips	115% PC	70% ~~PC~~	~~0.9~~	~~115% PC~~	85% PC	1
Fuel Prices	1.80$/L	0.90$/L	1.35$/L	1.80$/L	0.90$/L	1.35$/L
Transit Service (hours)	PC	PC		PC	PC	
Transit Capacity	PC	67% ~~PC~~		~~PC~~	PC	

Note: PC = Pre-COVID; peak = value attained at pre-COVID peak.

Source: TransLink

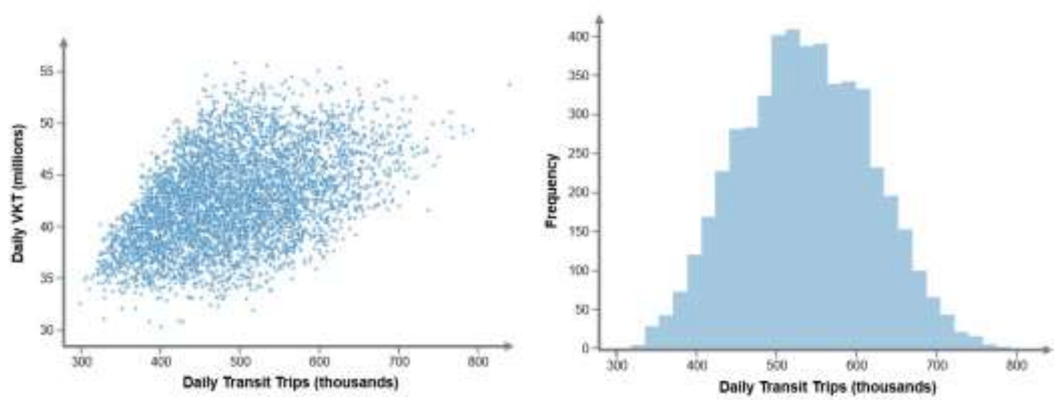
The TransLink team were uncomfortable with just positing these scenarios and even more so when pressed to characterize them probabilistically as requested by provincial authorities. They instead used TMIP-EMAT (Chapter 4) as an application for conducting an RDM analysis. Figure 3.3 illustrates the range of values for the uncertain factors whose influence on alternative plans they wished to weigh. The left-hand column lists the factors to be explored while the middle columns show the range of minimum, maximum, and peak values in a near-term post-COVID

[8] All information unless noted otherwise comes from a TMIP-FMIP webinar presented 7 December 2021 (Elgar and Bindra 2021) and subsequent discussions with the authors of the analysis, Ilan Elgar and Sumit Bindra, upon which the webinar was based.

scenario for these variables. The right-hand columns, however, were generated at a later date, when it was known that high efficacy vaccine is about to be available and define the range of values that might be plausible under conditions of effective vaccine availability.

The Metro Vancouver regional transportation model, like most travel demand models, produces one point estimate for model outputs per run.[9] Theoretically a modeler would have to run the model 1000s of times to produce a distribution of outcomes which is time consuming. It also is difficult to design model runs that take into account the correlations and interactions of different model inputs. With TMIP-EMAT, the TransLink team instead quickly produced 5,000 runs spanning the region described by the variable ranges in Figure 3.3. Figure 3.4 shows on the left a scatterplot of runs measuring the two variables of number of daily transit trips on the horizontal axis and vehicle kilometers traveled on the vertical axis. The view on the right presents a histogram of daily transit trips from which the 10th, 50th and 90th percentiles values were obtained.

Figure 3.4. Plot of outcomes from 500 cases using uniform sampling across uncertainties



Source: TransLink

The TransLink team used TMIP-EMAT to determine which factors had the most influence on outcomes. *Feature scoring* determines which factors had the most influence on outcomes of interest in a sample of cases generated according to a specific experimental design (see Figure 3.3.)[10] Table 3.3 shows the feature scores for five measures of outcome (Daily

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[9] The language used in DMDU analyses tends to treat the words 'run' and 'simulation' as synonyms. We have not made a distinction in this report. In the TransLink application, however, the analysts distinguish between the two with 'runs' referring to the process of operating the transportation demand model to produce the input and output variables to facilitate the estimation of meta models. The term 'simulations' is reserved by then to refer to the individual instances of outputs generated using the meta models.

[10] It is important to note that feature scoring is not absolutely determinative of relative importance. That is, it pertains only to the sample of cases the outcomes of which are also determined by experimental factors such as variables selected for analysis, metrics used to assess outcomes, number of cases in the sample, etc. The iterative

transit trips, PM speed, Sustainable mode share, Daily VKT, and Daily fare revenue.) The factors that changed across cases (Discretionary trips, Employment, Gas prices, Propensity for vehicle ownership, Propensity to ride share, Vehicle capacity, and Telecommuting/Remote learning) are shown as columns with the feature score for that factors given in the cell corresponding with each measure of outcome. The top box are the feature scores in the absence of effective vaccination while the bottom box are for cases in which vaccination succeeds. The figure shows that in the case of no vaccine, the dominant factors are Propensity to ride share for measures associated with transit outcomes while Telecommuting/Remote learning explains the largest degree of variance in outcomes associated with motor traffic. This largely holds true when vaccination succeeds, except that Propensity for vehicle ownership becomes the leading factor for Sustainable mode share and generally the leading factors in each case are not so overwhelmingly dominant.

Table 3.3. Feature scores of uncertainties in determining outcomes with or without vaccines

	Discretionary Trips	Employment	Gas Prices	Propensity for Vehicle Ownership	Propensity to Ride Share	Vehicle Capacity	Telecommuting/ Remote Learning
Daily Transit Trips	0.09	0.09	0.09	0.08	0.45	0.04	0.16
PM Speed	0.07	0.13	0.04	0.22	0.07	0.03	0.43
Sustainable Mode Share	0.08	0.08	0.10	0.21	0.41	0.04	0.07
Daily VKT	0.09	0.14	0.06	0.22	0.06	0.03	0.40
Daily Fare Revenue	0.07	0.09	0.09	0.08	0.42	0.05	0.20

	Discretionary Trips	Employment	Gas Prices	Propensity for Vehicle Ownership	Propensity to Ride Share	Telecommuting/ Remote Learning
Daily Transit Trips	0.12	0.15	0.11	0.10	0.34	0.17
PM Speed	0.07	0.22	0.06	0.23	0.06	0.36
Sustainable Mode Share	0.09	0.09	0.09	0.38	0.21	0.13
Daily VKT	0.07	0.25	0.08	0.22	0.08	0.30
Daily Fare Revenue	0.11	0.17	0.10	0.11	0.31	0.21

Note: The top box presents feature scores for the influence of uncertain factors on outcomes listed in the left-hand column in the absence of effective vaccines while the bottom box presents the same information for these measures in the cases in which an effective vaccination occurs. The values across rows sum to equal 1.0.

Using the distribution of outcomes of interest (example shown in Figure 3.4), the TransLink team identified the low (5th), medium (50th) and high (95th) percentile of each outcome. To extend the analysis, TransLink might have also used TMIP-EMAT built-in scenario discovery

property of RDM analysis and the relative ease of conducting many trials in TMIP-EMAT would allow more substantial inferences to be drawn on the basis of more than just one trial.

tools to suggest how this distribution of outcomes might affect the choice of policy response. That is, they could have posited alternative strategies for operating the connected TransLink systems, model those strategies using the same set of input variables as used to generate Figure 3.4, and then used scenario discovery to identify stressful scenarios for each strategy. The agency could then identify probability thresholds, that is, the likelihood one would have to assign to each strategy's stressful scenario(s) to justify choosing an alternative strategy and compare these thresholds to any available probabilistic information (Popper et al. 2009).

The TransLink analysis was used to inform several key decisions facing TransLink and Metro Vancouver. These included 2021 budgeting based on ridership and revenue projections, recovery expectations and updating of service level plans, and perhaps most importantly for the system and the millions of customers it serves, funding discussions with regional, provincial, and federal governments.

Los Angeles Water Quality

The City of Los Angeles had developed an implementation plan to meet Federal water quality standards on the Los Angeles River. The plan consisted of an optimal mix of regional projects such as spreading basins, green streets, and building codes requiring low impact development on private property. But this initial plan did not include consideration of climate change. The city used an RDM analysis to examine how climate change might affect the plan's ability to meet water quality goals and identified an adaptive decision strategy to ensure that it would. While not focused on transportation, this case study is helpful because it demonstrates the connection between RDM stress tests and subsequent development of adaptive strategies.

Development of Water Quality Implementation Plan for Los Angeles' Tujunga Wash

The City of LA's existing water quality implementation plan for the Tujunga Wash, one of the watersheds that feeds the Los Angeles River, was produced and given regulatory approval on the basis of a predict-then-act analysis (Tariq et al. 2017). As part of their responsibilities under the Clean Water Act, jurisdictions are required to prepare such implementation plans that specify the steps they will take to reduce the pollutants reaching impaired water bodies. Jurisdictions are also required to provide a evidence, in the form of a reasonable assurance analysis (RAA), that these steps will result in the required pollutant load reduction. As is common, the City of LA used a rainfall runoff simulation model and an optimization analysis to identify a least-cost set of interventions that would meet regulatory goals, informed by assumptions about future climate, hydrological, socio-economic, land use, and other conditions. The city then used this analysis to prepare its water quality implementation plan and to provide the required reasonable assurance analysis.

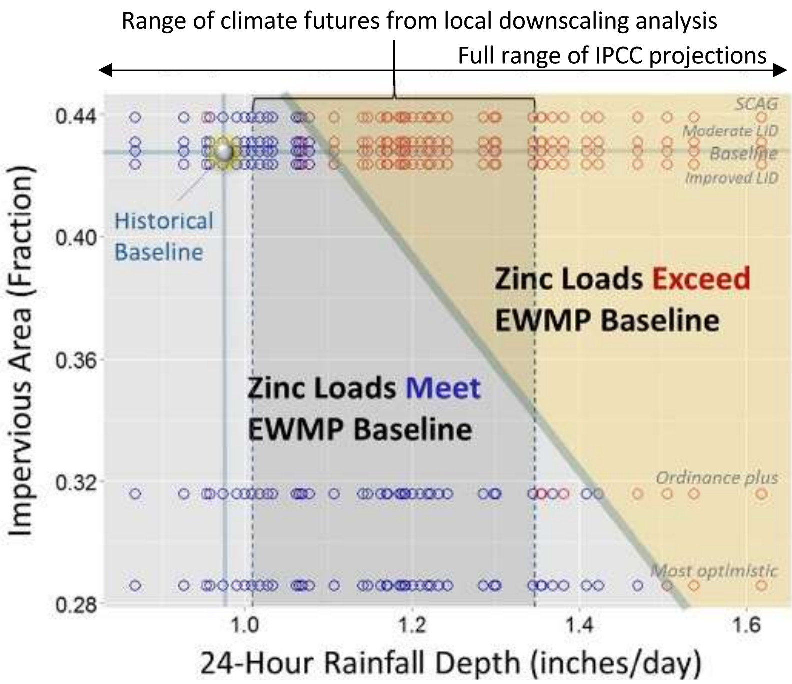
RDM stress test

Los Angeles' water quality implementation plan for the Tujunga Wash had been developed without consideration of climate change. To understand the extent to which climate change might affect the plan, the city partnered with RAND to conduct an RDM analysis.

The analysis focused on two main uncertainties: the extent to which climate change would affect the rainfall runoff that carries pollution into the Los Angeles River and the extent to which land use would affect the permeability to water of the urban landscape. The study used a set of forty-seven alternative projections of future climate in the Los Angeles basin that had been employed the Los Angles County Flood Control District in its own RDM analysis of its flood control infrastructure (Alexanderson et al. 2014). The study also examined six land use scenarios gathered by the study team from various organizations. These included the official projections by Southern California Association of Governments (SCAG), which the city had used for its predict-then-act analysis as well as a very much more optimistic (high permeability) scenario generated by a local advocacy group.

The study used the same simulations models as used in the city's regulatory assurance analysis to evaluate the performance of the Tujunga Wash implementation plan in each combination of 47 climate and land use futures. The resulting database contained records for each of the 282 dots marked in Figure 3.5. The dark (blue) dots indicate futures in which the implementation plan meets Federal water quality goals in 2036. The light (red) dots indicate futures in which the plan does not meet water goals. Each horizontal line represents one of the six land use scenarios. The large dot indicates the best-estimate future used to prepare the implementation plan, with current climate conditions and the land use as projected by SCAG.

Figure 3.5. Water quality stress test: Futures in which City of LA water quality plans meet and miss water quality goals



Note: the scenario labeled "Zinc loads meet EWMP Baseline" represents those futures in which the plan meets Federal water quality standards and the scenario labeled "Zinc loads exceed EWMP Baseline" represents future in which the plan exceeds those standards. EWMP refers to the city's Extended Water Management Plan, used by the study to quantify the federal standard.

Source: Tariq, A., R. J. Lempert, J. Riverson, M. Schwartz and N. Berg (2017).

The study then used 'scenario discovery" classification algorithms to identify the combination of uncertainties most important to distinguishing the futures in which the water quality plan meets and misses Federal water quality goals in 2036. The algorithm identified the two axes shown in Figure 3.5 as the two most important. The first of these is the change in rainfall intensity of the maximum 24-hour storm relative to the current climate. A 1.0 on horizontal axes indicates no change in such intensity. A 1.2 indicates the storm intensity increases by 20%, and so forth. The second important uncertainty is the fraction of the urban land surface that is impervious to water, which range from 44% in the SCAG land use scenario to almost 28% in the most optimistic TreePeople scenario. The best-estimate used in the regulatory assurance analysis is roughly 43%. If successfully implemented, Los Angeles' storm water master plan, labeled 'Ordinance plus' in Figure 3.5, would reduce impervious area to about 32% of the urban surface.

Using these two axes, the algorithm draws the line across the figure that best separates the 282 futures into two distinct regions: one in which the plan generally meets water quality goals and the other in which it doesn't. Figure 3.5 shows the when about 43% of the urban surface remains impervious to water, the intensity of the 24-hour storm cannot increase more than a few percent before the plan fails to meet its goals. However, if impervious land surface drops to 28%, the intensity of the 24-hour storm can increase by 50% before the plan fails to meet its goals.

The study next provided two estimates of the effect of climate change on the intensity of the 24-hour storm in the Los Angeles basin. As one bounding case, the ensemble of climate models used in the IPCC Fifth Assessment Report generates the range of estimates shown on the horizontal axis, from a 20% decrease to a 60% increase. As another bounding case, downscaled, probabilistic climate projections from a research group at UCLA suggested a narrower range -- with 95% confidence the UCLA group estimated that the 2036 storm intensity would range from no change to a 35% increase. No probabilistic estimates were available for future land use.

Overall, this stress test suggests the city's water quality implementation plan is vulnerable to climate change unless the city successfully implements its ambitious storm water master plan. If the impervious area remains close to the base-case estimates, Figure 3.5 shows that the city's water quality plan will fail to meet its goals in most climate futures. However, if the city successfully implements its storm water master plan, the water quality implementation plan will meet its goals in all or most climate futures.

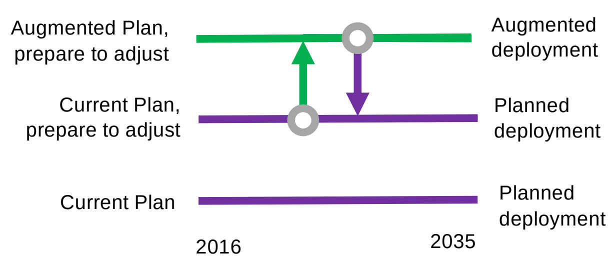
Adaptive pathways

The study next considered how the city of Los Angeles might best reduce this climate-related vulnerability to its water quality implementation plan. The city manages water quality under a State of California permit that explicitly calls for an adaptive management process to address uncertainty. The study thus considered an adaptive pathways approach in which a plan is specifically designed to evolve over time to new information. In particular, the study considered adaptive plans consisting of pre-determined near-term actions, signposts to monitor, and pre-determined contingency actions to take if the signposts cross a pre-determined threshold.

The scenarios that emerged from the stress-test inform the design of these adaptive pathways. First, the study used the "Plan Misses Goals" scenario to calculate the needed augmentations that might be required. Focusing on a future with baseline land use and 50% increase in storm intensity, the study employed the RAA models to calculate the optimum deployment of regional projects, low impact development, and green streets in a stressing climate scenario. This augmented deployment is about twice as large as that currently planned. Second, the study used the boundary between the "Plan Meets Goals" and "Plan Misses Goals" scenarios to suggest the signposts and thresholds the city could monitor. These are the intensity of 24-hour storm and the impermeability of the urban land surface. If observed or projected changes moved the expected future into the "Miss Goals" scenario, this could constitute a tipping point that required a change in strategy.

Figure 3.6. Adaptive water quality implementation pathways

Plan Meets Goals Scenario		Plan Misses Goals Scenario	
Water quality	Cost	Water quality	Cost
Yes	Highest	Yes	Lowest
Yes	Slightly higher	Yes	Slightly higher
Yes	Lowest	No	Highest



Source: RAND, adapted from Tariq, A., R. J. Lempert, J. Riverson, M. Schwartz and N. Berg (2017).

Using this information, the study identified three alternative strategies, as shown in Figure 3.6. One adaptive pathway, labeled "Current Plan, Prepare to Adjust," would begin with the currently planned deployments, monitor land use trends and improving knowledge regarding storm intensity and, if necessary, augmenting the deployments. In the near-term, this pathway would also require preparing for any future augmentations. For instance, the city might retain ownership of land it might need for additional regional projects, using it for what could be temporary uses, such as recreation, rather than committing it now to uses which involve more permanent structures such as industry or housing.

Another adaptive pathway, labeled "Augmented Plan, Prepare to Adjust" would begin with the augmented deployments, monitor land use trends and improving knowledge regarding storm intensity, and if possible reduce the deployments to those currently planned. As a third option, the city could pursue its "Current Plan" without any explicit preparations for monitoring and for future augmented deployments.

The study used a simple multiple-scenario, multi-objective comparison to evaluate tradeoffs among these alternative strategies. The study considers two objectives: whether the implementation plan meets water quality goals and the plan's cost. As shown in the left-hand panel of Figure 3.6, all three plans meet water quality goals in the "Plan Meets Goals" scenario. In this scenario, the current plan is least-cost and the augmented plan is highest cost. The "Current Plan, Prepare to Adjust" costs slightly more than the current plan because, although the initial deployment is the same, the plan incurs costs to monitor and prepare for future adjustments. In the "Plan Misses Goals" scenario, the "Current Plan, Prepare to Adjust" and "Augmented Plan, Prepare to Adjust" both meet water quality goals. Although both these two plans end with the same deployments of projects, the augmented plan is slightly less expensive because it could sequence those investments most efficiently over time. In this "Plan Misses Goals" scenario the "Current Plan" misses water quality goals and is most costly because the study assumes the city would be forced to rapidly respond to these missed water quality goals.

This analysis suggests that the "Current Plan, Prepare to Adjust" is the most robust water quality implementation plan for the city. It performs better than the alternatives over both objectives of interest in both plausible scenarios and never performs significantly worse than the alternative in either scenario.

Decision Framing Used in this Study

Table 3.4 displays the XLRM factors used in this water quality study. These factors were developed in discussion with city staff in response to the question "will the city's water quality implementation plans still be successfully in meeting federal water quality standards in the presence of climate change?"

Table 3.4. XLRM factors in Los Angeles water quality analysis

Uncertain Factors (X)	**Policy Levers (L)**
• Climate change • Land use	First iteration of analysis • City's proposed plan Second iteration adds: • Adaptive pathways
Relationships (R)	**Performance Metrics (M)**
• Hydrology and optimization models used in city's regulatory approval analysis	• Meet water quality requirements • Cost effective

Culver City and the Rancho Higuera neighborhood

The previous examples of introducing DMDU concepts to transportation planning have involved quantitative, model-based methods. This is consistent with the usual analytical style found in MPOs. The need to generate mandated planning documents and operate in reliance upon data and legacy modeling suites suggest the value of such approaches for early forays into seeking DMDU enhancements to existing interactions between modelers and planners (see Chapter 5).

However, one aspect of creating within MPOs a capacity for wider-focus strategic foresight suggests the potential value of also considering non-quantitative DMDU methods as well. That would be in seeking wider engagement with community or governmental stakeholders at an early, conceptual stage of strategic deliberations. Such qualitative methods may be used to guide a process that is sufficient in itself, designed to create a shared framing and vocabulary among heterogeneous audiences and to frame the main issues and strategic alternatives they face in common. Or, such a process can be an entry point, something of a study design, for a more model-based analysis that may then be made the core of a deliberations-with-analysis process (see Chapter 4) that may, in turn, segue into the more usual channels of MPO process.

Culver City, with 40,000 residents, lies at the crossroads of key transportation corridors between downtown Los Angeles and the beaches of Santa Monica. Culver City has become a magnet for 21st century digital media as well as higher end design and architecture studios. These economic engines, however, mean traffic increasingly clogs the city's streets. Up to 70 percent is cut-through traffic, passing across the city on its way to someplace else.

The increase in traffic is especially consequential for Culver City which has long prided itself in providing a distinctive urban environment for its residents and visitors. In 2017, Culver City released its Transit Oriented Design (TOD) Visioning Study, a blueprint re-imagining future mobility in the city's downtown district. The TOD aims to reduce reliance on cars by reshaping the urban landscape and creating multiple alternative mobility.

Implementing the TOD vision presents a significant challenge. The TOD vision represents transformational change requiring significant shifts in the city's landscape and the expectations and habits of its citizens – all at a time of rapid expansion of mobility options.[11] As a particular case, the Rancho Higuera neighborhood provided a microcosm of issues to be resolved. In 2018, Culver City called upon a RAND team to apply new approaches to planning towards ambitious visions during uncertain times (Lempert et al. 2019).

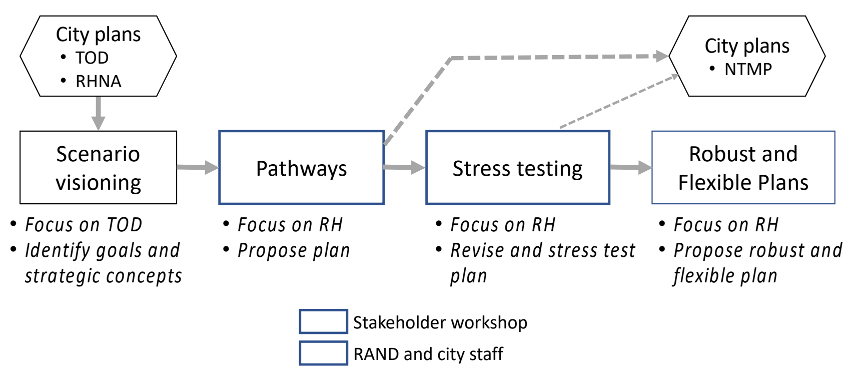
The process, with participation by both city staff and the Rancho Higuera Neighborhood Association (RHNA) who had previously come to an impasse, focused on two key concepts: DMDU and a "shadow" process of citizen involvement in parallel to and interacting with more

[11] For instance, within a year of the TOD study release, electric scooters belonging to two competing providers, Bird and Lime, became commonplace on the streets of near-by Santa Monica, adding an unannounced and unexpected element to the possibilities envisioned by the TOD.

formal planning. It was conducted a series of scenario and stress-testing workshops with city staff, developers, and Rancho Higuera residents.

Up to 10,000 cars a day travel through this residential neighborhood in the morning and evening. RHNA concern is that this traffic, some of which is aggressive and high-speed, endangers pedestrian safety and residents' access to local schools and businesses. An original RHNA proposal, however, raised several challenges. First, it could generate adverse consequences by making it more difficult for employees coming from outside the city to reach their jobs, diverting congestion onto the streets of adjoining neighborhoods, and making it difficult to move around Rancho Higuera itself. Second, the plan might run afoul of a number of disruptive future trends or developments, such as failing to account for or take advantage of new mobility options (e.g. scooters, ride sharing) that might make its goals easier to reach; or, on the other hand, failing to anticipate the unexpected ways people might respond to attempts to divert them from neighborhood streets. Finally, implementing the RHNA plan would require generating a flow of realized and anticipated benefits that outweigh in people's minds the inconvenience of adjusting their daily routines.

Figure 3.7. Process used in Culver City - RHNA engagement



Source: Lempert, R. J., T. McDonald, S. W. Popper, D. Prosdocimi and T. A. Small (2019).

As shown in Figure 3.7, the process proceeded through four steps. First, a scenario visioning exercise was conducted with community members and city staff. This approach obviates a too-early focus on strategies (means) without sufficient explicit exploration of objective values (ends) to be used in evaluating outcomes. The exercise used two classic DMDU methods. *Scenarios* generate stakeholder engagement and expand the range of futures they consider, contemplate their choices and goals from a wider range of views and vantages, and engage more comfortably with potentially troubling tradeoffs. *Backcasting* starts with defining a desirable future and then works backwards to identify policies and programs that will connect that specified future to the present (Robinson 1988).[12]

Next, RAND and Culver City staff generated a proposed implementation pathway from the elements surfaced by the scenario visioning employing another DMDU framework, *Three Horizons Foresight* (Curry and Hodgson 2008). The horizons represent distinct time periods that evolve as a result of decision-making, external forces and societal evolution. Briefly, the first horizon is the present while the third horizon describes a future that could resemble the envisioned desirable scenario or prove less desirable depending on choice of pathway and uncertain future trends or surprises. This focuses primary attention on the second horizon represents a transition phase articulating how society shifts from the current state to the desired future state.

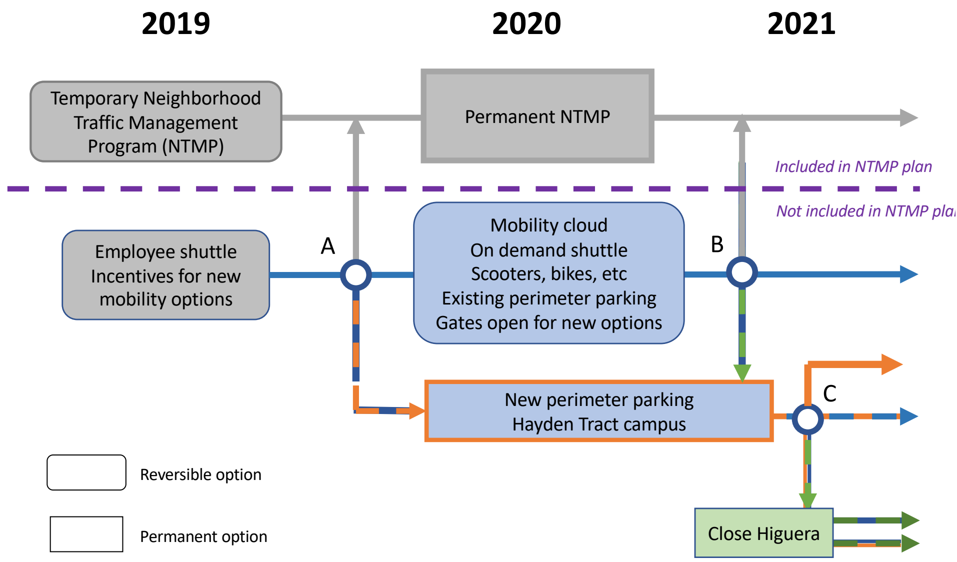
In the third step, community members critiqued the proposed implementation plan and tried their hand at crafting alternatives. They then stress-tested these alternatives plans using a DMDU method called *Assumption Based Planning* (ABP) (Dewar 2002). ABP uncovers vulnerabilities to explicit and, often more importantly, implicit assumptions underlying the plan – particularly those identified as load-bearing or central to a plan's success. Participants in the stress-testing workshop used ABP to identify such key assumptions underlying their favorite plans.

Finally, all prior information was used to propose a robust and flexible plan --one that would achieve multiple goals over a wide range of future scenarios – by applying the technique of *adaptive pathways* (Haasnoot et al. 2013). Adaptive pathways charts alternative paths at each tipping point (emerging conditions under which continuing to follow the path would lead to failure) and, importantly, highlights actions that can be taken in the near-term to prepare for the alternative paths (see Ecola et al. 2018 for another transportation application combining backcasting, three horizons foresight, and assumption based planning).

Figure 3.8 shows the dynamic pathway used to inform the re-imagined RHNA plan. This plan aims to meet the needs of Rancho Higuera residents, reduce deleterious effects of the TOD on surrounding communities and businesses, and enhance robustness of the TOD against a range of potential surprises. Perhaps the most important result was to enhance articulation and sharing of the vision for a satisfactory outcome for Rancho Higuera as well as to achieve consensus among residents, city officials and stakeholders on a course of implementation

[12] This brings to the fore an important point. It is difficult to think about the future because of its many branch points and possible manifestations. It is easier to begin with a specific future and think backwards.

Figure 3.8. Adaptive implementation pathways for the final augmented RHNA plan



Source: Lempert, R. J., T. McDonald, S. W. Popper, D. Prosdocimi and T. A. Small (2019).

Chapter 4. Methods and Tools in Agency Application

DMDU methods consist of analytic tools and a process for employing them in support of decision making and stakeholder engagements. This chapter describes common methods used for DMDU participatory processes and software packages available to support DMDU analytics.

DMDU Participatory Process

MPOs often develop their transportation and land use plans using participatory processes with stakeholders. Such engagement provides a rich and contextual understanding of local knowledge relevant to planning, the often diverse and conflicting community values that the plans seek to serve, as well as enhancing legitimacy and acceptance of the resulting plans and process of plan development. In addition, federal rules require MPOs to engage in public involvement, participation, and consultation.[13]

Public engagement is an important component of DMDU. Such engagement has been most prevalent in the water and coastal management sectors (Groves et al. 2013, Fischbach et al. 2017, Bouwer et al. 2018, Groves et al. 2019, Wong-Parodi et al. 2020), including deliberative processes with Louisiana on its Coastal Master Plan (Jones et al. 2014 Box 2.1, Wong-Parodi et al. 2020); among the parties to the Colorado River Compact (Groves et al. 2013); and a multi-jurisdictional collaboration in North Carolina (Zeff et al. 2016). Among the case studies described in this report, public engagement played the largest role in the Culver City effort. The Los Angeles water quality work also provided a forum for input and review by various city and county agencies, as well as local non-governmental organizations (NGOs). The SACOG case begin with workshops with staff from several neighboring MPOs.

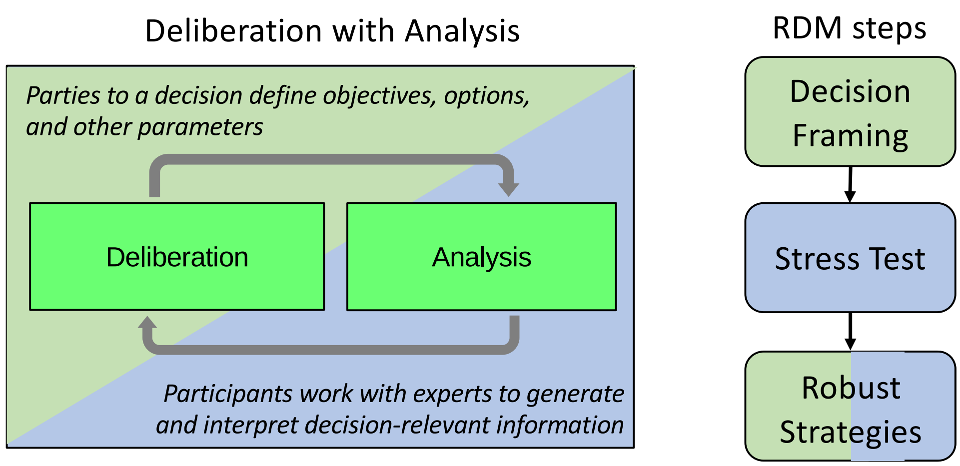
DMDU methods are designed to support a particular process of stakeholder engagement called deliberation with analysis (NRC 2009). As shown in Figure 4.1, deliberation with analysis is an iterative learning process in which stakeholders deliberate on their objectives, options, and problem framings; researchers then define decision-relevant information; and then the parties to the decision revisit their objectives, options, and problem framing influenced by this new information. Deliberation with analysis is intended for situations in which the problem formulations, understanding of system functioning, and the set of promising solutions emerge gradually through interactions among the involved parties (Dewulf et al. 2005, Edenhofer and Kowarsch 2015, Kwakkel et al. 2016). As such, the process is thus well-suited to support

[13] https://www.transit.dot.gov/regulations-and-guidance/transportation-planning/public-involvement-outreach

MPOs in engaging the public with multiple rounds of review and comment at key decision points in their planning processes, as required by Federal regulations and guidance.

DMDU processes and analytics are designed to support the deliberation with analysis. As shown in Figure 4.1, RDM's first, decision framing step embodies deliberation, the stress test step focuses on analysis, and the robust strategies step includes both deliberation and analysis. RDM information products are designed to inform this process. Scenarios that illuminate vulnerabilities are designed to help stakeholders with different expectations about the future gain a common understanding of potential vulnerabilities and opportunities. For instance, the scenario discovery results in Figures 3.1 and 3.2 helped SACOG understand potential vulnerabilities of its 2016 MTP/SCS. Robust strategies and adaptive pathways, along with information regarding the tradeoffs among them, are designed to support discussion and agreement on actions by stakeholders with differing expectations and values. The multi-scenario, multi-objective comparisons in Figure 3.7 helped Los Angeles officials consider alternative adaptive water quality implementation plans.

Figure 4.1. Deliberation with analysis



Source: RAND

The XLRM framework described in Chapter 3 often facilitates this process and provides a bridge between deliberative and analytic steps. The deliberative decision framing often begins with an open-ended discussion with workshop participants, who can include agency staff and/or community stakeholders. Facilitators pose a question such as How can our MPO reach its goals? or What mobility future does our community desire? Participants discuss the question, with occasional prompts from facilitators to ensure the conversation touches on all four of the factors in Table 3.1. During the discussions, the facilitators take notes aimed at creating a draft XLRM. At an appropriate point in the discussions, the facilitators present that draft XLRM and seek participants' feedback. Several iterations of this process, which may occur in a single workshop or over a period of several weeks, generate a set of XLRM factors that the analyst team can then use to conduct an initial RDM stress test.

In subsequent workshops, facilitators then present the results of this stress test to participants, which often results in discussions which add to the XLRM factors. For instance, such discussions often suggest additional policy levers as participants seek to address the vulnerabilities and opportunities revealed by the initial RDM results.

DMDU Software Packages

Several software packages exist that can assist MPOs in conducting DMDU analysis. The Travel Model Improvement Program's Exploratory Modeling and Analysis Tool (TMIP-EMAT) is built on a platform called the Exploratory Modeling Analyst's Workbench (Kwakkel 2017). A similar platform is called Rhodium (Hadjimichael et al. 2020).

Both the Exploratory Modeling Analyst's Workbench (EMAW) and Rhodium DMDU packages have similar high-level designs as shown in Figure 4.2. Each regards a simulation model such as might be used by an MPO (the R's in Table 3.1) as a function that is called with a set of input parameters representing uncertainties and policy levers and returns the resulting measures. Using the XLRM framework, we can write

$$M = R(X, L)$$

where R represents the functional relationships among the M, X, and L's.[14]

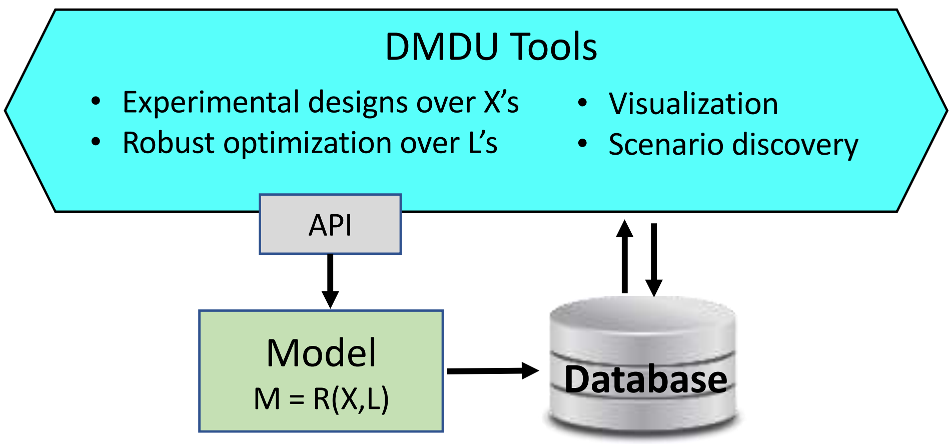
The DMDU packages assume the user has a model they wish to employ. The packages then provide functionalities that exercise the model and databases with results of multiple model runs to implement the steps of a DMDU analysis. These functionalities include running the model many times over a suitable experimental design, storing the results of these computation experiments, employing robust optimization to identify potential strategies, and analyzing and visualizing the results. In addition, EMAW and Rhodium both provide application programming interfaces (APIs) that link models written in various programming languages (e.g. C++, Python, R, Excel) to the other functionalities in the system.

EMAW and Rhodium both enable the user to generate experimental designs over the input parameters to the simulation model. In exploratory modeling, an experimental design is the choice of model runs that aims to efficiently and effectively sample the set of plausible futures in order to answer the users' policy questions (Bankes 1993). The user specifies the model

[14] Note that this equation states the relationship between the four main factors in the XLRM table. However, in the XLRM table itself, as in RDM, there are no "left-hand" and "right-hand" variables. That is, the definition of the 'M's and systematic exploration of possible alternative configurations are as much a part of RDM as applying the same process to the 'X's or 'L's. The heart of the method lies in examining consequences for alternative specifications in all four quadrants: none are regarded as the 'tail' and none the 'dog' analytically privileging one over the other.

inputs to be varied. Generally, there will be a separate experimental design for those inputs regarded as uncertainties (the X's in Table 3.1) and those regarded as policy levers (the L's). EMAW and Rhodium include algorithms that can generate full-factorial samples over each of the input parameters, a stochastic sample such as Monte Carlo over the space of model inputs, or a quasi-random sample such as Latin Hypercube (Stein 1987, Lemp et al. 2021, p. 74). In a typical application, the user employs EMAW or Rhodium to generate an experimental design, run the model for each case in the sample, and stores the results in a database. Where appropriate, the DMDU platforms enable running models on multiple processors to speed run times.

Figure 4.2. Main components of DMDU Software



Source: RAND

EMAW and Rhodium also include visualization packages commonly used for DMDU analyses. These include standard visualization types, including scatter plots and parallel axis plots, as seen in the Metro Vancouver application (Chapter 3), which are used to explore the model runs stored in the database. These visualizations are often interactive, allowing for instance the user to move slider bars to view different subsets of the stored runs.

These DMDU platforms allow the user to run scenario discovery classification algorithms, a key element of the DMDU stress test, to identify clusters of policy-relevant futures among the model runs in the database. Commonly used scenario discovery algorithms include Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999) and Classification and Regression Tree (CART) (Breiman et al. 1984). In a typical application, a user might use scenario discovery to identify the key factors that differentiate policies which meet and miss an MPOs goals (Lempert et al. 2006, Bryant and Lempert 2010). For instance, Figure 3.2 provided example results from a scenario discovery analysis for SACOG. Of the seven uncertainties considered in that analysis, only four are most important in distinguishing futures in which SACOG meets and misses the goals of the agency's transportation plan. If the value of these uncertainties lies within the solid (green) bars shown in the figure, the agency is likely to meet its goals. If one or more uncertainties lies outside these ranges, the agency is likely to miss one or more goals.

Finally, EMAW and Rhodium provide algorithms for multi-objective robust optimization that can identify potential strategies (combinations of L values) robust over a range of scenarios given the MPO's multiple objectives (the Ms). Both platforms support several different multi-objective evolutionary algorithms often used in multi-objective robust decision making (Kasprzyk et al. 2013). Such algorithms can output sets of multi-objective *pareto satisficing* solutions (Lemp et al. 2021, p. 76). A pareto optimum solution is one that is non-dominated in the sense that there are no other solutions that do better on one or more objectives without doing worse on at least one other objective. A pareto satisficing solution is one that is on or close to the pareto surface in each of a wide range of scenarios. In a typical application, a user might use scenario discovery to identify a small number of policy-relevant scenarios and then use a multi-objective robust optimization algorithms to find a set of strategies that are pareto satisficing over these scenarios and all the objectives of interest (see, for instance, Hamilton et al. 2021). The user might then visualize these strategies using one of the visualization packages. However, such calculations can require thousands of model runs, so may present computational difficulties in many MPO applications.

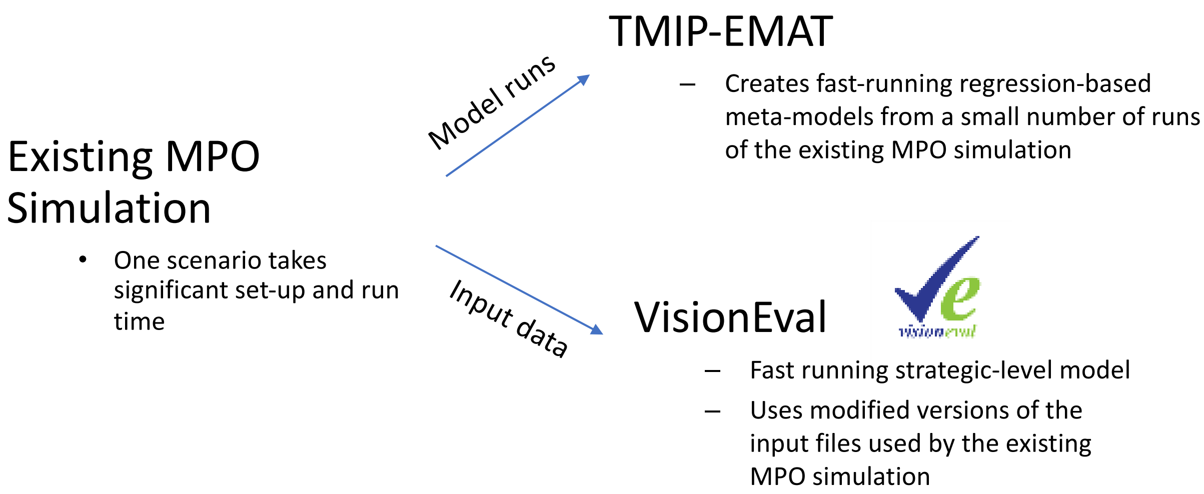
Suitable Models for MPOs Using DMDU

Obtaining a suitable forecasting model (the R's in Table 3.1) presents a major challenge for MPOs using DMDU approaches. MPOs typically employ forecasting models that are computationally intensive and require laborious construction of data files for each individual run. It thus proves difficult to run such models over a wide range of plausible futures. The simple cohort model employed in the SACOG example application (See Chapter 3) provided a useful foundation for exploring the impact of external drivers such as gas prices and economic growth. But it is difficult to use this simple model to examine alternative plans because it lacks appropriate treatment of feedbacks among various elements such as mobility and land use as well as lacks details on how such policies might affect different cohorts (Lempert et al. 2020).

There currently exist two distinct alternatives MPOs can use to obtain a suitable forecasting model for DMDU analyses, as shown in Figure 4.3. An MPO can use runs of its existing, slow-running forecasting model to generate a fast-running response surface simulation that allows exploration of a much wider range of futures. The SACOG application in Chapter 3 gives a simple, hand-crafted example of this approach. More generally, the Travel Model Improvement Program-Exploratory Modeling and Analysis Tool (TMIP-EMAT) software package enables a more systematic means of implementing this approach (Milkovits et al. 2019, Lemp et al. 2021). Alternatively, an MPO can use a fast-running strategic level model that uses aggregated versions of the input data used by more detailed simulations. The VisionEval software package (Wang et al. 2018) enables this second approach.

The reader interested in more operational details of both TMIP-EMAT and VisionEval will find in-depth descriptions of each alternative in Appendix A of this document.

Figure 4.3 Alternatives for obtaining a simulation model for DMDU analysis



Source: RAND

Chapter 5. Implementation within MPO Organizations

> “*Our next transportation plan update is faced with the problem of looking at extremes. Do we presume business as usual or that everything has changed and will change further? We need to consider alternative pathways*.”
>
> – Member of MPO planning staff in conversation with the authors

In previous chapters we have discussed some of the changes in the environment in which transportation analysis and planning is taking place. We then discussed alternative methodological framings for us under conditions of deep uncertainty -- when prediction is neither feasible nor perhaps even the best analytical strategy for supporting transportation planning. In the previous chapter we discussed specific tools designed for DMDU analysis in transportation agencies as well as other public sector mission agencies and showed examples of application. But everyone who has worked within such an agency knows that making a credible case is only the opening salvo. What needs to be done for actual change to take place?

The document to this point has laid out a vision and has shared examples suggesting that there is more behind it than just a hope for change. But transportation agencies are highly organized institutions with many objectives and a complicated job on their hands. As such, they will exhibit considerable care in balancing the promise of new capability against the risk entailed by the introduction of any novelty. In this final chapter we will seek to address the issues involved. First, we will lay out the prospects for benefit from incorporating new tools and methods to enhance strategic exploration of operationally meaningful alternative scenarios. Then, we will lay out several of the obstacles likely to be faced even if there is both will and intent to incorporate them. Finally, we offer thoughts on how it may be possible to on-board those means that could bring new capacities to agencies that they currently find difficult to exercise.

The Value Proposition is Key

In Chapter 2, we discussed the difference between scenarios constructed to be predictive and those constructed for exploratory purposes or to illustrate normative choice. In the same way, organizations may engage in analyses that attempt to reduce the uncertainty they face by trying to forecast. What may be more valuable is to conduct analyses that engage in strategic foresight, an examination without the intent to predict but instead to raise organizational awareness and support an explicit process of managing risk by identifying and weighing alternatives.

As logical as this may sound, it is not easy to achieve. Most hierarchic organizations with mission goals do not take naturally to foresight activities or even strategic planning in general. In fact, such activities can be classified as precarious values. A precarious value within an organization or process is one that has not been sufficiently defined, is not seen to have received sufficient legitimacy through leadership support, or appears to be inimical to widely held understanding of vital missions (Clark 1956). Activities and functional teams seen as failing to, not contributing to, or perhaps even distracting from activities focused on the organization's bottom line will be sidelined—either consciously or unconsciously—and potentially ostracized functionally or eliminated entirely.

Within transportation agencies, the precariousness stems first and foremost from the timelines and workloads under which modelers and planners work. Other barriers and concerns will be discussed below. The present point is that asking difficult questions of busy folks, or asking them to go beyond the tools and processes they have come to rely upon, risks a rejection that comes from the best of intentions on the part of dedicated professionals seeking to responsibly carry out activities tuned to organizational objectives.

One of the few ways to protect a precarious value within an organization is to demonstrate its value. If there is demand for that value that arises directly from those with line responsibility for workflow, that mitigates to a greater or lesser degree the forces that would tend to undermine its presence within the organization. Therefore, it is useful to enumerate some of the dimensions of value that would be added through means to engage more regularly and with reduced cost in strategic overviews of the landscapes facing transportation planning agencies. They fall in three categories.

Enhanced credibility with external audiences.

After global events such as the COVID-19 pandemic and the Great Recession – and even less momentous but none-the-less trend-breaking events in the world of surface transportation such as the sudden proliferation of micro-mobility on demand – it becomes less credible to the audiences of MPO output that forecasts absent explicit analysis of uncertain elements will be perceived as constituting due diligence. Decisions regarding investment in transit will also need to be foresightful about the penetration of connected autonomous vehicles – a development currently difficult to forecast with single projections of timing, rates of fleet turnover, and even the very nature of the vehicles themselves and of their connectivity.

Projections, and by extension analyses and recommendations based on those projections, are made difficult when (often implicit) assumptions of no fundamental change in the underlying systems affecting demography, economy, technology, society, mobility behaviors, and the politics for supporting transportation infrastructure grow less valid. Even if the main process documents required by law remain unchanged, to have them be accompanied by small excursive studies that examine the implication of differing assumptions about currently unknowable factors will enhance both the credibility of those studies and could potentially yield greater acceptance at the local level among those receiving them. (Nevertheless, having the theoretical opportunity to do so while still meeting the federal requirements for supplying single-point forecasts within available resource constraints may make this a difficult task to implement in practice.)

Greater coherence across MPO processes, objectives, and teams.

Mission agencies such as MPOs are susceptible to several organizational pathologies when confronted with the problem of uncertainties that are difficult to resolve or cannot easily be treated probabilistically. DMDU methods can help alleviate some of these tendencies.

While *stove piping* – the tendency for information or activities to be largely pursued in vertical channels or siloes that do not sufficiently interact with each other – can arise even without the presences of deep uncertainty, the consequences can become exacerbated when such conditions prevail. This can be especially problematic when one work group's focus of effort is for another merely one of a series of buried assumption in the modeling framework used by them. This makes model linkages and therefore integrated assessments difficult to manage. With the explicit recognition of the role of assumptions in DMDU and its project of systematically understanding the implications for outcomes and how to characterize different courses of action for achieving them on the basis of those assumptions, past work has shown that unknowns can actually serve to facilitate discussion and sharing among planning and modeling groups working different aspects of a complex planning problem. When all understand that many hundreds or thousands of cases are going to be generated as part of the analytical approach, it reduces some of the conflict over assumptions that would otherwise be present if only a handful of cases would have to carry the full weight of analysis.

Another problem that may appear is the phenomenon of *uncertainty absorption* (Simon 1959). In a hierarchy or an organization with several channels feeding information to senior decisionmakers, those at the lowest levels have a strong sense of the quality of the information with which they work as well as the assumptions that have been made. But such knowledge is difficult to pass upwards in the chain of command without clogging the channels with nuance. Instead, work product and analyses are used to convey the essence of what lower-level teams observe or create. This means that the organization effectively loses a sense of the degree of uncertainty contained in such messaging – or the true degree of the uncertainty it and its decisions may face. DMDU approaches make it possible to retain in large measure a greater sense of the nature of these uncertainties without adding to complication because it also helps characterize their implications for higher level decisionmaking. Model-based methods such as RDM also usually have a drill down capacity. That is, while RDM supports systematic reasoning across myriad individual cases, it also retains the ability to look at individual cases to see what aspects of uncertainty and which assumptions yield successful or unsuccessful outcomes from specific courses of action.

Any policy choice can also be viewed as a policy experiment in a sufficiently complex and uncertain environment. This is a break with behavior that is more consistent with an implicit assumption that a policy once implemented is a policy that need not be revisited. Of course, experience teaches us that this is almost never the case. But there is relatively little hard-wired expectation that change may be required. This becomes a less valid premise when seeking to chart a course through changing times.

Part of the problem is *lack of integration among analysis, planning, and evaluation.* They most often are pursued in series rather than being part of a recursive process. Engaged in as separable, self-sufficient activities, they may be conducted with limited interaction other than feeding results into the next step along the chain. A more responsive approach to policy support, formulation, and evaluation of implementation results would require that these functions be more closely integrated. The tools of DMDU analysis provide a platform for just such integration. The iterative nature of these methods and the emphasis placed on widely shareable outputs make it possible to conduct analysis, planning, and evaluation within a single framework. The hypothesis testing that is inherent in DMDU analyses will naturally accommodate evaluative updates of the results of prior testing assumptions and can be incorporated at any point into the next round of hypothesis forming and evaluation. The feedback between analysis and planning approaches the ideal elaborated by the National Academy of Sciences of creating a process of 'deliberation with analysis' required when framing policy-relevant investigations in complex problem areas (NRC 1996). That is, the deliberation provides guidance to the types of analyses required and the output of those analyses, in turn, guide the deliberations and the tuning of the next round of questions to address. Analysis and policy planning can engage in an ongoing dialogue with each other to the enhancement of both.

Greater latitude for MPO professionals.

Perhaps nowhere within an MPO is the gap between current practice and the ambition for enhanced strategic foresight felt as strongly as among the modeling and planning staffs themselves:

> *"If we try to look at transit planning scenarios, we stall out with the current set of tools. This is especially so to the extent to which goals are conflicting, especially among key stakeholders."*

--Member of MPO planning staff in conversation with the authors

The talented and dedicated professionals who comprise an MPO's modeling and planning staffs understand very well the challenges being faced by their organizations and those whom the MPO serves. In addition to its current offers, these staffs would like both the capability and agility to better respond to the question, "*What if…?*" Current tools and methods are necessary for producing the analyses required by law and should by no means be abandoned nor lose their centrality. The question is whether in addition something more can be offered to address the nuance that is so clearly coming into view for many of an MPO's clientele.

Such a capability could potentially fill present gaps. It would allow greater ability to respond to currently unanswered questions from Board members. It would certainly enhance the scope and realm of the issues that staff could address, thus enhancing their value along the entire value chain. There are issues that arise regularly from modeler/planner interactions. A capacity for relatively rapid DMDU prototyping could provide a means to turn potential impasses to value-creating exchanges to the benefit of both endeavors.

An expanded methodological tool kit could provide the means and capacity to do more rapid and agile studies of a strategic character. This can, in turn, enhance the power of what already exists. DMDU micro-studies could provide both context and perspective for LRTP, TIP, other required outputs that they might either contribute to or accompany. Because of the focus on generating widely sharable visual output, DMDU methods such as RDM can provide new types of outputs to be shared internally, with a governing Board or other public sector body, or to engage the wider community. One means for sharing large data bases of RDM-generated simulation runs is to place them in a well-designed Tableau-type workbook (See, for example, Groves and Molina-Perez 2019). Such documents can be web shared to disseminate "What if?" analyses widely to give others a much better sense of how differing assumptions might affect the desirability of alternative candidate courses of action as future conditions unfold.

The greatest value that would accrue is that the perspective of analysts, planners, and senior officials could undergo change due to exposure to DMDU methodological outputs. This itself could result in greater sophistication within MPOs in dealing with and operating under uncertainty. Modeling approaches based on prediction tend to result in plans that appear like timetables. That is a gross caricature, but then again not far off the mark. Such plans can all too quickly diverge from the way the world actually unfolds given the likelihood of unforeseen or low probability perturbations. This perspective can be tempered by early and explicit exposure to the possibility of multiple pathways and focus on the criteria that might suggest the advisability of shifting from one to the other. Indeed, the very concept of considering before plan implementation what would constitute important external signals of how the future and the plan are unfolding would impart a more flexible and adaptive attitude to the planning process itself.

At its heart, the practice of regional transportation planning is a multi-attribute problem. That is, there is no bottom-line measure sufficient in itself to assess success. Rather, there are several public-facing goals that MPOs need to achieve, among them safety, mobility, equity, sustainability, and infrastructure preservation. There are also more inward-facing objectives: budgetary balance, workforce training and staffing, liability limitation, and others. This is the origin of growing interest within MPOs on performance indicator tracking and monitoring. Some policy levers used to enhance outcomes according to one goal may work to the detriment of another (control of cost being the most frequent counter-poise but, for example, some measures to enhance sustainability could have consequences for equity if they place an additional burden on marginal households.) The problem, therefore, lends itself to an optimizing, forecast-based paradigm than would be the case if there were only a single bottom line. Rather, a multi-attribute problem under severe uncertainty is really an exercise in 'satisficing': decision makers seek a hedged position that will both do well enough according to the various criteria outcomes will be judged by while avoiding being so over-extended that unlooked-for trend breaks or surprises could lead to poor results in one or more dimensions.

Once again, RDM and other DMDU tools are purpose-designed to support satisficing organizational behaviors. This is a skill that all people learn at an early age. But hierarchies have a difficult time in engaging in the type of sustained, systematic, and rigorous balancing that is required to employ the same approaches at scale. Therefore, part of the DMDU value proposition is that the ability to not only discover alternative hedged position but to be able to share them and demonstrate their properties is one that is becoming increasingly necessary when planning in an era of dynamic change.

There are organizational barriers to strategic foresight method adoption

Despite the value of the strategic foresight capabilities that DMDU methodology might mobilize within an MPO, there are powerful barriers to their adoption. These should not be dismissed as hidebound carryovers from the past. On the contrary, many objections stem from entirely legitimate concerns to preserve the integrity of MPOs as institutions and protect their ability to perform the tasks expected of them. It is important to enumerate them explicitly to understand challenges that could lie ahead for would-be agency innovators. Once more, they fall into three larger categories.

External expectations.

MPOs operate within a tight regime of schedules, deliverables, and regulatory structures that largely determine the pace and style of their operation. The nature and content of their deliverables are constrained by the need to meet several formal requirements. Prediction-based analysis persists, even in circumstances for which the fidelity (or even value) of predictions might be heavily affected by the dynamics of change, because that is the form of analysis and therefore plan document required by law – e.g., the state environmental agency requires of regional authorities their predictions of GHG emissions while federal transportation regulations require from them projections of future demand under the proposed MTP.[15] In constructing predictive analysis based on large-scale transportation demand models, analysts are following long-established practice. Change from that practice would be difficult to achieve unilaterally and even the introduction of new elements in addition to what is already required could be a challenge.

Beyond the strictures of law and regulation, some of the decisionmaking audiences of MPO output demand predictions. Here there is something of a chicken and egg conundrum. Senior planners may ask of analysts what they have come to expect is the type of analytical product that is credible to request, namely forecasts. The analysts, on the other hand, are responsive to the

[15] The Planning Rule (23 CFR 450.324(f)(1) says the plan shall include current and projected transportation demand of persons and goods.

requests of those whose deliberations they are mandated to support. One problem, therefore, is lack of awareness of the different type of decision-focused rather than assumption-focused analytical product that analysts might be able to produce and that would come closer to answering the senior executives' fundamental question. Not so much, "What will happen?" -- the focus of the predictive predisposition discussed in Chapter 2, but rather "How can we choose a sound course of action in the absence of reliable predictions?" -- the exploratory and normative stance also discussed in Chapter 2 lying at the heart of strategic foresight.

There is also a quite human reaction to the presence of uncertainty: it creates discomfort. Some members of regional governance boards might reject either openly or less obviously having MPO staffs introduce 'more complexity' into the deliberations of which they are a part. Concreteness, even when many are aware that faith in that concreteness may be misplaced, leads to less anxiety. Being able to describe a path according to which the future is likely to unfold is a surprisingly common reaction within hierarchic organizations seeking to deal with uncertainty. This is especially true when there seems little alternative to doing so. But such misplaced concreteness can lead to an illusion of possessing control to a greater degree than the organization is able to achieve in practice. The end result may be considerable difficulties down the line.

Resource demands.

MPOs managers and staff do not have a great deal of time to spare. On the contrary, their staffs may usually be found engaged in concerted efforts to make certain that requisite analyses and documents are timely and meet a high standard of professionalism. Even with a strong desire within both these staffs and the MPO itself to build up a DMDU capacity, the time and resources are often too constrained.

In the experience of the authors working with MPO personnel and their management, this may be among the most binding of constraints. It represents a serious obstacle to moving forward with a program of enhancement and change. More directly, the design, data validation, and explorations required to install capacity for DMDU analyses in an MPO asks for a major increment of effort from an already overburdened modeling staff. To be clear, most of these efforts would be labeled as start-up costs. That is, once in place, the marginal costs of conducting analyses within the erected frameworks would be less, perhaps considerably so. It is also the case that not all of the methods described in Chapter 4 would involve similar investments. VisionEval, for example, would require an investment in the type of data structures necessary for its operation even if most of those data could be derived from the databases informing the travel demand models. TMIP-EMAT could prove less costly on the front end because the contours of the response surfaces would be generated from runs of the travel demand models themselves. RDM analyses can be conducted relatively simply and cheaply but they would require models to act as scenario generators even if only relatively simple Excel spreadsheets or other rapid-build modeling applications.

Currently, travel model staff work on their core travel demand models close to full time. The requirements for validation of these predictive modeling instruments are non-trivial. And as demand models become more detailed, they become a barrier in themselves. When the time to perform a single run becomes a matter of days, such effort militates against more exploratory, rapid response approaches. What may be required is to develop sub-teams not directly tied to the demand model to develop an ancillary analytical capacity for more strategic, exploratory, and rapid-response excursions that would require myriad model runs – far more than would be feasible with the demand model base present in most MPOs.

The expedient of expanding or running parallel teams, however, is itself a non-trivial challenge. It is beyond the scope of this report to dwell on this obstacle. The resolution may lie in exploring some of the incremental steps to be discussed in the next section.

Internal resistance to change.

Some of the most persistent obstacles to incorporating new tools for assisting analysis and planning under deep uncertainty are also the most amorphous. They stem from deeply seated factors themselves rooted in aspects of training, experience, organizational behavior, and human psychology. Agency culture also comes into play. Some agencies are less data-driven than others. They may respond more to “squeaky wheel” issues or directions informed by the vision of their leadership. So, analysis may be less of a continuous presence within agency decision-making. Among the clearest of potentially problematic factors is the resistance that arises when vested interests in what currently exists appear to be under challenge. There is a natural tendency to preserve what has been built by those who were themselves the builders or who operate within those processes routinely. Change causes anxiety to the extent that individuals are uncertain of their place within the changed circumstances or harbor concerns, as dedicated professionals are admirably wont to do, about their ability to maintain their excellence of performance. As one member of an MPO staff put it:

> *Are you saying that we were wrong? What’s wrong with travel models? We have sixty years’ experience with the most valuable tool in our arsenal.*

--Member of MPO modeling staff as conveyed to the authors by MPO manager

That statement points to a pressing need for clarity in what is being proposed. As will be elaborated in the next section, there are currently no serious suggestions that an enhanced strategic foresight capability based on DMDU methods will supplant current highly detailed analyses based upon the operation of predictive travel demand models. What is being proposed is an enhancement of what already exists. Nonetheless, this source of reticence, whether voiced openly or lying unspoken beneath the surface is a serious matter that is worthy of considerable consideration by MPOs undertaking an effort along the lines discussed in this report. Both messaging and substance will need to account for it.

Another issue that might arise either explicitly or tacitly is the desire to take advantage of strategic ambiguity as a tactic. That is, some interests are better served if uncertainty is left untreated. In fact, one of the most common approaches to hedging against uncertainty at the regional level finds expression in a propensity to build infrastructure and systems when the money to do so is available: build it now when you have the dollars; you may not have the option to do so in the future. Of course, the downsides of this approach are clear. It is possible that the built systems become stranded assets (e.g., building out transit infrastructure in a world in which connected autonomous vehicles (CAVs) constitute a major portion of the fleet.) And in any case, the approach entails considerable costs. Rightly or wrongly, the net result is for some MPOs a propensity away from adaptive behaviors and approaches because of an inability to count upon a conducive future environment for subsequent actions. The very implementation uncertainty that makes the case for DMDU-mediated strategic foresight can stand as an impediment stemming from organizational culture to its wider application.

There are almost certain to be paradigmatic obstacles as well. These are grounded in the training, experience, and background of individuals within MPO systems. The most prevalent disciplinary backgrounds among MPO staff (and increasingly so the higher up one proceeds in the organization's hierarchy) are those of civil or transportation engineering. The concept of failure is central to understanding engineering (Petroski 1985, p. xii). Each issue of *The Structural Engineer*, the organ of the British Institution of Structural Engineers, propounds its members' professional mission:

> Structural engineering is the science and art of designing and making, with economy and elegance, buildings, bridges, frameworks, and other similar structures so that they can safely resist the forces to which they may be subjected. (Petroski 1985, p. 40)

Engineering design, therefore, consists of successively improving upon proposed solutions until achieving one that will be successful *without fail* (Petroski 1985, p. 44 emphasis in original). For a seasoned structural engineer, this can seem a far cry from implementing solutions that appear inductively to be hedged against failure but cannot be proven deductively to be so. The DMDU approach will feel 'wrong' somehow: that is not the way a well-skilled engineer has been trained to approach problems of design. Tolerances should be adjusted so that no room for failure is present in the resulting construction. Risk aversion is a strong professional norm for engineers – and with very good reason.

Such an approach serves engineering well and rewards the confidence that its customers and society places in its outputs. But the larger frame within which transportation agencies operate does not lend themselves so aptly to this precise approach. The human systems involved do not always conform to the norms of the "there are twelve inches in a foot" approach found in engineering to specifying the challenges that will be faced. Neither do the many processes ranging from climate change outcomes to technological innovation pathways resemble the straightforward linearities present in most aspects of engineering design. Therefore, there is the possibility of an impedance mismatch between the DMDU perspective and that of the well-trained engineer likely to be making management decisions within an MPO (Petroski 1985, p.

44, emphasis in the original).[16] There may be a visceral objection to an approach that does not seem to be the right way to go about things.

There is some irony in this. What the DMDU perspective attempts to do is to search for, discover, and test precisely the type of hedged position that an engineer imparts when she determines the tolerances required to make a designed construction fail safe. The differences are largely ones of approach and style of analysis rather than a fundamental disjointedness in the objects or outcomes of analysis in support of planning. Nevertheless, the impediments on the personal and managerial level may be sufficient to retard efforts to introduce DMDU-based analytical capabilities.

Finally, a concern expressed by some of the interlocutors with whom we spoke resides in the centrality of the modeling enterprise within MPOs. The massive transport demand modeling infrastructure and its outputs represent a source of authority within MPOs on substantive questions. Once again, a perceived threat to this primacy might raise an antibody response to a perceived infection from the foreign body of either different analytical paradigms or creation of an alternative or additional groups of modelers within the MPO. This, along with the other sources of internal resistance whether conscious or unconscious should be considered by MPO innovators. Obviously, a more desirable state would be for new perspectives to be perceived as supplementing what currently exists and creating a whole greater than the sum of its parts.

Tactics to bring more strategic foresight into MPOs

The previous sections laid out the potential value along with the widely present obstacles to incorporating DMDU methods to improve the strategic foresight activities of MPOs. The premise of this chapter is that while there are technical issues to be solved in doing so, these tend not to be the prime cause of disappointing outcomes in organizations. Every adoption of a new technology is also an act of innovation in microcosm as well. That is, while there may be both available embodiments of that technology (e.g., a piece of equipment or an available software package), every locale in which installation takes place is different. The technology, whether of long-standing or a novel application, must be fit to local circumstances. And perhaps the most important of these – surely in the case of methodological innovations such as the approaches to analysis and planning discussed in this report – have less to do with the material and technical aspects involved than of the managerial and organizational arrangements as well as the social setting in the proposed new adopter.

[16] MPO staff have suggested to the authors that employees coming from less traditional disciplines such as computer science, mathematics, or physical and social sciences are less likely to achieve senior leadership positions than those trained in civil or transportation engineering.

Social aspects of DMDU adoption in MPOs

Several approaches to incorporating this consciousness of the balance between technical and more social aspects of adoption tend to be consistent with more successful outcomes. All should be considered as part of a process checklist for piloting the introduction of DMDU tools in MPOs:

- Identify, cultivate, and empower ***local champions*** for the change within the MPO. Of course, attaining top- or mid-level managerial support is also necessary in almost all cases. But the human element is greatly eased when one or more individuals within the organization make themselves responsible for championing the envisioned change. They will be best placed to deal with the inevitable issues that will almost certainly emerge.
- It is crucial to engage with and **work for *buy in*** from those asked to carry out the strategic foresight efforts and the analyses that will support them. That is, the end users of the new tools must be on board. This usually requires a process. Managers, innovators, and internal champions should frame a transition process that will begin at the end: what is needed to ensure that by the last day of the effort a change in 'ownership' will have occurred, that those who may have been reluctant at first or dubious of the outcome will actually be the ones directing the final stages of tool adoption and usage.
- One of the early discoveries attending the first installations of numerically controlled machine tools in the manufacturing industry is that if the former 'dumb' machine tool was merely replaced in the line by the NCMT version, the looked-for benefit did not appear. It came to be realized that new tools also require a ***reconceptualization of the entire work process*** to either elicit the newly looked-for capability or prevent an early rejection reaction from those on the shop floor. The managers or work teams within MPOs could also profit from ensuring that their introduction of DMDU tools is thoughtful in the sense of being adjusted to existing workflows. Perhaps those workflows themselves will need to be changed, but that is unlikely to happen before the new analytical capabilities are able to demonstrate their value to analytical and planning teams and to the organization as a whole. This mindfulness, therefore, should not only be applied to the targeted activities the DMDU tools are intended to advance but also to the ancillary workflows that will be carried out alongside them.
- This larger goal can be aided by two ancillary efforts. The first would be to ***communicate the nature of intended change*** to all along the value stream. Certainly, this would apply to anyone whose job description is being asked to conform to the intended change. But it is probably also valuable to instill a larger organizational awareness of what is being attempted and what the end vision for success looks like.
- Closely related to this point, it is important to think through in advance where ***potential turf issues*** might lie. Perhaps the greatest of these within the MPO will be with those who are already involved in the production of model-based analyses. Another will be

possibly with planners who in turn are responsible for interacting with public agencies and regulators -- regional, state, or federal – who will necessarily be the public face for the MPO in explaining its efforts. These large topics are dealt with in the following two sections.

Living alongside or within transportation demand model suites.

As suggested above, a major challenge will be to clarify the roles of DMDU modeling, activities, and performers with respect to the established modeling team within the MPO. In almost all instances, this will center on affirming the respective place of the large run-time demand forecast models and those used for the purposes of engaging in strategic foresight. Though this will loom as a major concern, it need not do so. There is little to no prospect that the new incumbents will supplant the legacy software systems. Instead, they are likely to interact synergistically.

For one thing, federal regulations and reporting requirements have detailed, forecast-oriented analyses as a central focus. It may take some time before the innovative methods treated in this report will receive formal recognition as playing a role in lieu of the current and expected analytical outputs. At best, they will be seen as an ancillary effort. But, this is also properly the way they should be viewed by the MPOs. There are at least two ways for this to apply this approach.

The first is to think of the ***DMDU suite as playing a role similar to a smaller, ranging telescope*** fixed to the side of the main instrument for investigation. As noted, the run times for the standard transportation demand forecast suite are extraordinarily long. They are ill suited to the type of iterative explorations and generation of large ensembles of cases that DMDU methods require. So, leave to the new tools the task of identifying the best purposes to which the main analytical software could be put. If there are only a limited number of runs that can realistically be performed during the period of preparing required planning documents, those runs should be focused on illuminating the regions that are crucial for deciding upon MPO strategic plans. Put another way, DMDU can help discover analytically which future scenarios are the most important to understand for either making choices among, or enhancing the robustness properties of, alternative regional transportation plans.

This utilization of DMDU methods and tools can occur during and even intertwined with the major analysis design based on the long runtime demand models. But if that is difficult to manage at first, the DMDU suite could be ***used at the beginning of the planning process*** itself. It could be used as a way to bring modelers, analysts, planners, managers, and decision makers on board at the beginning to frame a conversation and use of shared vocabulary that may persist during the cycle even if the DMDU outputs do not form a formal deliverable as part of the planning documents produced.

Wider engagement with regulatory or public sector actors.

At the other end of the plan development process are the planning staffs. It is they who must satisfy the external regulatory bodies that what has been asked for has been delivered. To the extent that they are asked for forecasts and point estimates of future values, they could find themselves in an awkward position.

We have already alluded to the sometimes chicken-and-egg relationship that exits between those who request plans or analyses and those who provide them. The gradual introduction of DMDU approaches could prove to provide a venue for the type of discussion among public agencies that should occur but all to routinely fail to take place. During the course of the project that resulted in this report, a view was expressed by some MPO staff is that ***early joint exposure to DMDU methods and tools*** could provide an occasion for MPOs and regulators to consider possibilities for analysis and planning. That is, awareness of what might be possible and the potential utility of the type of output that MPOs could also produce could lead to a different type of exchange between the MPO and its regional and state regulators. Engaged in as a joint process of problem solving, this could perhaps influence what regulators ultimately choose to require before formal roll out of regulatory requirement documents. This would be to take advantage of an inherent property of DMDU methods to build accessibility to heterogeneous stake holder groups as well as to enfranchise different bodies of knowledge and experience that often find themselves excluded from more traditional model-based, predictive analytical processes. Both aspects also have taken on increased importance as agencies seek more actively to introduce equity considerations into their processes and outputs.

In any case, this should not be left as the sole problem for the planning staff who prepare the plans and reports. An effort to include more strategic foresight into MPO activities will need to also explicitly consider what needs to be done to ***ensure support from (or at least acceptance by) other partners outside the MPO***, including federal, state, and local government bodies.

Gaining greater management and staff awareness.

The prior two sections considered the circumstances surrounding modelers and planners. We conclude with consideration of how managers and the MPO as an organization may be brought to a willingness to evaluate a role for DMDU methods.

There are several insights to be gained from the Metro Vancouver use case of TMIP-EMAT as well (see Chapter 3). The opportunity arose due to extraordinary circumstances that were recognized as such by most. The working team was small and had been aware of the availability of a DMDU approach to solving the problem of determining an appropriate course forward under unprecedented circumstances. They were able to draw upon prior examples of use experience from other early adopter agencies. And the output was put into a form that could be seamlessly inserted into the operational concerns of the transit operational staff as well as senior management.

The Vancouver use case can be generalized into a checklist of questions (Table 5.1) for an MPO to consider in seeking to achieve greater strategic foresight through DMDU methods and concepts.

Table 5.1. Checklist of questions for MPO considering employing DMDU methods

1.	*What application areas can provide early and convincing 'wins'?*
2.	*What methods and tools can be most useful for early adoption?*
3.	*What would constitute a good learning path for staff and units looking to innovate?*
4.	*What can be done to develop external and internal allies?*
5.	*What assistance would be helpful to receive from outside?*

1. ***What application areas can provide early and convincing 'wins'?*** We have laid out several of the general benefits for DMDU use in MPOs. But these are less tangible than would be specific applications to either existing problems of long-standing or novel applications to areas that had been neglected for lack of tools that could operate under uncertainty not easily treated probabilistically. Doing so would require at least some internal staff to be familiar with options such as those discussed in Chapter 3 and to give thought to where initial limited areas of application may be found.

   Areas to consider for early adoption would be internal uses that would enhance the interaction between modelers and planners and make both more valued partners to the others. A large consideration would be to review prior interactions between staff and MPO leadership for expressions of need that might now be practicable using DMDU approaches. Prior interactions with external audiences who are important recipients of MPO outputs could be reviewed in a similar fashion for similar entry points. Small investigatory analyses could have disproportionate effects on the ability to communicate more nuanced understanding of the relationship between uncertainties and policy pathways for the region served by the MPO.

   As for specifics, most MPO staff with whom the authors have spoken highlight two areas of large concern that nonetheless are difficult to treat within existing agency modeling structures. The first would be to examine on a regional level what the impact of telework might be going forward, particularly on mobility (congestion) and sustainability (GHG emissions) but not exclusively. VMT or fuel consumption taxes as the means to ensure the financial underpinnings of a region's infrastructure can also be a major concern -- largely irresolvable given our current information when we cannot even be certain at this writing what the future course of something as fundamental as the rebound of office work post-pandemic might be. Telework would also have large bearing for those MPOs that are both the planners and operators of regional transit districts. The second area would add in the uncertainty regarding the speed and depth of AV penetration. Combine the two and the problem truly becomes one of decision making under deep uncertainty.

2. ***What methods and tools can be most useful for early adoption?*** This depends on the intended purpose, staff interest and capability, audiences involved, and situational factors. So, the short answer would be to try whichever methods suits the purpose of providing an early demonstration for which the obstacles appear to be fewest and the prospects for wide awareness greatest.

   The nature of the problem being addressed is a principal driver of choice. Devoting computational and staff resources to seeking greater predictability when that is unlikely to prove feasible will come at the opportunity cost of fuller exploration of what confronts the decision makers.

   But the agency objective matters as well. If staff wish to support a wider, strategic-level exploration of choices across different scenarios, Vision Eval presents an attractive, self-contained package for doing so independent of the travel demand model. While it is limited to the set of investigations that it has been designed to perform, these are a rich enough selection to expand both foresight and the agility with which it may be acquired and performed. If the principal driver is to enhance the types of analyses that may be included in the agency's formal planning documents, then TMIP-EMAT recommends itself because its framing ultimately derives from the agency's own demand models. The data base is already installed and well-known to staff.

   Nevertheless, there is considerable overlap between the two. Both Vision Eval and TMIP-EMAT can be useful in exploring the larger questions and conjectures that may be looming prior to engaging in the effort to produce the legally required planning documents. Other factors would come in to play in deciding between the two applications of DMDU analysis. (The Oregon Department of Transportation currently uses both in combination in preparing the Oregon Transportation Plan update.)[17]

   If the decision is taken to devote resources to the non-predictive exploration track, Table 5.1 provides a rough subjective evaluation of DMDU techniques based upon several practical considerations on both the cost and benefit sides of the ledger. The rankings are based solely upon the authors' impressions of both the tools themselves and the use cases available for review. The applications within transportation are still comparatively few so these represent some of the teething issues likely to recede when the community of MPO professionals gain wider shared experience.

   Table 5.2 is divided into three parts across three columns, one each for TMIP-EMAT, Vision Eval, and more qualitative approaches. (See the discussion of Culver City in Chapter 3.) The first part roughly characterizes what has been the user experience (albeit limited) of

[17] See also Connecting TMIP-EMAT and VisionEval for ExploratoryAnalysis | TMIP FMIP, last accessed July 31, 2022.

early adopters of each. Each cell is graded by a numerical scale in which “3” represents the most favorable rating for the criterion listed for each row while a “1” denotes the least favorable assessment with “2” falling in between. A similar scale appears in the second part in which each application is rated according to more technical and substantive criteria. Finally, a few short remarks have been gathered to discuss salient aspects of each, both pro and con.

Table 5.2. Comparison of alternative means for MPOs to develop models suitable for DMDU

	TMIP-EMAT	***Vision Eval***	***Qualitative***
USAGE			
Ease of learning	1	1	3
Initial set up	1	1	3
Recurring set up	2	3	1
Data prep	2	1	3
Time required	1	1	3
SUBSTANCE			
Use existing models	3	2	1
Output as input to other analysis	3	3	1
Best Features	• Uses existing transport demand model outputs; • Potentially wide set of scenarios	• Once data validated, high flexibility; • Greater detail on specific policies e.g., vehicles, fuels, pricing, budgets.	• Easiest means for disparate groups to attain shared awareness and identify policy alternatives
Issues	• Response surface may sample model behavior coarsely • Not easily expanded to areas outside of original model design spec	• Scenario types limited by existing programming • Data validation may be lengthy	• Lacks quantitative support

NB: 3 = most favorable; 2 = medium; 1 = least favorable
Ease of learning = relative time for staff to gain sufficient knowledge of the method or tool
Initial set up = time required to prepare the tool for performing the desired tasks
Recurring set up = time required for performing successive analyses
Data prep(aration) = time required to enter and validate data specific to a region
Use existing models = extent to which legacy models already within the MPO may be used
Time required = time requited to set up and conduct an analysis

Output as input to other analysis = extent to which output may be input into ongoing, traditional processes
Best features = principal 'selling point' for each DMDU approach
Issues = known shortcomings that may affect either implementation or outcomes

Of course, both TMIP-EMAT and Vision Eval are applications of DMDU methodology that have been developed specifically for use within transportation agencies at various levels. Nothing precludes a transportation agency from using an existing model of any form – regression, systems dynamics, spreadsheet, neural net, or other – within one of the general-purpose RDM packages, EMAW or Rhodium (see Chapter 4), designed to be model agnostic, to conduct tailored, bespoke DMDU analyses. This is the norm in many public agencies outside of transportation that seek to wield this capability. To date, however, there are few if any good examples of doing so perhaps owing to constraints transportation planning agencies find themselves operating under. Hence the emphasis in this report on the two applications designed for suiting the purposes of MPOs.

3. ***What would constitute a good learning path for staff and units looking to innovate?*** This is the first among a series of questions that can best be resolved based on local circumstances and opportunities. They are worth listing so that teams weighing the prospects of exploring DMDU methods to enhance MPO strategic foresight will keep them prominently in mind as they design their effort. Any project worth doing for its substance, that is for a product outcome, should also be mindful of the opportunity for and importance of a process outcome as well. Over time, the letter could even outweigh the value of the product outcome that is the formal occasion for the exploratory DMDU study. Given the nature of the MPO's organization and culture, how best to frame the effort to achieve both types of outcome? How can the project be framed to set in motion a dynamic path toward more use of DMDU applications?
4. ***What can be done to develop external and internal allies?*** This seems an obvious point but is worth pondering as well. Such allies may be of two types. *Champions* may be internal to the MPO such as senior or mid-level leaders who are willing to initiate through their formal or informal authority a DMDU analytical effort. They act as both protectors of and potential spokespersons for the effort, interpreting it for the benefit of others in terms well understood throughout the organization. They may also be individuals external to the agency but whose views are influential over how MPOs perceive their impact. It is worthwhile to identify individuals who may serve as champions beyond the personnel of the directly performing project team.

   It is also useful to be aware of a second group of potential allies. The previous point called attention to the value of thinking in terms of a learning path in addition to the substantive design of a DMDU study. But learning should be thought of more broadly than the education and experience of the performing team. There is also a need to educate the potential recipients of DMDU analyses to help them comprehend how it should be understood and what role it can play in their own deliberations or work processes. This attention to raising awareness of the potential utility of DMDU outputs can play an important role in the transformation of agency orientation and process.

5. ***What assistance would be helpful to receive from outside?***

> *Once we can point to this happening elsewhere it helps with management to then bring it in-house. The ability to stand up and bring a new tool into the suite is a serious concern because of bandwidth and other issues.*
>
> --Member of MPO planning staff in conversation with the authors

In other words, it helps to be able to point to examples to reassure managers that DMDU can both be viable and produce valuable output. FHWA and other transportation offices and associations, as well as entities outside of transportation, such as the DMDU Society, have tried to develop communities of practice when seeking to proliferate new tools and approaches. This document serves, in part, as a means for collating some of the most relevant currently available experience with DMDU in the transportation sector. It would be useful for any group seeking to add themselves to this number to reach out and garner the insight and experience that others have attained through their own endeavors. There is almost certain to be considerable interest among the pioneering agencies to see how further efforts along these lines fare.

Although it falls beyond the scope of this report, other assistance could be forthcoming if the transportation community as a whole considered it to be of value. Clearly, more facilitation or pilot testing would be valuable to potential adopters in the transportation sector. This would enhance access to trained practitioners (including how to interpret TMIP-EMAT charts/visualizations). But it would be useful to the sector as a whole to gain more shared experience and means for evaluating the potential for such methodology more generally. Further federal support for piloting such work would be helpful in expanding DMDU use. It may also be the case that DMDU methods could fall under the purview of a TRB committee with calls for paper, shared conferences, and creating peer exchange communities of practice.

A checklist for incorporating DMDU strategic foresight into planning

This report has drawn from discussions with MPO staff to suggest a need for new methods of strategic foresight and uncertainty management in transportation planning. Several early-stage examples of both quantitative and model-based as well as more qualitative approaches were presented. In this final chapter, the benefits and obstacles have been enumerated with some suggestions for introducing changes incrementally and integrating them within long-standing regional planning processes. This raises the question of how an agency might be able to benchmark its own progress along the path of enhancing its capacity for strategic planning under conditions of considerable uncertainty.

A study panel of the Society for Decision Making under Deep Uncertainty conducted a multi-year process to determine items of method and practice that could form an agreed list of that would constitute 'good hygiene' when conducting analyses and planning decisions under changing and uncertain conditions.[18] In the words of its authors:

> Each step can be revisited over time, including the decision framing, as conditions, stakeholders and preferences change. Participation of stakeholders in the DMDU process will provide buy-in to the decision outcomes and will provide more robust decision making at all stages of the process. When applied to problems that have deep uncertainty at many levels of decision making, about the system of concern and in the analysis process, the checklist provides a prompt for deep uncertainty to be explicitly considered, thus enabling adjustments to be made over time and avoid lock-in of decisions that can be more costly when they fail to deliver on objectives.

The full findings of this DMDU Society study panel may be found in Appendix B. The panel first generated a list to illustrate analytical practice that would be consistent with DMDU principles. Conveniently, these are laid out sequentially in a framing that would be consistent with most if not all methods associated with DMDU.

The study panel also developed a set of frequently made mistakes in analyses attempting to conform to the DMDU guidelines present in the first list. While the entire list is worthy of attention (and is also presented in Appendix B), Table 5.3 synthesizes several points of particular relevance for the discussion in this report. As can be seen, most of these errors arise from not taking full advantage of the characteristics of DMDU analysis and instead following a more traditional analytical style.

[18] See DMDU-checklist-November-12.docx (live.com)

Table 5.3. Selected "Frequently Made Mistakes"

DMDU Society "Frequently Made Mistake"	NOTES
Not considering broader values and diverse alternatives early on in framing	Though seeming to risk-complication, not considering widely at the outset may miss opportunities to discover important alternatives.
Not allowing dissenting critiques early and often	"Red teaming" lies at the heart of DMDU methods. Organizations working on deadlines may find that behaviors that might be viewed as counter-productive in other processes are essential in DMDU.
Using "best estimates" or averages for uncertainty	Under deep uncertainty, probabilities are just another assumption. Instead, strive to understand what influence different guesses about probability may have for the plans being considered.
Using probabilistic methodologies where uncertainty is high [or where probabilities cannot be accurately defined because of deep uncertainty about the future]	A better approach is to utilize DMDU to discover challenging or stressful scenarios for one or more alternative plans. Then trade-off analysis can occur by asking how the rank order of preference among alternatives would change if different probabilities were assumed for that scenario to occur.
Not providing initial and ongoing opportunities for participation of stakeholders in the decision process as conditions change over time	The best DMDU analysis is one for which project ownership changes from the analysts to the eventual recipients of the analysis. Deliberation with analysis is the model for this interaction.
Not keeping the decision makers abreast of how uncertainty can be considered	Senior decision makers do not like probabilities. Yet, they expect them. Characterizing uncertainties based on agency goals and means for achieving them may need to be carefully explained.
Confusing normative and exploratory scenarios (what we'd like to happen is not the same as what could happen)	Sometimes there is pressure to keep some alternative strategies or potential future states of the world off the table as a matter of policy. Doing so threatens to undercut the value of a DMDU analysis.
Optimism bias / not considering full range of scenarios (e.g. only considering / developing those which go in one direction)	

Selected from DMDU Society select committee checklist on DMDU guidelines (DMDU-checklist-November-12.docx (live.com))

No matter where a specific MPO may be on the path toward achieving an enhanced perspective on its strategic choices in the face of so many unknowns, these principles may be referred to as a means to determine what further incremental steps might be doable and practicable in moving further toward that goal. The authors of the checklist further point out – as, indeed, do the authors of this report – that following the checklist does not guarantee that the decision at the end of the process will lead to a resilient plan or project. But the approaches recommended in the checklist and in the current report do enhance the prospects for decision makers having the best available information on the possible future outcomes of the decision in a world in which change and surprise are endemic. Consequences of risks from failure would have been considered transparently for all stakeholders even if choices are taken that do not result in resilient and robust decisions. This objective – no guarantee of good outcomes but a guarantee that decisions makers have used the best available information and process – is one worth striving for.

Acknowledgments

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Appendix A. TMIP-EMAT and VisionEval Technical Discussion

This appendix provides the interested reader with greater technical detail on the two main modeling software applications discussed in Chapter 4.

Response Surface Simulations

The Travel Model Improvement Program's Exploratory Modeling and Analysis Tool (TMIP-EMAT) is a suite of software tools that enable an MPO to conduct DMDU analyses with existing travel demand models (Milkovits et al. 2019, Lemp et al. 2021). In particular, TMIP-EMAT can help the user create a fast-running meta-model, a regression model that estimates outputs from the MPO's existing model, which can be used within EMAT to supplement the more limited set of results available from a slow-running existing model.

TMIP-EMAT expects that the user will bring their own core model, defined as any application or region-specific transportation model that can project future values of factors (e.g. VMT, trips, emissions, access, cost of travel, etc.) of particular interest to the user and estimate how policy actions might affect those factors. The core model represents the Relationships (R's) in Table 2.1, and in practice can consist of multiple models and/or post-processed outputs to a model. In some cases, this core model may be fast-running sketch model (e.g. a few minutes or less per run), in which case TMIP-EMAT can utilize the model directly. However, the core model might be an activity-based or trip-based travel demand model which may take hours or days per run. In such cases, TMIP-EMAT can generate a meta-model, a fast-running statistical summary (milliseconds per run) of the core model. Such meta-models are developed in two stages. A linear regression model captures overall trends and simple linear relationships. A gaussian process regression model then captures a wide range of non-linear effects (TMIP-EMAT 2021).

TMIP-EMAT helps the user choose a small experimental design for a slow-running model appropriate for generating a meta-model or a larger experimental design appropriate for exploration over a fast-running meta-model or core model.

To use TMIP-EMAT an MPO must identify the simulation model they wish to use and obtain the data for the model. The MPO then needs to link the model to the TMIP-EMAT via the API, as shown in Figure 4.2. Milkovits et al. (2019, Section 2.4.2) describe in detail this interfacing and API development process. In brief, the user writes code that can initialize a core model run, assign values generated by the TMIP-EMAT software to model input variables, launch and run the core model, and return model outputs in a form readable by TMIP-EMAT. The user also writes scripts within the TMIP-EMAT API to pass data between the API and this code that drives the model.

Once the core model has been linked to TMIP-EMAT, a typical application would then run the core model over an experimental design of about a dozen cases in order to generate the meta-model. For modelers used to estimating models from survey data, it can be useful to consider TMIP-EMAT as creating its own "survey data" from the many scenarios of inputs/outputs, and then estimating a meta-model from this date.[19] The user would then generate a much larger experimental design over the meta-model and store the results in the database. The user could then employ TMIP-EMAT visualization, scenario discovery, and other sensitivity analysis tools to explore the robustness of the MPOs plans, the uncertainties to which the plan is most sensitive, and how the MPO might adjust their plans to make them more robust.

TMIP-EMAT has been employed by several MPOs. In an organized 2019 beta test (Milkovits et al. 2019), the Greater Buffalo Niagara Regional Transportation Council (GBNRTC), the Oregon Department of Transportation (ODOT), and the San Diego Association of Governments (SANDAG) conducted tests of the system and compared results. GBNRTC evaluated policy and investment uncertainties associated with improvements along a corridor using as their core model a four-step travel demand model. ODOT examined the uncertain impacts of new technologies and trends using a new Activity Based Model. SANDAG evaluated policy and investment uncertainties associated with travel demand from Mexico across the border to San Diego using an Activity Based Model. These beta testers linked their core models to TMIP-EMAT, generated meta-models, created data bases with 5,000 cases, generated scatter plots, and conducted scenario discovery analyses. The MPOs reported it initially took about 100 to 400 hours of labor to achieve a running system. Subsequent iterations with new problem framings took about 40 to 80 hours. The beta testers generated policy-relevant insights and provided suggestions for improvements in TMIP-EMAT interfaces and tools.

FHWA's Travel Model Improvement Program (TMIP) has provided handbooks and online resources to assist MPOs in using TMIP-EMAT (Milkovits et al. 2019, Lemp et al. 2021).

Strategic Planning Models

MPOs can also employ a fast-running strategic planning model for DMDU analyses. VisionEval provides an open-source programming framework the MPOs can use to develop and customize such strategic planning models.[20] The VisionEval software framework is written in the R programming language for statistical computing and graphics. The purpose of the model system and framework is to enable models to be created in a plug-and-play fashion enabling model upgrade to be more useful and focused thus faster/less resource intensive, as well as using different geographic scales to use the same modules which are also distributed as R

[19] We thank Tara Weidner from ODOT for this point

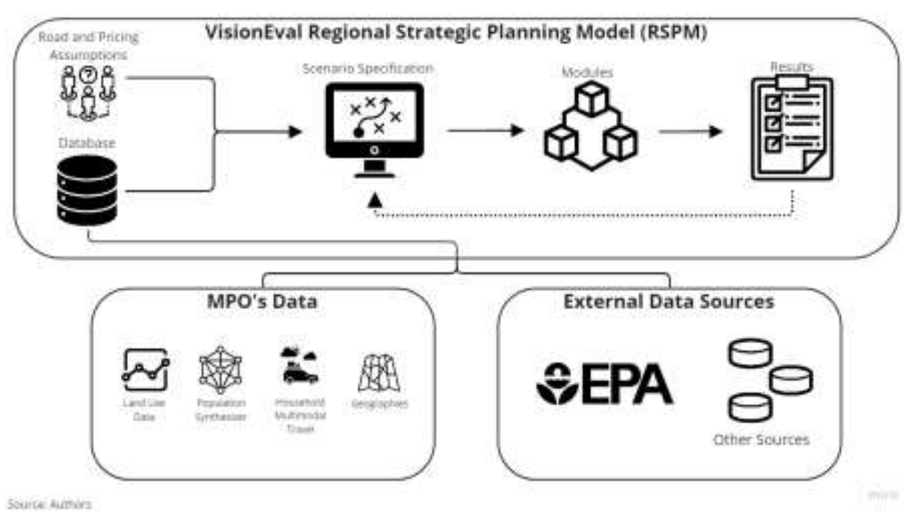
[20] https://visioneval.org

packages. A simple R script is used to implement a model by initializing the model environment and then calling modules successively.

VERSPM is the implementation of the Regional Strategic Planning Model (RSPM) (Wang et al. 2018) in the VisionEval model system. The model run files are organized into two directories to reflect how the RSPM model has been used in strategic assessments in which hundreds of model runs are carried out to explore the decision space. Typically, several land use scenarios are developed and then several transportation scenarios are run for each land use scenarios. VisionEval has some "staging" capabilities that allow users to run components asynchronously. For example, users can "pre-run" land use scenarios that can be later used with different transportation assumptions. While the VisionEval framework software is built to support that workflow, the initial testing of VERSPM modules runs all land use and transport modules in one sequence. This is done in the Tests1 directory. Later testing will split apart land use and transport scenarios, splitting them into separate directories

Structurally, VisionEval may be described as a disaggregate demand/aggregate supply model. This means, it combines rich demographic and socioeconomic detail from a synthetic population with aggregate treatments of travel (multi-modal VMT and congestion without explicit trips, or transport networks). The implication of the "aggregate supply" model is that VisionEval cannot be used to evaluate the performance of specific projects or corridors. VisionEval allows for a high-level evaluation of congestion and speeds across broad functional classes (arterials and freeways) within the MPO. It is also able to incorporate ITS policies and speed's impact on fuel efficiencies and thus emissions. The architecture of VisionEval is shown in Figure A.1.

Figure 3.4. VisionEval components



Source: RAND

What VisionEval can do, and even make especially simple, is to evaluate a myriad of scenarios, allowing the exploration of combinations of alternative future conditions and how these might affect performance measures. In general, travel demand models sacrifice flexibility for network detail. It is difficult in such models to explore important novel behaviors such as an increased propensity to use inexpensive ride-hailing services, or to express shifts in vehicle ownership and occupancy that may be influenced by multiple factors some of which have not yet been observed. VisionEval makes it relatively simple to explore risks and opportunities that may eventually be realized as new transportation options mature.

VisionEval will not help MPOs determine if a particular highway segment should be built or upgraded, or what kind of transit service improvements should be extended into new areas. But it can help examine the market for new technologies and explore future scenarios that are based on changing circumstances (altered demographics, increased congestion, or alternate road pricing strategies) as well as on changing behaviors (including behaviors that might happen, but that we have not yet observed because the key enabling technologies are too early in their deployment). VisionEval results can be explored in detail by market segment, asking questions about how benefits might be distributed regionally, and what overall system performance might look like. VisionEval would help set the level of transit service as part of a portfolio of policies and/or investment programs that best meets a region's goals and stress test it against uncertainties.

Ultimately, VisionEval is a system for asking a very broad range of "what if" questions about transportation system performance, and how its benefits and costs might be distributed over the community. It can efficiently process hundreds of scenarios looking at many different types of interventions, alternative policies, and hypothetical future conditions and travel behaviors. The results can inform strategic questions, helping decision makers answer questions such as "What are our options for achieving this performance result?" or "What are our risks if new transportation technologies develop in these different ways?"

VisionEval is intended to complement other types of transportation modeling (such as travel demand models or corridor microsimulations). It helps determine what is worth the effort to code into these more detailed models and explore and document novel assumptions about the future that may require extra effort to implement, and that would be prohibitively expensive to explore through traditional planning models.

VisionEval is typically set up to run many scenarios that explore a broad set of alternative policies and investment priorities that may result from a variety of possible categories of policy and project interventions, or from a range of possible future conditions (strong or weak economic growth, demographics that shift at different rates), or from uncertain deployment of new technologies such as app-based ridesharing (Transportation Network Companies or TNCs). A full application of VisionEval may evaluate future outcomes over hundreds or even thousands of permutations of inputs. The resulting database of results can then be analyzed using the DMDU visualization and statistical packages available in TMIP-EMAT and other packages.

Notwithstanding its typical application as a strategic model, VisionEval does allow detailed investigation of certain phenomena such as fleet composition and vehicle ownership in relation to Greenhouse Gas Analysis. It also is unique in its ability to explore budget constraints on travel. Its simulation of individual households enables it to assess policies that would be difficult or impossible to model successfully with traditional models.

A key value of VisionEval is how it facilitates running many scenarios or possible futures. In practices, the user typically starts by setting up the model with a reference scenario, best estimate of future conditions. The model can be validated at this point. This Reference scenario then serves as a pivot point for manual or automated scenario testing. Typically, that includes a mix of the following, reflecting "what if?" type questions:

- Sensitivity tests (manual): Ad hoc tests that change a single category of inputs for each run.
- Combination scenarios (automated): Several combinations of categories combined

Because VisionEval uses a full factorial experimental design, the number of scenarios grows quickly. For instance, all combinations of 3 levels each of land use transit, bike, parking, and TDM policies and 3 fuel price scenarios would result in 243 scenarios (3x3x3x3x3). For this reason, categories are often used that combine multiple inputs. Automated processes aid in the set-up and running of these scenarios, which the analyst can use a variety of data mining and visualization tools to explore the results.

Running VisionEval

VisionEval is implemented entirely in the open-source R statistical language and operates on recent versions of Microsoft Windows. All development work is done there, although macOS and Linux versions are usually distributed. A fully self-contained installer for the more recent production release of VisionEval can be found on the download page. It permits installation of the full VisionEval platform, to include example data, even behind firewalls that prevent access to R Project and GitHub repositories.

Once installed the user assembles data into a standard directory structure. This data directory contains dozens of detailed input files that the model uses to run its multiple interconnected modules. This data preparation process can take several person-hours to complete. The user customizes the model run script and it then is typically run from a command prompt. Running it in this manner allows several different scenarios to be run at the same time with minimal user interaction. The results can then be mined or visualized using a variety of VisionEval and third-party products. Some users use R Shiny, Tableau, or similar interactive environments for summarizing and visualizing the output from VisionEval.[21] Such an environment is especially useful when comparing key metrics from many scenarios.

VisionEval generates a large set of performance metrics at varying summary levels. Several pre-defined metrics are compiled for mobility, economic, land use, environmental, and energy categories in each model run. They can be tabulated for individual scenarios or compared to other scenarios, as well as visualized using a variety of tools.

The intermediate data generated during the various VisionEval module steps can be compiled as performance metrics, both in absolute and per-capita terms and at various geographies. Traditional transportation network metrics such as VMT, vehicle and person hours of travel, and total delay are easily compiled by overall or focused areas within the model. Likewise, emission estimates and fuel consumption are tabulated. VisionEval operates at broad geographic levels and without explicit network representations to enable very fast analyses across scores of different assumptions and inputs. However, VisionEval is not well suited for project level design analysis.

To date, several agencies have started implementing VisionEval tools into their strategic planning, such as Virginia's Department of Transportation (Miller et al. 2022), Massachusetts's Metropolitan Area Planning Council (Gately and Reardon 2021), Oregon's Department of Transportation (Wang et al. 2018), and New York State's Department of Transportation.in collaboration with the Capital District Transportation Committee and the Ithaca-Tompkins County Transportation Council (Resource Systems Group 2019). These implementation efforts have a wide range of objectives, including exploring scenarios of interest (VDOT), forecast impacts from behavioral changes post COVID-19 (MAPC), testing feasibility of use in existing planning workflows (NYDOT), and setting visions for GHG reduction targets at the state and MPO levels and monitoring progress over time (ODOT).

For more information about VisionEval, its components and implementation options, check out the website https://visioneval.org. Although VisionEval does not have explicit "out-of-the-box" support for integration with TMIP-EMAT or Rhodium, VisionEval could be used in either framework with a significant programming effort. In either framework, VisionEval can be designated as a Core Model for analysis, but computational requirements can be large since Python and R would be running concurrently. We have not attempted this integration and thus cannot recommend or guide any such efforts.

[21] See, for instance, https://gregorbj.github.io/RSPM-Viewer/

Appendix B. Society for Decision Making under Deep Uncertainty Best Practice Checklist

The text below contains the complete list developed by a DMDU Society study panel as a guide to best practice in applying DMDU concepts and methods. The list and other materials may be found as a Word file on the Society's website (DMDU-checklist-November-12.docx (live.com)).

DECISION FRAMING

1. IDENTIFY STAKES & STAKEHOLDERS: *TO WHOM IS THE DECISION RELEVANT?*
    a. Identify relevant stakeholders
    b. Map stakeholder relationships
2. DEFINE GOALS: *WHAT DO STAKEHOLDERS ASPIRE TO?*
    a. Identify broad goals
    b. Identify values and positions across stakeholders
    c. Define performance metrics and thresholds for failure
    d. Identify the most appropriate team and rules of engagement
3. BASELINE KNOWLEDGE AND ASSUMPTIONS: *WHAT DO WE KNOW?*
    a. Describe system and boundaries (when boundaries are known)
    b. Identify known and perceived issues
    c. Document uncertainties (including in system boundary)
    d. Engage a "devil's advocate" reviewer pool across multiple interests
4. IDENTIFY A FIRST SET OF ALTERNATIVE POLICY ACTIONS
    a. Stakeholder participation to reflect preferences
5. IDENTIFY ANALYTICAL METHODS: *WHAT METHOD(S) SHOULD BE USED?*
    a. Match method to decision context and uncertainties
    b. Select analytical method(s) and train / trial with stakeholders
    c. Define robustness criteria (e.g. range of scenarios; least regret; risk reduction; path dependency)
    d. Agree on evaluation approaches (e.g. modelling; stakeholder trade-offs)

SCENARIO AND VULNERABILITY ANALYSIS

6. SCENARIO GENERATION: *WHAT FUTURE STATES OF THE WORLD SHOULD BE EXPLORED?*
    a. Create scenarios, futures, and narratives that explore uncertainties
    b. Screening: how do uncertainties affect performance objectives?
7. DEVELOP PORTFOLIOS OF POLICIES AND ACTIONS
    a. Option development (through modelling or expert elicitation)

    b. Portfolio construction
    c. Search / long-list candidate portfolios
8. DEVELOP DECISION TRIGGERS AND CONTINGENCY ACTIONS
    a. Design indicators for decision triggers to change course ahead of failures
    b. Identify alternative actions and pathways when objectives cannot be met or they fail
9. PORTFOLIO VULNERABILITY ANALYSIS: *HOW DO ACTIONS/POLICIES PERFORM?*
    a. Model system vulnerability
    b. Model system with candidate portfolios
    c. Stress test the performance of portfolios/ pathways
    d. Identify failure causes
    e. Search / shortlist portfolios (e.g. Pareto-optimal)
    f. Iteration e.g. add options; edit portfolio

STAKEHOLDER PREFERENCE EVALUATION

10. PORTFOLIO PATHWAYS EVALUATION: *WHICH PORTFOLIO(S) OR PATHWAYS ARE PREFERRED?*
    a. Stakeholder participation to reflect/update preferences
    b. Evaluate options/portfolios/pathways e.g. Multi-criteria analysis to assess relative values

IMPLEMENTATION

11. IMPLEMENTATION PLAN
    a. Make short-term decisions and/or long-term options that can retain flexibility for shifting to other portfolio/ pathways if and when needed
    b. Use planning and regulatory responses to support adaptive /flexible implementation that fit the changing risk situation e.g. flexible measures compared with static measures
    c. Apply adaptive design (intra-option flexibility) criteria for buildings/ structures
    d. Develop project implementation plan that can be adjusted over time as conditions change.

MONITORING

12. MONITOR
    a. Secure adequate funding for monitoring system design and its execution
    b. Develop the monitoring plan using the decision triggers designed in 8b above
    c. Monitor trends, signals and triggers
    d. Assign responsibility for monitoring signals and triggers
    e. Create an accountability system (e.g. transparent performance indicators)
    f. Monitor portfolio/pathways performance
    g. When signals and triggers reached, responsible agency reviews adaptive plan

13. REVIEW & ADJUST
    a. Adopt contingency actions e.g. switch pathway, or adjust options
    b. Identify where trends / events might require new analysis and re iterate through the checklist
    c. Revisit the decision framing and repeat all steps if necessary
    d. Share information with stakeholders
    e. Make decisions as to forward looking strategy

FREQUENTLY MADE MISTAKES

1. Not considering broader values and diverse alternatives early on in framing

2. Limiting in advance the issues of concern

3. Insufficient consideration of a diversity of metrics that capture broader stakes and impacts in the system

4. Ignoring institutional instability and shocks

5. Not allowing dissenting critiques early and often

6. Using "best estimates" or averages for uncertainty

7. Using timeframes for planning, design and investment that are mismatched with the ‘real’ lifetime of the asset, which can be longer

8. Using economic assessment tools that are ill-suited to uncertain and changing risk situations i.e., relying upon pre-defined or static conditions based on historic or current conditions

9. Using high discount rates that discount the benefits from taking adaptive action now that is not realized until sometime in the future

10. Using static planning instruments spatially for managing changing risks

11. Using probabilistic methodologies where uncertainty is high [or where probabilities cannot be accurately defined because of deep uncertainty about the future]

12. Not providing initial and ongoing opportunities for participation of stakeholders in the decision process as conditions change over time

13. Not keeping the decision makers abreast of how uncertainty can be considered

14. Confusing normative and exploratory scenarios (what we’d like to happen is not the same as what could happen)

15. Optimism bias / not considering full range of scenarios (e.g. only considering / developing those which go in one direction)

16. Assuming linearity in systems / not incorporating feedback mechanisms

17. Using models that are ill-suited just because they are available/well known

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