Ministerie van Infrastructuur en Waterstaat

TU Delft Delft University of Technology

Managing Uncertainties in Mobility Policy

Integrating Exploratory Modelling and Analysis for Informed Decision-Making in Dutch Passenger Rail Policy

Rhys Evans, MSc Engineering and Policy Analysis

Managing Uncertainties in Mobility Policy: Integrating Exploratory Modelling and Analysis for Informed Decision-Making in Dutch Passenger Rail Policy

Master thesis submitted to the Faculty of Technology, Policy, and Management at Delft University of Technology in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in Engineering and Policy Analysis

by

Rhys W Evans

Student Number: 5633273

Graduation committee

1st Supervisor, Chair	:	Dr. Jan Anne Annema, Transport & Logistics
2nd Supervisor	:	Prof.dr.ir. Jan Kwakkel, Policy Analysis

To be defended in public on 19 August 2025

This research highlights how adaptive mobility policy can contribute to SDGs 9, 11, and 13 (UN, 2015).

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

TU Delft

Contents

Executive Summary

Policy-makers working on Dutch passenger rail confront a world that is increasingly unpredictable. Population growth, urbanisation and climate change mean that conventional forecasting tools like the Landelijk Model Systeem (LMS) cannot easily characterise the range of futures planners must consider. The LMS is computationally intensive so it risks leaving decision-makers blind to “deep uncertainty,” where the shape of the system and the relative plausibility of future scenarios are unknown. Decisions made without fully appreciating uncertainty can lock rail systems into costly or inflexible trajectories. To fill this gap, this research investigates whether Exploratory Modelling and Analysis (EMA) and Multi-Objective Robust Optimization (MORO) can broaden the policy community’s understanding of future mobility and lead to more resilient strategies. EMA was selected to complement traditional modeling because it can generate thousands of simulations rapidly, providing a richer picture of uncertainty than traditional modeling alone.

The research focuses on Dutch passenger rail because the must satisfy sometimes conflicting objectives, such as supporting ridership growth, securing revenue, reducing CO2 emissions and promoting equity. Each objective is shaped by uncertain forces such as technological change and travellers’ preferences. The study therefore aims to support policy analysts responsible for designing fare policies by demonstrating how EMA and MORO can illuminate trade-offs and highlight robust strategies. Such an approach is not just a technical fix as it aligns with broader goals of building resilient infrastructure, promoting sustainable cities, and advancing climate action as reflected in the United Nations Sustainable Development Goals (SDG 9, 11, and 13). This research is motivated by the need for a new decision-making paradigm that can handle deep uncertainty in long-term rail policy and support national objectives for sustainable, resilient mobility.

Research Questions

The research poses ome overarching question: How can Multi-Objective Robust Optimization be applied to enhance long-term passenger rail demand forecasting under deep uncertainty, particularly in evaluating fare policy levers? Two sub-questions are also asked: (1) What are the potential impacts of implementing extreme fare interventions on rail ridership, revenue, and CO_2 emissions across a wide range of uncertain future scenarios? and (2) How can fare policies be structured or adapted over the 2024–2070 horizon to remain effective in achieving transportation objectives despite deep uncertainty in future mobility trends?

To answer these questions, a simplified elasticity-based model of Dutch passenger rail was built. The model uses behavioural elasticities from the Netherlands Institute for Transport Policy Analysis (KiM, 2021) to simulate how ridership responds to changes in economic, demographic and policy variables. Time-series forecasting techniques (Prophet) provide long-term trend inputs, and machine-learning methods identify patterns in the results.

Methodology

Traditional transport models, such as the Dutch Landelijk Model Systeem (LMS), evaluate only a few deterministic scenarios and struggle to capture deep uncertainty. This study integrates Exploratory Modeling and Analysis (EMA) and Multi-Objective Robust Optimization (MORO) to explore thousands of plausible futures and identify robust fare policies. MORO employs a multi-objective evolutionary algorithm to search the policy space, evaluating each candidate fare policy across many uncertainty scenarios before assessing performance. This transforms forecasting from a point-prediction exercise into a robust planning exercise, yielding a Pareto-optimal set of policies that balance multiple objectives and remain effective across a spectrum of futures. Practically, MORO identifies fare strategies that trade off objectives (e.g., ridership vs. revenue) efficiently while maintaining performance under uncertainty. The open-source EMA Workbench was used to implement MORO (via an ε-NSGA-II algorithm), forming the methodological core of the study. This approach represents a methodological contribution to transport policy analysis, demonstrating that robust, multi-objective optimization can inform fare policy design under deep uncertainty.

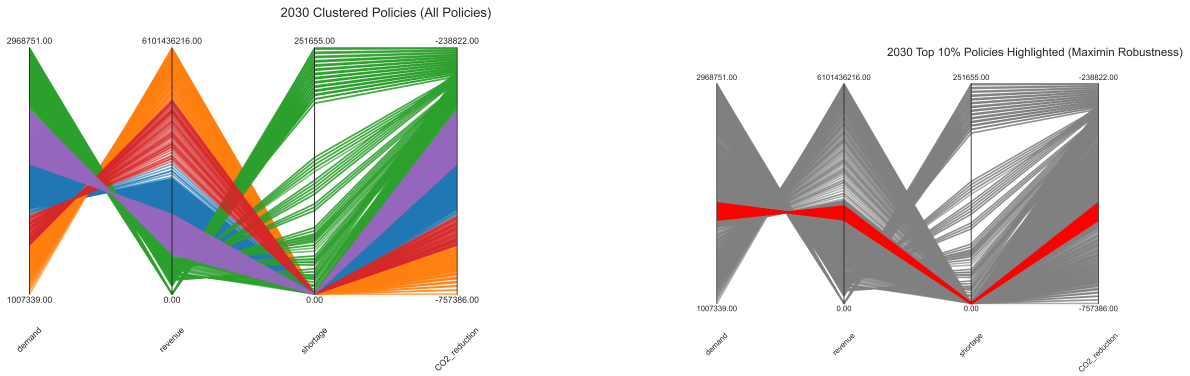
Given that directly applying EMA to the full LMS is computationally infeasible, a simplified elasticity-based simulation model of Dutch rail demand was developed. This model integrates baseline demand projections with fare elasticity response functions, enabling rapid computation of ridership, revenue, and emissions outcomes. Flexibility was prioritized, intentionally trading some detail for the capacity to run thousands of uncertainty–policy combinations.

One main problem formulation and one main filter frame the analysis: the "Balanced" problem formulation, where capacity constraints are active and overcrowding may occur, and the "Unrestrained Balanced" filter, where capacity is assumed unconstrained to isolate fare policy effects without supply limits. Both are analyzed over a short-term horizon (2030) and the Balanced problem formulation is analyzed over a long-term horizon (2024–2070). Despite simplifications, the model captures how fare changes influence demand via elasticities, demand interacts with capacity and emissions, and uncertainties push these outcomes in varied directions over time.

Key Findings

The 2030 results reveal a fundamental policy trade-off. At one extreme, aggressive fare cuts or elimination significantly increase ridership and achieve CO_2 reductions via modal shift, but sharply reduce revenue. At the other extreme, high-fare strategies maximize revenue but suppress demand and limit environmental benefits. Neither extreme proves robustly optimal. Instead, hybrid pricing strategies are necessary.

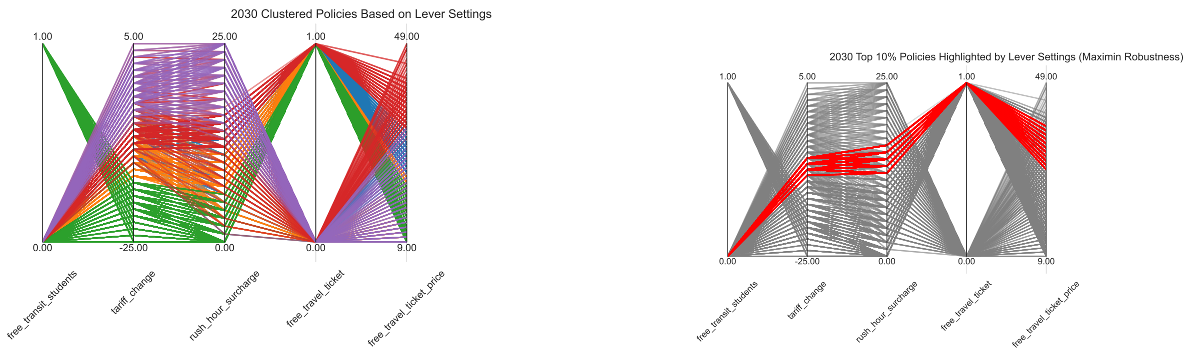
Cluster analyses on the MORO outcomes showed that top-performing policies fell into hybrid archetypes, combining reduced fares with mild rush-hour surcharges and an unlimited travel ticket similar to the €49 "Deutschlandticket". Effective combinations included affordable unlimited travel passes (e.g., €49/month) alongside base fares and mild surcharges to safeguard revenue and manage demand. These findings are illustrated in Figures ES.1 and ES.2, which show the clustered structure of policy levers and the top-performing policy configurations.



(a) Clustered outcomes for the 2030 Balanced Formulation.

(b) Outcomes associated with the top 10% performing policies in 2030 for the Balanced Formulation.

Figure ES.1: The 2030 results for the Balanced Formulation based on outcomes.



(a) Clustered policies based on lever settings for the 2030 Balanced Formulation.

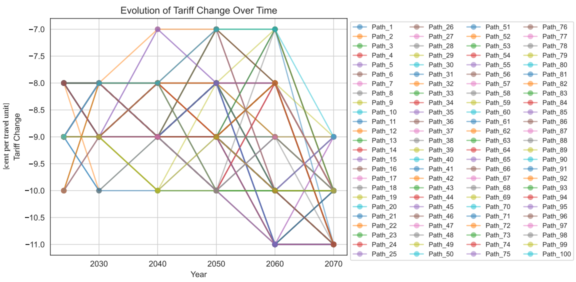
(b) Top 10% performing policies based on lever settings in 2030 for the Balanced Formulation.

Figure ES.2: The 2030 results for the Balanced Formulation based on lever settings.

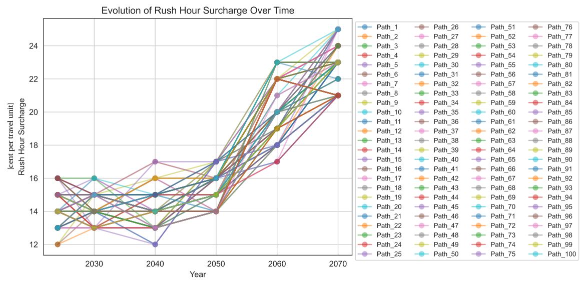
Long-Term Policy Pathways

Policy pathway analysis for 2024–2070 confirmed that no static fare policy remains optimal over decades. Figure ES.3 presents adaptive policy trajectories for base fares and peak surcharges. The diversity of robust pathways illustrates that multiple adaptive strategies can succeed under different conditions. Some pathways maintain low fares for extended periods, gradually increasing later; others introduce fare adjustments earlier or apply staged surcharges as demand evolves.

The overarching insight is clear: adaptability outperforms rigidity. Rather than locking in a fixed fare plan, it is recommended to implement a Dynamic Adaptive Policy Pathways approach. This involves deploying an optimized near-term policy (e.g., the identified 2030 strategy), regularly monitoring key indicators, and adjusting fares or surcharges when trigger points or thresholds are reached. Periodic reviews can help maintain alignment with evolving objectives.



(a) Policy pathways for ticket price change in the Balanced Formulation. This figure illustrates how much ticket prices are adjusted per distance travelled over the years.



(b) Policy pathways for rush hour surcharge in the Balanced Formulation. This figure illustrates how much of a surcharge is imposed per distance travelled during peak hours.

Figure ES.3: Potential future policy pathways for fare price and a rush-hour surcharge from 2024-2070.

This research demonstrates that integrating an EMA framework substantially enhances long-term transport policy planning under deep uncertainty. As seen in Figure ES.3a, all 100 policy pathways begin with significant fare reductions, with most simulations implementing a drop of between 8 and 10 cents per travel unit by 2030. These reductions remain largely consistent across the following decades. While some fluctuations occur, especially between 2050 and 2070, the majority of strategies hover in a relatively narrow band, typically between −8 and −10 cents, indicating long-term fare reductions are a stable and recurring feature of robust policies.

The lack of strong upward trends suggests that increasing base fares is rarely chosen, even as demographic or fiscal conditions change. Notably, no pathway returns to neutral or positive fare levels by 2070, reinforcing the interpretation that maintaining affordability is central to long-term success under capacity constraints.

As shown in Figure ES.3b, all 100 balanced policy pathways implement a rush-hour surcharge by 2024. The initial values cluster between 12 and 16 cents per travel unit, indicating a general consensus around modest peak-period pricing from the outset. This early adoption may reflect a shared recognition of the potential to manage congestion and raise revenue without politically sensitive increases to base fares.

From 2040 onward, a consistent upward trend emerges across most pathways. By 2060, nearly all strategies impose surcharges above 18 cents, with several exceeding 22 cents. This suggests a gradual but persistent escalation in peak pricing, likely driven by growing demand pressures and fiscal needs.

This work offers a proof of concept that advanced tools can support more resilient, exploratory, and adaptive policymaking, moving beyond static, scenario-limited approaches.

Policy Insights

Based on the exploratory modeling and MORO analysis presented in this research, several strategic insights emerge that may inform fare policy deliberations in the Dutch passenger rail context. These insights are not intended as fixed prescriptions but rather as evidence-based considerations to support robust, adaptive policymaking:

1. Implement Low-Cost Unlimited Travel Ticket

The model suggests that introducing affordable flat-fare transit passes (in the spirit of Germany's €49 "Deutschlandticket") could stimulate ridership and support a shift from car to train travel. A possible approach would be to pilot such a scheme on a limited-time basis, similar to the German trial, and evaluate its impacts on ridership, revenue, and crowding. If the benefits prove robust and costs remain within acceptable bounds, policymakers could consider expanding or institutionalizing the program over time.

2. Introduce a Moderate Peak-Hour Surcharge as Part of Demand Management

To address capacity constraints and provide funding for improvements, policymakers could explore pricing structures that differentiate between peak and off-peak travel. Simulation results indicate that implementing a modest rush-hour surcharge may help mitigate peak capacity pressures while improving financial sustainability (e.g., +50% on base fares for trips starting or ending during weekday peaks). This measure should be accompanied by clear public communication emphasizing its purpose and revenue generated from peak pricing should be transparently earmarked for capacity investments, such as additional trains, staff, or infrastructure upgrades. Many simulations suggest reducing off-peak ticket pricing at the same time as implementing a rush-hour surcharge. Doing so would lessen the economic burden of the surcharge and likely increase public acceptability.

Policy Analyst Insights

While this research provides empirical insights into fare policy design, a key contribution lies in demonstrating how the MORO framework can support the work of policy analysts operating under deep uncertainty. MORO does not prescribe singular solutions; rather, it enables analysts to structure uncertainty, reveal trade-offs, and communicate robust yet flexible strategies that remain valid across a range of plausible futures.

By generating policy sets that perform well under diverse scenarios, MORO helps analysts shift the conversation from prediction to preparation. Instead of asking “What will happen?” the focus becomes “What actions could perform well, regardless of what happens?” This shift aligns well with the analyst’s role as a translator between technical findings and decision-making under uncertainty.

The MORO framework also highlights trade-offs that might otherwise remain hidden. In this study, it became evident that policies promoting ridership and emissions reduction, such as ultra-low fares, can undermine revenue and overburden capacity unless balanced with complementary measures like peak-hour surcharges. Exposing such tensions is a valuable step toward more transparent and inclusive policymaking, allowing decision-makers to weigh competing goals explicitly rather than pursuing single-objective optimization.

In addition, MORO supports the development of adaptive strategies rather than static policy recommendations. The results suggest that a fare policy effective in 2030 may not remain so by 2040. MORO enables analysts to identify robust starting points while also providing insight into when and how these strategies might need adjustment. This supports the use of adaptive policy pathways, where policies evolve in response to observed developments rather than being fixed in advance.

The use of MORO enhances the legitimacy of policy advice by making the assumptions, uncertainties, and trade-offs embedded in modeling more visible. Analysts can demonstrate not just what is optimal under one future, but what performs reasonably well across many. This transparency supports more credible and democratic decision-making, especially in contested domains like public transport pricing.

In sum, the value of MORO lies not only in identifying robust strategies but in supporting the deliberative processes that underpin good policy. It strengthens the analyst’s capacity to inform rather than dictate—to guide decision-making by revealing what is possible, plausible, and prudent given the uncertainties ahead.

1
Introduction

In a rapidly changing world marked by uncertainties, policymakers confront the grand challenge of planning for an unpredictable future. This complexity is particularly notable in the domain of mobility policy, where decision-makers must consider variables like population growth, urbanization, and the climate crisis, factors that contribute to a state of "deep uncertainty." Deep uncertainty exists when stakeholders do not know or cannot agree on the system models that describe interactions between variables, or the probabilities of various future scenarios[1]. In such a landscape, the stakes are high, as incorrect or short-sighted decisions can lead to long-term inefficiencies, increased costs, and reduced adaptability in transportation systems.

The Netherlands traditionally relies on the Landelijk Model Systeem (LMS) for its mobility planning, which is a comprehensive computational tool designed to evaluate the potential outcomes of different transportation policies in the short term. However, when it comes to capturing the broader range of possibilities inherent in deeply uncertain systems, LMS may be less effective. Its computational intensity limits its application to just 2 or 3 scenarios, typically requiring an entire night for each run. This constraint might leave policymakers ill-equipped to fully account for a spectrum of potential future developments, such as rapid technological innovations, demographic fluctuations, and changes in public attitudes toward transportation.

To address this gap, this research investigates the potential of applying Exploratory Modelling and Analysis (EMA) to mobility policy—a domain where EMA has not yet been widely applied. Unlike the LMS, EMA is designed to quickly analyze thousands of scenarios, offering a broader understanding of uncertain systems. Since the application of EMA directly to the LMS is computationally infeasible, this research adopts an alternative approach by developing a simplified, integrated model of the Dutch passenger rail network that is compatible with EMA.

The central aim of this research is to assess whether EMA can be a catalyst for more robust, adaptive, and insightful policy decisions in the Dutch mobility landscape. In other words, this study serves as a proof-of-concept, striving to demonstrate that when navigated with the agility of EMA, the uncertain terrains of mobility policy can become more manageable and strategically negotiable. Such an approach is not just a technical improvement, but also aligns with broader objectives like fostering resilient infrastructure, promoting sustainable urban development, and combating climate change, as articulated in the United Nations Sustainable Development Goal (SDG) 9, SDG 11, and SDG 13 (UN, 2015).

Accordingly, this research contributes both to the academic discourse on uncertainty in policy modelling and to the practical evolution of Dutch transportation policy. By enabling more comprehensive scenario analysis, it provides a methodological foundation for designing sustainable and resilient mobility strategies under deep uncertainty.

1.1. Case Study: Dutch Passenger Rail

This research focusses on the integration of EMA into the Dutch mobility policy-making process. As a case study, this research looks specifically at the passenger rail network in The Netherlands. This scope was chosen due to the number of uncertainties in rail policy, the political timeliness of more sustainable

[1] Deep Uncertainty is defined by Kwakkel et al., 2010b as a Level 3 Uncertainty where a policy-maker is able to enumerate multiple scenarios, but they are not able to rank the scenarios in terms of how likely or plausible they are (Kwakkel et al., 2010b)

mobility options, and the availability of data. EMA is a methodological approach that allows exploration of a wide range of plausible futures and the identification of robust strategies that perform well under different conditions (Kwakkel et al., 2015; Walker et al., 2013). By integrating EMA into the policy-making process, this research aims to improve the ability of decision makers to navigate deep uncertainties and make more informed, resilient, and sustainable policy decisions (Walker et al., 2013).

This research is important for several reasons. First, it addresses a critical gap in the current policy making process, which often struggles to adequately consider and manage deep uncertainties (Cook et al., 2013). Second, it contributes to the theoretical understanding of EMA and its application in policy contexts (Walker et al., 2013). Third, it provides practical insights and recommendations for policymakers, stakeholders, and researchers in the field of mobility policy (Font Vivanco et al., 2016). By exploring these issues, this research aims to contribute to the development of more resilient, sustainable, and inclusive mobility policies in the Netherlands and around the world.

EMA's value is especially apparent when considering the dynamic nature of passenger mobility, which is influenced by factors such as population growth, urbanisation, technological advances, and changing societal attitudes towards different modes of transport. Traditional modelling methods may struggle to adequately capture these dynamics and the resulting uncertainty (Moallemi & Köhler, 2021). EMA, on the other hand, is designed to handle these complexities, making it a valuable tool for Dutch mobility policy.

1.2. Research Question

Given these considerations, an interesting question arises:

> **Research Question**
>
> How can Multi-Objective Robust Optimization be applied to enhance long-term passenger rail demand forecasting under deep uncertainty, particularly in evaluating fare policy levers?

To address this question, this study will perform an analysis of the potential EMA applications in Dutch passenger rail, while drawing on case studies and model outputs. The aim is to provide information on how EMA can enhance the robustness, adaptability, and legitimacy of transportation policies in the face of deep uncertainty.

Sub-Questions

1. What are the potential impacts of implementing extreme fare interventions on rail ridership, revenue, and CO_2 emissions across a wide range of uncertain future scenarios?
2. How can fare policies be structured or adapted over the 2024–2070 horizon to remain effective in achieving transportation objectives despite deep uncertainty in future mobility trends?

Research Approach Overview

To achieve the research objectives, the following approach was undertaken:

1. **Baseline Model Development and EMA Proof-of-Concept:** A simplified elasticity-based demand model of the rail system was constructed as a baseline. This model was run with EMA to demonstrate feasibility and to provide initial insights.
2. **Model Enhancement with Trend and Pattern Analysis:** The model was extended by incorporating time-series forecasting for long-term trend inputs (using tools like Prophet) and by integrating machine-learning-based analysis techniques. After running large ensembles of simulations, scenario discovery methods (PRIM and CART) and clustering were applied to identify patterns in the results.
3. **Evaluation of EMA Value and Policy Insights:** The outcomes from the exploratory analysis were evaluated to assess the added value of EMA relative to traditional approaches. In absence of a direct LMS comparison (due to computational constraints), a qualitative contrast was made to illustrate how EMA unveils insights (such as robust policy strategies and trade-offs) that might remain hidden in a limited-scenario analysis. This stage also distilled the findings into policy-relevant insights and potential pathways for implementation.

1.3. Disclaimer

This research was carried out in collaboration with the Kennisinstituut voor Mobiliteitsbeleid (KiM), a research branch of the Dutch government that provides knowledge input for the preparation of the mobility policy of the Ministry of Infrastructure and Water Management (IenW). KiM aims to ensure that policy is developed with a solid knowledge base through the analysis and explanation of developments, exploratory studies, the development of scenarios, and the analysis of the effects of policy instruments (KiM, 2023b). The views expressed in this research may not reflect the views of KiM, IenW, or TU Delft. KiM did not review the final version of this document.

Additionally, during the period in which this thesis was written, the author also completed an unrelated internship at the United Nations Human Settlements Programme (UN-Habitat) in Lao PDR. This internship did not influence the scope, methodology, or findings of the present research.

1.4. Thesis Overview

This thesis is structured to provide a comprehensive understanding of managing uncertainties in Dutch mobility policy, focusing on passenger rail transportation. It explores the integration of Exploratory Modeling and Analysis (EMA) as a tool for informed decision-making under deep uncertainty.

- **Chapter 1: Introduction**
  This opening chapter introduces the case study of Dutch passenger rail, lays out the research questions guiding the thesis, and discusses relevant disclaimers. It sets the stage for the following detailed analysis.

- **Chapter 2: Literature Review**
  The second chapter delves into the concept of deep uncertainty in mobility policy, reviewing key methods such as Robust Decision Making (RDM), Dynamic Adaptive Policy Pathways (DAPP), and EMA combined with Multi-Objective Robust Optimization (MORO). It also examines the current state of mobility modelling in the Netherlands and discusses how deep uncertainty methods integrate with traditional transport models, alongside political considerations.

- **Chapter 3: Model Setup**
  This chapter details the development of the Dutch passenger rail system model, describing the input parameters—including elasticity, uncertainties, policy levers, and data requirements—along with the model's outputs, internal logic, and limitations.

- **Chapter 4: Experimental Setup**
  Here, the research methodology is outlined, including the design of policy scenarios and the setup of the MORO framework within the EMA Workbench. The chapter explains calibration of epsilon values, convergence monitoring, and approaches for post-optimization analysis such as multi-dimensional visualization, clustering, and pathways calculation.

- **Chapter 5: MORO Results (2030)**
  This chapter presents the results of applying MORO to the 2030 Balanced Scenario and the Unrestrained Balanced, Max Revenue, and Max Demand filters. It provides insights into policy performance across these futures.

- **Chapter 6: Policy Pathways (2024–2070)**
  Chapter six analyzes dynamic policy pathways over the full 2024 to 2070 horizon, focusing on Balanced pathways and specific measures such as Rush-Hour Surcharge and Free Transit Incentives.

- **Chapter 7: Discussion**
  This chapter evaluates the model's performance, synthesizes simulation outcomes across the study period, discusses policy implications for long-term fare strategies, and reflects on limitations of the analysis.

- **Chapter 8: Conclusions**
  The final chapter summarizes the research questions and key findings, provides policy recommendations based on the results, and outlines directions for future research.

2 Literature Review

An important aspect of the MSc Engineering and Policy Analysis programme at TU Delft is the exploration of wicked problems—international grand challenges that, by their very nature, are fraught with deep uncertainty (Alexander et al., 2022; van der Voort, 2022). According to Rittel and Webber, these problems lack fixed sets of solutions and are characterized by inherent complexity and the difficulty of finding definitive answers (Rittel & Webber, 1973). This research aims to specifically address the wicked problem of deep uncertainty within the realm of transportation policy. Such uncertainty arises when stakeholders either do not know or cannot agree on the models that describe interactions between variables, or the probabilities of different future outcomes. To navigate these complexities, EMA has emerged as a robust framework, offering a structured approach for understanding various uncertainties and making more resilient policy decisions. This chapter introduces the concept of deep uncertainty, its implications for transportation policy, and the tools and frameworks that can support adaptive and robust decision-making.

2.1. Understanding Deep Uncertainty in Mobility Policy

Deep uncertainty arises when decision-makers cannot agree on, or lack sufficient information to define, the relationships between key variables, the probability of future events, or the values that should guide policy (Bankes, 2002; Lempert et al., 2003). This is especially relevant in mobility systems, where policy outcomes are shaped by volatile factors such as technological change, demographic shifts, evolving travel behaviour, and environmental disruptions.

In Dutch passenger rail policy, such uncertainty manifests in challenges like anticipating demand for new services, adapting to emerging modes of transport, or forecasting the impacts of climate policy. Traditional modelling techniques often fall short in such environments, as they typically focus on predicting a single "most likely" future.

EMA offers a structured framework for exploring large sets of plausible futures, identifying policies that are robust across them, and highlighting conditions under which policies may succeed or fail. Its strengths lie in helping policymakers move beyond prediction toward preparedness and adaptability. By engaging with a wide range of possibilities and stakeholder perspectives, EMA supports the design of strategies that can remain effective even as real-world conditions shift (Bankes, 1993).

This perspective is further exemplified by a recent case study by Führer et al.(2024), which explores the complexities faced by the City of The Hague in pursuing a climate-neutral transport system. Their work highlights how deep uncertainty emerges not only from unpredictable technological and behavioral trends but also from institutional entanglements, conflicting stakeholder priorities, and cross-sector dependencies, such as interactions between transport, housing, and energy systems. By explicitly accounting for these interdependencies, the study provides empirical support for the argument that deep uncertainty in mobility policy extends well beyond model uncertainty alone.

Over the past two decades, several methodological frameworks have been developed to address deep uncertainty in policy-making. These include Robust Decision Making (RDM), Dynamic Adaptive Policy Pathways (DAPP), and EMA. Each offers different strengths in coping with uncertainty, with EMA being the primary method used in this research.

2.2. Robust Decision Making (RDM)

Robust Decision Making (RDM) is an iterative decision support methodology designed to help policymakers make decisions in situations characterized by deep uncertainty (Lempert et al., 2006). Instead of focusing on the most likely scenario, RDM emphasizes the identification of policies that are robust across a wide range of plausible futures. The process begins with scenario discovery, where a diverse set of scenarios that challenge the proposed policies are identified. These scenarios are then used to stress-test potential policies, evaluating their performance across these challenging scenarios. The aim is not to find the optimal policy for a given scenario but to identify strategies that perform satisfactorily across a vast range of scenarios. As the future unfolds, RDM promotes adaptive planning, where strategies can be adjusted in response to new information or changing conditions. This iterative approach ensures that decisions remain both robust and flexible, allowing for adjustments as the landscape of knowledge and circumstances evolves (Lempert et al., 2006).

2.3. Dynamic Adaptive Policy Pathways (DAPP)

Dynamic Adaptive Policy Pathways (DAPP) is another approach that acknowledges the dynamic nature of decision-making in the face of deep uncertainty (Haasnoot et al., 2013). Central to DAPP is the concept of "pathway maps", which are visual representations illustrating how decisions might evolve over time in response to changing conditions or new information. These maps guide decision-makers, showing potential routes and decisions that might be taken as situations change. Another crucial component of DAPP is the identification of "Adaptation Tipping Points (ATPs)". ATPs are specific points in time when the current policy or strategy no longer meets its objectives, indicating that a change in direction is necessary. By recognizing these tipping points, DAPP ensures that strategies remain relevant and effective even as conditions change. Furthermore, DAPP emphasizes the importance of "signposts", which are indicators or triggers that inform decision-makers when it might be necessary to switch from one pathway to another. By sequencing decisions and understanding when and how to adapt, DAPP provides a framework for designing strategies that are both resilient and adaptive, ensuring that policies can respond effectively to a changing environment (Haasnoot et al., 2013).

2.4. Exploratory Modeling and Analysis (EMA) with Multi-Objective Robust Optimization (MORO)

Both RDM and DAPP rely on exploratory simulation of many scenarios. Exploratory Modeling and Analysis (EMA) is the broader methodological paradigm enabling such simulation-based exploration of uncertainties (Bankes, 1993). EMA, as defined by (Bankes, 1993), advocates constructing many plausible model instances (varying uncertain assumptions) and investigating “what-if” consequences of policies across these instances, rather than making a single best-estimate prediction. In practice, EMA involves running computational models thousands of times over wide-ranging combinations of uncertain factors (e.g., travel demand growth, fuel prices, behavioral trends in a transport model) and policy levers (e.g., pricing strategies, infrastructure investments). The results are used to map the outcome space to inform robust decision-making (Kwakkel, 2017; Kwakkel et al., 2010b).

Tools for EMA often include design of experiments, global sensitivity analysis, and visualization, as well as techniques like scenario discovery to pinpoint scenarios that illuminate policy vulnerabilities (Lempert et al., 2003). In the context of transport policy, EMA allows analysts to integrate complex models into a deep uncertainty analysis. This way, instead of using the model for point forecasts, it is used as a generator of many plausible futures and policy outcomes, supporting the search for strategies that work across these futures.

A powerful approach within EMA, and the central method in this research, is Multi-Objective Robust Optimization (MORO). MORO is an advanced decision-analytic technique that integrates multi-objective optimization with robustness analysis (Hamarat et al., 2014). Whereas traditional optimization finds a single “optimal” solution for a given scenario or set of assumptions, MORO searches for a set of Pareto-optimal policies that balance multiple objectives and remain effective under a spectrum of future scenarios (Kwakkel, 2017; Kwakkel & Haasnoot, 2016). In other words, MORO yields policy options that represent efficient trade-offs among competing goals while also achieving robust performance across uncertainties. The result of a MORO analysis is typically a robust Pareto front: a frontier of non-dominated solutions, none of which can improve one objective without sacrificing another. Decision-makers can then examine this Pareto front to understand the trade-offs and select a policy that best fits their preferences and risk tolerance. Hamarat et al. (2014) demonstrated that incorporating robustness directly into the search, rather than only evaluating robustness after optimizing, can yield strategies that are more immune to uncertain disturbances. MORO has also since been employed in combination with DAPP. In these applications, MORO extends the idea from Many-Objective Robust Decision Making (MORDM) by bringing the robustness considerations into the search itself (Hamarat et al., 2014; Kwakkel, 2017). In practical terms, this means the optimization algorithm (often a genetic algorithm like NSGA-II) evaluates each candidate policy on multiple objectives across a sample of scenarios, rather than a single scenario (Kwakkel, 2017; Kwakkel & Haasnoot, 2016). Candidate solutions are rewarded for performing well under many futures, not just one, thereby directly evolving robust policies.

The benefits of MORO in the EMA framework are applicable to transport policy design under uncertainty. Transport planners often face multiple conflicting objectives, such as efficiency, equity, environmental impact, and cost and deep uncertainties, such as economic growth and demographic shifts. MORO allows exploration of policy trade-offs in a rigorous way: for instance, it can reveal strategies that slightly sacrifice optimal travel time reductions in exchange for significantly improved robustness to uncertain demand growth. It highlights policies that offer a good balance. By quantifying these trade-offs, MORO supports more transparent decision-making as policymakers can see the extent of performance compromise required to achieve greater robustness. This is crucial for deep uncertainty contexts, where stakeholders may be willing to accept a lower performance ceiling if it means avoiding catastrophic failure in certain futures.

2.5. Implementation in the EMA Workbench

To apply MORO in this research, the open-source EMA Workbench for Python developed by Jan Kwakkel is used (Kwakkel, 2017). The EMA Workbench provides tools for conducting exploratory modeling, scenario discovery, and robust optimization. In particular, it offers an optimization function that enables multi-objective search under uncertainty.

The `MultiprocessingEvaluator(model).optimize()` routine is employed to perform MORO on the transport model. This routine runs a multi-objective evolutionary algorithm in parallel, evaluating each potential policy across an ensemble of scenarios before assigning it fitness. By leveraging the EMA Workbench's parallel computation capabilities, it becomes possible to efficiently explore a large policy space and uncertainty space simultaneously. EMA with MORO forms the methodological core of this study as it provides a systematic way to discover robust transport policies.

One of the tools built on the EMA Workbench is the TMIP-EMAT (Travel Model Improvement Programme - Exploratory Modelling and Analysis Tool). TMIP-EMAT is specifically designed for transportation models and supports the entire EMA process, from model experimentation to uncertainty quantification, to visualisation of results (Milkovits et al., 2019). TMIP-EMAT is designed to apply EMA to existing travel demannd models, such as the LMS. However, as previously discussed, the LMS is too complex of a model to be computationally compatible with EMA.

The MATISSE (Modelling and Assessments for Transitions: Integrated and Sustainable Solutions for Energy) model is another application of EMA, focussing on the transition to sustainable mobility systems (Moallemi & Köhler, 2021). Similarly to TMIP-EMAT, the MATISSE model uses exploratory modelling to navigate uncertainties in the future of mobility. However, the two models differ in their scope and modelling approach, with the MATISSE model focussing specifically on sustainable mobility transitions, while TMIP-EMAT is designed for a broader range of transportation modelling applications.

2.6. Mobility Modelling in The Netherlands

Mobility refers to the movement of people or goods from one place to another, encompassing various modes of transportation such as public transportation, private vehicles, walking, and cycling. Mobility policy, in turn, refers to the set of strategies, regulations, and initiatives implemented by governments and relevant stakeholders to shape and manage transportation systems, promote sustainable mobility, and address societal needs and challenges in transportation infrastructure, accessibility, and environmental impact.

The Netherlands has a long history of advanced mobility modelling. This reflects its dense population, extensive transportation infrastructure, and commitment to sustainable mobility. The most significant examples of this modelling are the Dutch National Model System (LMS) and the Nederlands Regionaal Model (NRM) (Rijkswaterstaat, 2023).

The Dutch National Model System (LMS) & the Nederlands Regionaal Model (NRM)

The LMS and NRM are integrated transportation model systems that allow for comprehensive simulation of passenger and freight transportation activities in all modes of transport (Rijkswaterstaat, 2023). The model systems integrate various submodels to represent diverse aspects of the transportation system, from land use patterns and transport demand to the operation of transportation networks. These models are used to provide insight into the consequences of spatial-economic developments for mobility, the effects of policy measures on mobility, and to provide input for environmental studies and cost-benefit analyses.

The LMS and NRM are comprehensive tools that have been instrumental in shaping transport policies in the Netherlands. They allow the analysis of a broad range of transportation policies and plans, including investments in infrastructure, fare policies, and environmental regulations. They have also been used to evaluate the potential impacts of new technologies and innovations in the transportation sector (Rijkswaterstaat, 2023).

The LMS and NRM comprise several interconnected models that simulate distinct aspects of the transportation system. These include a base year matrix, which provides the basis for the model calculations; a spatial distribution model, which distributes the growth in mobility over the various origins and destinations; a modal split model, which divides the total number of trips between different modes of transport; and an assignment model, which assigns the trips to the network. These components work together to simulate the effects of various factors on mobility, providing a comprehensive understanding of the transportation system (Rijkswaterstaat, 2023).

In recent years, transportation modelling has been evolving to cope with increasingly complex and uncertain transportation futures. Factors such as the advent of autonomous vehicles, shared mobility services, and other technological innovations pose new challenges and opportunities for transportation planning and policy (Rijkswaterstaat, 2023).

The LMS and NRM have undergone several updates and enhancements to address these challenges. These include the development of a new model for the prediction of car ownership, the introduction of a new model for the prediction of bicycle use, the improvement of the freight model, the enhancement of the public transport model, the refinement of the model for the prediction of car use, and the improvement of the data and methods used for the calibration and validation of the models (Rijkswaterstaat, 2023).

Furthermore, the imperative of sustainability, as underscored by the UN Sustainable Development Goals, has forced a fundamental rethinking of transportation systems and their impacts on society and the environment. This rethinking is not only about reducing emissions or improving efficiency, but also about aligning transportation policies with broader societal goals such as social equity and the Rights of Nature. It calls for a change to a life-centred paradigm, where the health and well-being of all forms of life are considered in decision making processes (Phillips & Reichart, 2000).

This shift in perspective has led to a growing emphasis on models that can capture the interdependencies between transportation, land use, economy, and environment and that can facilitate the exploration of alternative futures and the evaluation of robust, adaptive strategies. These models are not just tools for prediction, but also instruments for envisioning and shaping a more sustainable, equitable, and life-affirming future (Rijkswaterstaat, 2023).

2.7. Integrating Uncertainty Methods with Traditional Transport Models

It is important to emphasize that frameworks such as RDM, DAPP, and EMA/MORO are not in competition with traditional transport modeling approaches, but rather complement them. Traditional transport forecasting models remain invaluable for detailed analysis of travel demand and network performance under assumed conditions (Rijkswaterstaat, 2023). Such models typically operate within a predict-then-act paradigm, which is well-suited for predictable or moderately uncertain futures. However, when facing deep uncertainty, reliance on one or a few forecast scenarios can create a false sense of security or lead to plans that are ill-prepared for surprises (Lempert et al., 2003).

Deep uncertainty methods such as EMA, RDM, and DAPP can augment and extend the insights provided by traditional models like LMS. Rather than replacing the LMS or similar tools, these methods integrate them into a broader exploratory analysis. Kwakkel et al. (2010b) illustrate this kind of approach in an adaptive strategic planning study for airport infrastructure, where a transport model was used in an iterative framework to evaluate options under numerous scenarios.

Crucially, each approach contributes unique value to the decision process. RDM provides a clear analytic process for stress-testing policies and identifying their failure conditions, informing the selection or design of adaptive pathways. DAPP (and related adaptive planning methods) supplies a framework for sequencing actions over time, ensuring that plans remain flexible and adjustable as the world evolves. EMA offers the computational experimentation platform to systematically evaluate many what-if scenarios, while MORO adds an automated search capability to identify promising policy candidates that might not be apparent through manual exploration. Meanwhile, detailed sector models like LMS contribute domain-specific realism and credibility to ensure that any strategy deemed "robust" is grounded in a realistic representation of traveler behavior and network dynamics.

2.8. Navigating Political Considerations in EMA Integration

Integrating EMA into the policy-making process requires careful attention to political considerations. Policymakers must navigate power dynamics, competing interests, and policy agendas to ensure the effective incorporation of EMA and the consideration of its results in policy decisions (Kwakkel et al., 2010a).

Transparency and inclusiveness are key principles for managing political considerations. Policymakers should strive to be transparent in their decision-making processes, providing access to information, and meaningfully involving stakeholders. Inclusiveness ensures that a wide range of perspectives are taken into account, avoiding undue influence from specific interest groups and fostering more legitimate policy choices (Lempert et al., 2003).

Building political support for EMA requires effectively communicating its benefits and value in addressing deep uncertainty. Policymakers should actively communicate the advantages of EMA to colleagues, superiors, and the public. Capacity-building activities, such as training workshops and knowledge-sharing initiatives, could be used to enhance policymakers' understanding of EMA and its application in policy contexts. By demonstrating the positive impact of EMA on policy outcomes, policy makers can foster a culture of evidence-based decision making and encourage its widespread adoption.

Navigating political considerations also involves addressing potential challenges, including resistance to change, conflicting interests, and limited resources. Strong leadership, effective communication, and the ability to build coalitions and consensus are essential to overcome these challenges. Policymakers should assess the political feasibility of the policy options identified through EMA, considering broader policy contexts, public opinion, and institutional constraints. By aligning EMA with political realities, policymakers can increase the likelihood of successfully integrating it into the policy making process.

3

Model Setup

This chapter outlines the research methodology, focusing on the development and application of a simplified model of the Dutch passenger rail system. The model integrates an elasticity-based demand logic with time-series trend forecasting, and employs machine-learning-assisted analysis of results. This unified modelling approach serves as a proof-of-concept for the potential benefits of EMA in this domain. The chapter details the steps involved in the model development and analysis, including scenario design, data requirements, and model evaluation metrics.

3.1. Model Input

Data sources, data limitations, and the raw data itself can be found in Appendix H.

3.1.1. Elasticity Parameters

Elasticity parameters form the behavioral core of the model. They quantify how rail travel demand responds to changes in various explanatory variables and are essential for simulating realistic demand shifts under different policy and scenario conditions.

All elasticity values used in this study originate from the Netherlands Institute for Transport Policy Analysis (KiM). These values were pre-processed from raw CSV files into a structured format compatible with the EMA Workbench. Within the model, they are applied endogenously: when scenario inputs change—such as an increase in fuel prices or road congestion—elasticity values determine the proportional effect on train demand. For instance, positive elasticities for fuel cost and congestion imply that, in scenarios where both increase, rail demand would correspondingly rise.

The elasticity framework covers a wide range of socioeconomic and infrastructural variables. Each elasticity captures the marginal effect of a 1% change in one input variable on train demand. These factors are enumerated in Section 3.1.2.

Elasticities are held static over the simulation horizon due to the absence of robust empirical evidence on their long-term evolution. While behavioral responses may change over time as societal preferences shift, keeping elasticities fixed allows the analysis to focus on structural uncertainties and policy impacts.

Table 3.1 below presents the elasticity values used in this study, along with the explanatory factors over the period 2020–2026.

Train 2020-2026	Parameter Development		Elasticities	Effect on Traveled Distance	
Explanatory Variables	Reference (BR)	Project (PS)	LMS	Reference (BR)	Project (PS)
Students	10.5%	10.5%	0.23	2.5%	2.5%
Residents	3.8%	3.8%	1.38	5.3%	5.3%
Jobs	3.1%	3.1%	0.29	0.9%	0.9%
Income	4.3%	2.3%	0.65	2.7%	1.5%
Car Ownership	6.8%	6.8%	-0.02	-0.2%	-0.2%
Schiphol Passengers	4.6%	4.6%	0.05	0.2%	0.2%
Congestion	31.2%	26.8%	0.03	0.9%	0.8%
Fuel Costs	1.3%	1.3%	0.11	0.1%	0.1%
Train Fare	0.0%	0.0%	-0.63	0.0%	0.0%
Train Quality	10.9%	0.0%	0.35	3.8%	0.0%
Total Elasticities	N.a.	N.a.	N.a.	17.4%	11.6%
Total incl. Behavioral Adjustment	N.a.	N.a.	N.a.	6.7%	1.3%

Table 3.1: Elasticities and the development of explanatory factors for train usage (in passenger kilometers) for the years 2020-2026. BV stands for Basisraming or Basic Forecast and PS stands for Pessimistisch or Pessimistic Scenario (KiM, 2021)

Dutch Names	English Translation	Python Variable	LMS Elasticity	Description
Studenten	Students	students	0.23	Number of students in the Netherlands
Inwoners	Residents	pop	1.38	Total population in the Netherlands
Banen	Jobs	banen	0.29	Number of jobs in the Netherlands
Inkomen	Income	inkomen	0.65	Average disposable income of residents
Autobezit	Car Ownership	autobezit	-0.02	Number of households owning a car
Schipholpassagiers	Schiphol Passengers	schiphol	0.05	Number of passengers traveling to/from Schiphol Airport
Brandstofkosten	Fuel Costs	brandstof	0.11	Average fuel costs for car travel
Treintarief	Train Fare	price_per_km	-0.63	Train ticket cost per km

Table 3.2: Mapping of elasticity names from Dutch to English and Python variables, including LMS Elasticities and descriptions.

3.1.2. Uncertainties

Uncertainties in this study represent factors that are outside the direct control of decision-makers and are characterized by deep, structural unpredictability. Within the EMA Workbench framework, these uncertainties are systematically varied to generate large ensembles of plausible future scenarios. By simulating across this uncertainty space, the model can evaluate how sensitive outcomes are to different external developments and assess the robustness of policy interventions under a wide range of future conditions.

The model uses 2019 as the base year for all simulations. This year was selected as the last full pre-COVID period, representing a “normal” baseline before the disruptions caused by the pandemic. To support the Prophet forecasting and to validate model behavior, a long-term dataset of Dutch rail usage was compiled. This includes annual ridership figures, ticket revenue, and other performance metrics of the Dutch Railways (NS) spanning 1985 through 2021. The historical NS data was used to train Prophet and to ensure the elasticity-based components produce realistic changes (for example, the elasticity for income can be checked against how ridership grew with GDP over decades).

The combination of all these uncertainties defines a very large space of possible future conditions. The EMA approach allows us to sample this space and see how policies fare across many combinations of these uncertain factors.

Uncertainties

- **Train Trips**: Average number of train trips taken per person per year.
- **Train Distance**: Total distance (km) traveled by train per year.
- **Weekday Train Usage** and **Weekend Train Usage**: Train usage rate (%) for Dutch students with weekday and weekend studentenreisproduct.
- **Non-student Train Usage**: Train usage rate (%) for people without a studentenreisproduct (international students and non-students).
- **Population**: Total population of the Netherlands. Linked to LMS elasticity Inwoners.
- **Students**: Total number of university students in the Netherlands. Linked to LMS elasticity Studenten.
- **International Students**: Total number of international university students in the Netherlands.
- **Traffic Participation**: Percentage of population without a studentenreisproduct participating in traffic every day.
- **Car Trips Per Day**: Average number of car trips taken per person per day.
- **Distance Per Car Trip**: Average distance (km) per car trip.
- **Car CO_2 Emissions**: Yearly CO_2 emissions from cars.
- **Jobs**: Total number of jobs in the Netherlands. Linked to LMS elasticity Banen.
- **Income**: Average income in the Netherlands. Linked to LMS elasticity Inkomen.
- **Car Ownership**: Car ownership rates in the Netherlands. Linked to LMS elasticity Autobezit.
- **Schiphol Passengers**: Number of passengers traveling through Schiphol Airport. Linked to LMS elasticity Schipholpassagiers.
- **Fuel Costs**: Average fuel costs. Linked to LMS elasticity Brandstofkosten.
- **Average Distance Per Train Trip**: Average distance (km) per train trip.
- **€9 Ticket Modifier**: Modifier for ticket prices due to a hypothetical €9 monthly subscription.
- **€49 Ticket Modifier**: Modifier for ticket prices due to a hypothetical €49 monthly subscription.
- **Train Capacity**: Total train capacity in passenger-kilometers.
- **Train Fare**: Price charged per kilometer of train travel. Linked to LMS elasticity Treintarief.
- **Peak AM Demand Modifier**: Percentage of total daily demand that occurs during the AM rush hour.
- **Peak PM Demand Modifier**: Percentage of total daily demand that occurs during the PM rush hour.
- **Car Substitution Rate**: Percentage of new train trips that were originally car trips.

The uncertainty ranges in this study are defined by applying a uniform variation of ±5% around the yearly input values projected by Prophet. Prophet forecasts provide the time-evolving baseline for parameters to ensure that the uncertainty ranges reflect plausible long-term trends. This design allows the model to explore how small-to-moderate deviations propagate through the system and influence policy outcomes.

For the €9 and €49 ticket modifiers, however, the uncertainty ranges are set specifically to reflect differences in observed demand effects. The lower bound is based on Germany-wide estimates, while the upper bound draws from demand increases observed in North Rhine-Westphalia, as detailed in Section 3.3.3.

This differentiation acknowledges that the impact of such flat-fare subscription policies can vary substantially by region.

3.1.3. Policy Levers

Levers in the EMA workbench context are akin to policy or strategy choices. These represent decisions or interventions that decision-makers can adjust. By manipulating these levers, the EMA workbench evaluates the performance of different policies or strategies across a multitude of scenarios.

The following levers were defined:

1. **Free Transit for Students:** A binary lever indicating whether all students are given free public transport (0 = No, maintain free travel for Dutch students and regular fares for international students; 1 = Yes, implement free travel for all students). This policy, if "on," removes fare revenue from student travelers but is expected to boost international student ridership to match Dutch student ridership.

2. **General Tariff Adjustment:** A continuous lever representing a uniform change in base ticket prices for everyone. This is expressed as a Euro increase or decrease in fares per fare unit. This lever directly affects revenue per trip and inversely affects demand through the fare elasticity.

3. **Rush Hour Surcharge:** An additional charge applied only during peak hours. This lever can be thought of as either off (no surcharge) or on (a surcharge of a certain Euro amount on top of the base fare for peak-hour trips). In implementation, a binary or discrete setting was used (e.g., 0 = no surcharge, 0.01 = apply a 1-cent surcharge per fare unit on peak trips). This policy is intended to manage peak demand and raise extra revenue from rush-hour travelers, potentially shifting some travel to off-peak times.

4. **Unlimited Travel Pass Price:** The price point of a monthly "free travel" ticket that allows unlimited train travel. This lever is discrete between €9 and €49 per month for an unlimited off-peak travel card. A lower price for this pass could greatly encourage people to use trains more (increasing demand) but yields less revenue per user, while a higher price does the opposite.

Levers

- **Free Transit for Students**: Indicator for whether free transit is available to all students (0 = no, 1 = yes).
- **Train Fare Change**: Euro change in the train fare, ranging from -0.25 to 0.25 per fare unit.
- **Rush Hour Surcharge**: Euro surcharge applied during rush hours, ranging from 0 to 0.25 per fare unit.
- **Unlimited Free Travel Ticket**: Indicator for whether a free travel ticket is available (0 = no, 1 = yes).
- **Unlimited Free Travel Ticket Price**: Price of the free travel ticket (ranging between €9 and €49).

3.1.4. Data Requirements

The reliability and utility of the modeling in this study are closely tied to the quality, accuracy, and coverage of the input data. Data was required for both model development and output interpretation. The primary data categories used in this research are outlined below. Further details can be found in Appendix H.

- **Elasticity Parameters:** Sourced from the Netherlands Institute for Transport Policy Analysis (KiM), these values quantify the responsiveness of train travel demand to changes in various explanatory factors. Accurate and up-to-date elasticity estimates are essential to capture how demand shifts in response to both policy interventions and external developments. The model incorporates elasticities related to: student population, residential population, employment, income levels, car ownership, air passenger flows via Schiphol, road congestion, fuel prices, train fares, and service quality (KiM, 2019, 2021, 2022, 2023a).
- **Demographic and socioeconomic Data:** To apply the elasticity framework meaningfully, detailed demographic and socioeconomic data aligned with the variables described above are required. These

datasets enable the model to project how long-term socioeconomic trends affect baseline travel demand over time (Centraal Bureau voor de Statistiek, 2021, 2023a, 2023b, 2023c, 2023d, 2023e).

- **Historical NS Ridership and Revenue Data:** Longitudinal data from Nederlandse Spoorwegen (NS) covering the period 1985–2021 provide critical context for evaluating historical patterns in train usage. These data are particularly important for validating the model's ability to replicate known demand responses to past fare policies and service adjustments, thereby strengthening the credibility of its future projections (Nederlandse Spoorwegen, 2023a, 2023b, 2023c).

Given the model's sensitivity to both structural inputs and behavioral responses, it is crucial that all data sources are comprehensive, consistent, and as current as possible. Incomplete or misaligned data could introduce biases or distortions in simulation outcomes, ultimately weakening the robustness of the resulting policy insights.

3.2. Model Outputs

Model outputs are the key performance indicators optimized in the MORO process. The following section describes these outputs as model outcomes.

3.2.1. Model Outcomes

Outcomes are the measurable results produced by the model for each combination of uncertainties and policy levers. They represent the metrics of interest and provide insights into policy performance, trade-offs, and potential impacts.

1. **Annual Train Demand**: Measured in passenger-kilometers. This reflects the ridership and is a proxy for accessibility and mode share. Higher demand is generally desirable for mobility and sustainability goals (more people using public transport).

2. **Revenue**: Total ticket revenue per year (in euros), calculated from the demand and fare structure (taking into account any free travel policies, discounts, or surcharges). This outcome addresses the financial viability of the policy for the rail operator and the government.

3. **CO_2 Emissions Reduction**: An estimate of the reduction in carbon emissions due to mode shift from car to train. The logic behind this is explained in Section 3.3.2. A higher value means the policy contributed more to climate change mitigation. This outcome aligns with climate-action goals, including Sustainable Development Goal 13.

4. **Seat Shortage (Unmet Demand)**: A count of how many passenger-kilometers (or passenger-trips) cannot be accommodated due to capacity limits. The logic behind this is explained in Section 3.3.1. A large seat shortage indicates that the policy would run into infrastructure constraints (crowding, denied boardings), highlighting a need for capacity expansion or demand management.

Outcomes

- **Total Train Demand**: Total demand for train travel.
- **Total Revenue**: Total revenue generated from train trips.
- **Seat Shortage**: Shortage in seat capacity to meet demand.
- **Additional Trains Required**: Number of additional trains required to meet demand.
- **CO_2 Reduction**: Reduction in CO_2 emissions due to train travel (compared to car travel).
- **Net CO_2 Emissions**: Net CO_2 emissions after accounting for reductions.
- **Cost of Free Transit for Dutch Students**: Total cost of providing free transit to Dutch students.
- **Cost of Free Transit for International Students**: Total cost of providing free transit to international students.
- **Cost of Free Travel Ticket**: Total cost of providing an unlimited free travel ticket.

3.3. Model Logic

The integrated model represents the Dutch passenger rail system at an aggregate level, capturing essential dynamics of demand and supply while remaining computationally light for EMA. Rather than building separate models, the unified model incorporates the core concepts of each approach: elasticity-driven demand calculations, time-series trend extrapolation, and data-driven analysis. Figure 3.2 provides a schematic of the model logic. The model is discrete in time, evaluating scenarios for 2024 and specific future years: 2030, 2040, 2050, 2060, and 2070. Within each simulated year, the model differentiates between daily rush-hour and off-peak periods to account for peaking characteristics and capacity constraints. This allows policy measures targeting peak times (such as a rush-hour surcharge) to be represented.

3.3.1. Demand and Capacity Logic

The model calculates annual passenger demand (in passenger-kilometers and trips) based on baseline travel metrics adjusted by elasticity factors. Starting from the 2019 base values, demand is scaled according to changes in exogenous factors (population, economic activity, etc.) and policy levers (fares, service offerings). Elasticity parameters determine the percentage change in rail demand for a 1% change in each factor. These elasticity-based adjustments are applied for all relevant drivers in each scenario year. The combined effect produces a projected unconstrained demand for that year under the given conditions. To incorporate daily peaks, the model divides the annual demand into a notional daily profile. A certain fraction of trips is allocated to rush-hour periods (reflecting typical Dutch rail usage patterns) (DutchNews.nl, 2023a). If a rush-hour surcharge policy is in effect, the model applies an additional cost to peak-period trips. This influences demand: peak trips become more expensive, tempering demand during those hours via the fare elasticity. Importantly, the model also checks against capacity constraints. Based on 2019 service levels, a fixed capacity (in terms of available seats per day during rush-hour) is assumed. When the calculated peak demand exceeds this capacity, the excess is recorded as unserved demand, leading to a seat shortage outcome. In other words, the model does not assume capacity expansion unless explicitly specified. Instead, it flags when a policy's induced demand would outstrip current infrastructure. This demand–supply logic ensures that each scenario yields not only ridership and revenue outcomes, but also any shortfall due to capacity limits.

3.3.2. Environmental Impact Logic

The model estimates changes in CO_2 emissions based on changes in passenger rail ridership, assuming partial substitution between rail and car travel. A continuous parameter, called the car substitution rate, was introduced to reflect uncertainty in how many train trips replace car trips. This parameter varies between 0.1 and 0.5, based on estimates from the Victoria Transport Policy Institute (Litman, 2024). The lower bound reflects cases where most train trips would otherwise be made using non-car modes or not made at all, while the upper bound reflects stronger rail-to-car substitution.

CO_2 emissions from car travel are calculated using national averages for emissions per passenger-kilometer. Rail travel emissions are assumed to be near zero due to the high electrification of the Dutch rail network and the use of renewable electricity. This allows the model to treat increases in rail ridership as a net environ- mental benefit, and declines as an increase in emissions.

The model does not consider broader systemic effects such as induced demand or changes in car ownership. However, uncertainty ranges are also applied to other key assumptions, including the average number of car trips per person per day, mean trip distance, and car emissions per kilometer, to reflect variation in travel behavior and vehicle efficiency.

3.3.3. Unlimited Travel Ticket Logic

To estimate the impact of unlimited travel ticket policies within the model, data from the German Federal Statistical Office was used. Specifically, the model uses ridership data from the 2022 implementation of the €9 unlimited travel ticket in Germany and its subsequent replacement with the €49 Deutschlandticket. Both programs offered unrestricted access to regional and local public transportation networks, leading to significant increases in ridership during their respective periods.

Due to the absence of equivalent programs in the Netherlands at the time of modeling, the German subscription was used as a proxy to infer potential behavioral responses. However, since the Netherlands may not be directly comparable to Germany as a whole, two separate cases were used. One case used aggregate data for Germany as a whole, capturing the average national effect, while the other used regional data from North Rhine-Westphalia (NRW), which exhibits socioeconomic and spatial characteristics more closely aligned with those of the Netherlands. The increase in rail ridership observed during the €9 and €49 ticket periods in these regions was translated into input uncertainty ranges for the relevant policy levers in the model. The observed demand increase under these policy shifts can be seen in Figure 3.1.

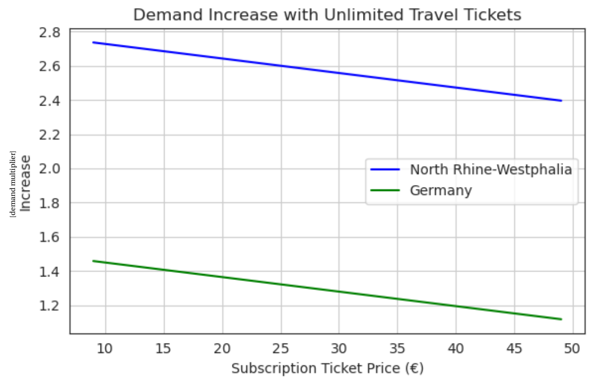


Figure 3.1: Demand response following unlimited travel programs, interpolated from €9 to €49. (Loder et al., 2022a, 2022b; Verband Deutscher Verkehrsunternehmen, 2022)

3.3.4. Time-Series Trend Extrapolation

Elasticity-based adjustments in the model capture demand responses to known, immediate factors such as fare changes or policy levers. However, longer-term baseline trends—driven primarily by demographic shifts and broader socioeconomic changes—also significantly influence travel demand over decades. To incorporate these macro-scale trends, the model employs a trend extrapolation approach using Facebook's open-source forecasting tool, Prophet (Facebook, 2017).

Unlike traditional time-series forecasting applications that rely on richly sampled historical data with seasonal and cyclical variations, the input data in this case consisted mainly of annual demographic and socioeconomic estimates. These data generally exhibited smooth, monotonic increases or decreases over time rather than complex fluctuations. Consequently, Prophet was used primarily as a smoothing and extrapolation tool to generate plausible projections of key baseline variables at future target years (2030, 2040, 2050, 2060, 2070). This allowed the model to extend the demographic-driven growth trajectories into the future in a consistent and data-informed manner (Taylor & Letham, 2018).

These smoothed trend projections serve as the evolving baseline inputs within the unified demand model. Once established, elasticity-based calculations adjust these baselines to incorporate the effects of policy levers, external uncertainties, and shocks. For example, Prophet provides the macro-level baseline trip generation numbers for a given future year, and the elasticity framework then models how demand would respond to fare changes or other interventions relative to this baseline. This two-tiered approach (trend forecast + EMA Workbench) enhances the model's realism by embedding steady long-term demographic momentum while retaining sensitivity to immediate policy impacts.

3.3.5. Causal Loop Representation of the Model

To visualize the internal logic of the model, Figure 3.2 presents a causal loop diagram (CLD). This diagram maps the interactions between policy levers, uncertainties, intermediate variables, and system outcomes. It captures key feedback mechanisms and dependencies embedded in the simulation logic.

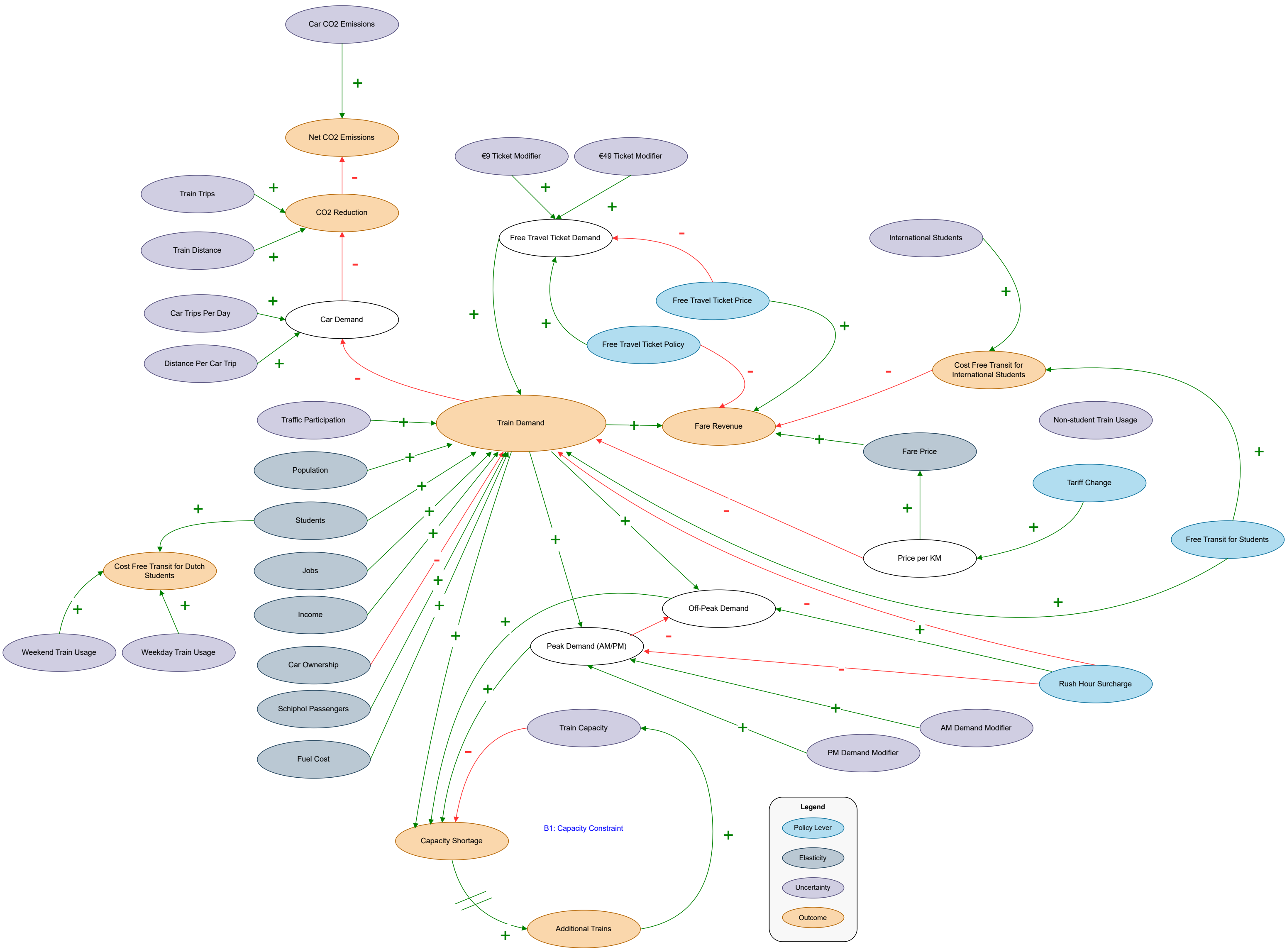


Figure 3.2: Adapted causal loop diagram of the model. This diagram shows the relations between the levers, uncertainties, elasticities, outcomes, and intermediary variables in the model.

3.3.6. Model Limitations

The model relies on several simplifying assumptions and contains notable limitations:

- **Capacity Constraints Not Dynamically Modeled:** In the "Balanced" scenario, capacity shortages are minimized, while in the "Unrestrained" scenario, they are ignored. However, dynamic congestion effects, like disuse due to overcrowding, are not modeled.

- **No Explicit Budget Constraint:** Policy combinations are not limited by a budget or subsidy ceiling. The fiscal feasibility of each scenario is assessed via outcome variables.
- **Simplified Modal Substitution:** The environmental impact logic assumes that between 10% and 50% of new train trips would've previously been private car trips (Litman, 2024). Other modes are excluded, potentially overestimating the net CO_2 impact.
- **No Behavioral Adaptation Over Time:** The elasticity values are static and do not reflect changing traveler preferences or habits across decades.

4
Experimental Setup

With the model structure defined and input data prepared, an experimental design was implemented to explore a wide variety of futures and evaluate passenger rail policy performance under deep uncertainty. The EMA Workbench was used to systematically vary uncertainties and policy levers, combining exploratory scenario analysis with multi-objective optimization. This chapter describes the experimental setup in detail, including the configuration of uncertainties, the multi-objective robust optimization (MORO) approach, the definition of problem formulations, and the post-processing and validation steps.

4.1. Experimental Design and Problem Formulations

For each prediction year (2024, 2030, 2040, 2050, 2060, 2070), the simulation model was initialized with year-specific baseline inputs. These were generated using Prophet time-series forecasting trained on Dutch historical data (1985–2021), providing projected baselines for variables such as population, income, fuel costs, and transport demand. Uncertainties were defined as ±5% ranges around these projections to capture plausible near-term variability. For the 9 and 49 ticket modifiers, ranges were set based on empirically observed demand effects, with the lower bound reflecting Germany-wide impacts and the upper bound reflecting North Rhine-Westphalia estimates, as explained in Section 3.3.3.

The experimental design included one optimization formulation and three filters, each defined by different policy priorities. These are summarized in Table 5.1, which shows which outcomes were set to maximize or minimize in each formulation. The "Balanced" formulation aimed to maximize demand, revenue, and CO_2 reduction while minimizing capacity shortages. The "Unrestrained Balanced" filter excluded capacity constraints from the Balanced Formulation, focusing purely on maximizing the three primary outcomes. The "Max Ridership" and "Max Profit" filters targeted only demand or revenue, respectively, to explore single-objective extremes. These setups allowed the analysis to examine both integrated policy trade-offs and objective-specific frontier cases.

Problem Formulation	Demand	Revenue	CO_2 Reduction	Capacity Shortage
Balanced	MAX	MAX	MAX	MIN
Unrestrained Balanced	MAX	MAX	MAX	-
Max Ridership	MAX	-	-	-
Max Profit	-	MAX	-	-

Table 4.1: Problem Formulation Setup

4.2. Multi-Objective Robust Optimization Setup

The core of the experimental setup is a Multi-Objective Robust Optimization (MORO) process, designed to search for policy lever combinations that achieve Pareto-optimal trade-offs among the chosen objectives while accounting for uncertainty. In MORO, each candidate policy is evaluated across a spread of future scenarios (sampling from the uncertainty ranges) to assess its robustness, and a multi-objective evolutionary algorithm (MOEA) is used to evolve a set of non-dominated (Pareto-efficient) solutions. This approach yields a robust Pareto front of policies: a frontier of options where improving any one objective would worsen at least one other, and all are vetted for performance under multiple scenarios rather than a single future. Decision-makers can use this Pareto front to understand trade-offs and identify policies that balance priorities while remaining resilient to uncertainty. Given the deeply uncertain context of long-term rail planning, MORO provides a systematic method to discover robust policy strategies not easily identifiable through manual scenario analysis.

The MORO search was implemented using the ε-NSGA-II algorithm available in the open-source EMA Workbench for Python. ε-NSGA-II, a variant of the well-known NSGA-II multi-objective evolutionary algorithm, incorporates ε-dominance archiving (i.e., maintaining an archive of non-dominated solutions with a minimum resolution ε for each objective to ensure diversity along the Pareto front).

Each optimization run corresponded to a single year and policy formulation configuration (e.g., a separate optimization for the year 2030 under the Balanced Formulation, another for 2030 under the Max Ridership Filter, and so on for each year from 2024–2070). In each run, the MOEA evolved a population of candidate policy solutions over many generations, with a budget of n_{fe} = 100,000 model evaluations per run. This budget allowed the algorithm to evaluate the objective performance of 100,000 candidate solutions (each representing a specific combination of policy lever settings) over the course of the evolutionary search.

4.2.1. Uncertainty Scenarios and Policy Evaluation

To assess policy robustness under deep uncertainty, each candidate policy was evaluated over a diverse ensemble of 217,464 scenarios, equal to the permutation of policy lever possibilities. Scenario sampling was conducted using Latin Hypercube Sampling to ensure stratified coverage across the uncertainty space.

To mitigate stochastic effects from initial population seeding and evolutionary dynamics, each run was independently repeated three times with distinct random seeds. The resulting Pareto-optimal archives were merged and deduplicated based on lever configurations to form a consolidated master archive for robustness scoring and post-processing.

4.2.2. Calibration of ε Values

During the search, the MOEA maintained an archive of non-dominated solutions under ε-dominance. The choice of $\boldsymbol{\varepsilon}$ values (one per objective) was critical, as these determined the resolution of the Pareto front approximation. Instead of static ε values, adaptive, outcome-specific values were used, tuned to each objective's scale and distribution. Prior to each optimization run, preliminary exploratory sampling was performed to calibrate ε settings. A broad ensemble of random simulations (~100 random policies evaluated under 100 random scenarios, yielding ~10,000 experiments) was used to estimate the outcome spread. The 1st and 99th percentile values for each objective were recorded, treating the 98% interval as the effective outcome range, excluding extreme outliers. Each ε was then set as a fraction of this range, ensuring approximately 100–200 potential ε-interval "steps" would span the interval. For example, if projected demand ranged from 50 to 150 billion passenger-km, an ε on the order of 1 billion passenger-km was applied. Logarithmic scaling was applied in cases of highly skewed distributions to avoid overly coarse or fine resolution across ranges.

4.2.3. Convergence Monitoring

The algorithm's progress was tracked using the $\boldsymbol{\varepsilon}$-progress metric, measuring improvements in the Pareto front over time in terms of ε resolution. At each generation, if no solution extended the Pareto front beyond the current archive by at least one ε on any objective, ε-progress was recorded as zero. As optimization proceeded, ε-progress typically declined; when it dropped below a small threshold over a sustained number of generations, the search was considered converged. A criterion was set such that if the Pareto front did not expand by more than ~1ε in any objective for 50 consecutive generations, convergence was assumed. In some cases of slow convergence, additional evaluations or follow-up runs with higher evaluation budgets were considered.

Full details on ε values and convergence diagnostics are provided in Appendix B, which includes tables listing the actual ε values used for each objective in each year's run, as well as plots of ε-progress and other relevant metrics.

4.2.4. Robustness Scoring Using Wald's Criterion

To interpret the robustness of each Pareto-optimal policy within the archive, Wald's maximin criterion was applied. In this context, robustness is defined as the ability of a policy to maintain acceptable performance across all objectives, even under the most adverse conditions. Rather than optimizing for the best-case or average performance, Wald's criterion focuses on minimizing vulnerability to poor outcomes.

Formally, for each policy in the Pareto archive, the outcomes across all objectives were normalized to the [0, 1] range using the minimum and maximum values observed in the archive for each objective. This normalization ensured comparability across objectives with different scales. The Wald score W_i for policy i was then calculated as:

$$W_i = \min_j \left(\frac{f_{ij} - f_j^{\min}}{f_j^{\max} - f_j^{\min}} \right) \tag{4.1}$$

where f_{ij} is the performance of policy i on objective j, and $f_j^{\min}$ and $f_j^{\max}$ are the minimum and maximum observed values for objective j across all policies in the archive. This score represents the policy's worst normalized performance across all objectives (Wald, 1950).

The rationale for using Wald's criterion is that it provides a conservative and risk-averse robustness metric, prioritizing solutions that avoid catastrophic underperformance in any objective. Policies with high Wald scores are those that perform consistently well across all criteria, making them attractive options in contexts of deep uncertainty where trade-offs are inevitable but failure in any one area is unacceptable.

This robustness metric was used to rank and interpret the Pareto-optimal solutions, providing decision-makers with a clear and intuitive indicator of worst-case resilience across objectives.

4.3. Pathways Calculation

To complement the year-specific robust optimization, a policy pathways analysis was conducted to explore how adaptive strategies could evolve over the full 2024–2070 horizon. The objective was to generate plausible, incrementally implementable sequences of policy decisions that perform well across multiple criteria.

4.3.1. Selecting Robust and Diverse Policies

The analysis began by identifying Pareto-optimal policy sets for each simulation year, based on key outcome metrics. To further narrow the set, Wald's maximin robustness criterion was applied.[1] The top 10% of policies per year were retained.

To ensure diversity among the retained policies, hypervolume contribution was calculated using a random sample of 30 policies per year. This metric quantifies how much each policy adds to the overall volume of objective space covered by the set. The 20 policies with the highest contributions were selected to form the nodes of the transition graph, representing the most diverse and robust trade-offs available.

4.3.2. Constructing Adaptive Pathways

The retained policy sets were linked across years using a directed graph, where nodes represent specific policies and edges represent transitions to future-year policies. Transition costs were calculated using a custom function that penalized large jumps in continuous levers (e.g., fare or surcharge levels) and reversals in categorical choices (e.g., withdrawing free student transit). This cost structure encoded feasibility constraints and discouraged unrealistic shifts in policy.

Using this graph, 100 adaptive policy pathways were generated via Monte Carlo sampling. Each pathway started from a 2024 policy and proceeded year by year by probabilistically selecting transitions with a preference for lower-cost edges. This approach captured the uncertainty and flexibility needed for long-term policy design, without assuming perfect foresight or fixed sequences.

4.3.3. Example Visualization and Interpretation

Figure 4.1 presents a stylized example of the transition graph and adaptive pathways. For visual clarity, this figure includes only the top 1.5% of policy sets and one Monte Carlo pathway per 2024 starting point. In contrast, the full analysis used the top 10% of policies and 100 pathways to assess robustness across the full horizon.

Notably, the number of policy sets in 2070 is smaller than in 2024. This is because fewer 2070 policies were retained in the top 1.5% due to lower Wald scores. This reflects an important dynamic: as uncertainty grows

[1] Wald's criterion evaluates each policy by its worst-case performance across normalized outcomes. The policy's robustness score is the best among these worst-case performances.

over time, fewer policies remain robust across all objectives, leading to a thinner Pareto front and reduced diversity. This temporal asymmetry is a natural consequence of deep uncertainty and is handled explicitly in the pathway analysis.

Edges in the figure reflect feasible transitions between years, colored lines show sampled pathways, and node positions are determined sequentially. This visual summary highlights the branching nature of robust long-term strategies under uncertainty.

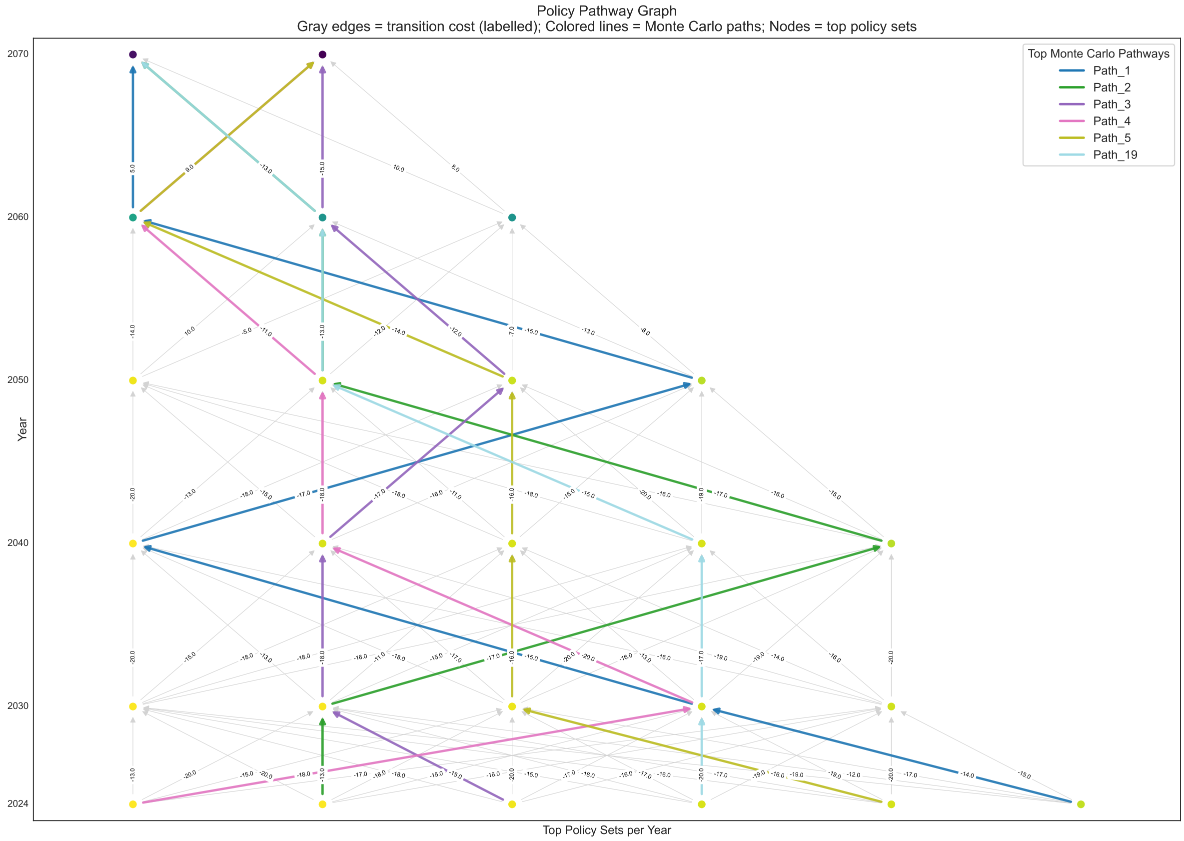


Figure 4.1: An illustrative transition graph showing policy trajectories over time. Nodes represent selected policy sets; gray edges indicate feasible transitions (weighted by transition cost), and colored lines indicate sampled Monte Carlo pathways. For clarity, only the top 1.5% of policy sets and one path per 2024 policy are shown.

5
MORO Results (2030)

Using the unified model, a large ensemble of simulations was run for 2024, 2030, 2040, 2050, 2060, and 2070, combining diverse uncertainty realizations with a wide range of policy lever settings. Using EMA Workbench's optimization functionality, the problem was treated as a multi-objective robust optimization (MORO) for a given year. The policy results are clustered to highlight distinct strategies and to note the top-performing policies. The results for 2030 are discussed in this chapter, while the results for other years can be found in Appendix F.

To guide the analysis, a set of representative problem formulations was defined. Each formulation prioritizes different policy objectives, such as maximizing demand, revenue, or emissions reductions, and serves as a benchmark for evaluating trade-offs. Table 5.1 summarizes the design of these formulations and filters based on their optimization targets.

Problem Formulation	Demand	Revenue	CO_2 Reduction	Capacity Shortage
Balanced	MAX	MAX	MAX	MIN
Unrestrained Balanced	MAX	MAX	MAX	-
Max Ridership	MAX	-	-	-
Max Profit	-	MAX	-	-

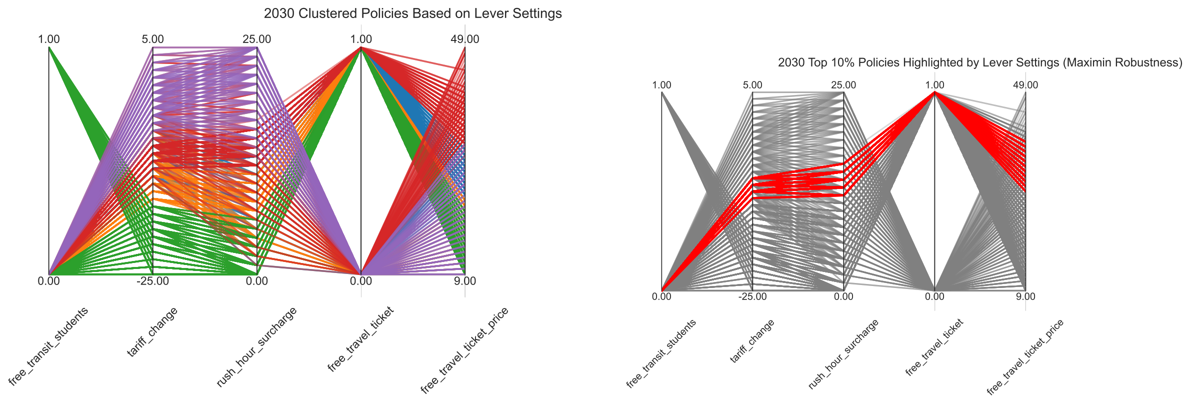
Table 5.1: Problem Formulation Setup

For each of the problem formulations for each year, a set of Pareto-optimal policy configurations was found. In essence, this search attempts to find policies that are non-dominated – meaning no other policy is strictly better in all objectives. The result is an approximation of the Pareto front of trade-offs, which is useful for understanding the extremes and compromises. For example, one extreme solution on the Pareto front might be the "maximize ridership at all costs" policy (very high demand, low revenue), while another is the "maximize revenue" policy (high revenue, low demand), and points in between represent different balances. The algorithm was run with a high number of iterations (tens of thousands of model evaluations) and converged when improvements became marginal. Appendix B provides convergence specifics.

The results for 2030 are discussed below. Results for other years can be found in Appendix F.

5.1. Balanced Formulation 2030

Figure 5.1 presents two views of the 2030 Balanced Formulation, in which policies were designed to optimize ridership, revenue, and emissions outcomes while minimizing capacity shortages. Rather than examining outcomes directly, these visualizations highlight how different policies are configured in terms of their underlying lever settings—shedding light on what types of interventions tend to dominate among high-performing strategies.



(a) Clustered policies based on lever settings for the 2030 Balanced Formulation.

(b) Top 10% performing policies based on lever settings in 2030 for the Balanced Formulation.

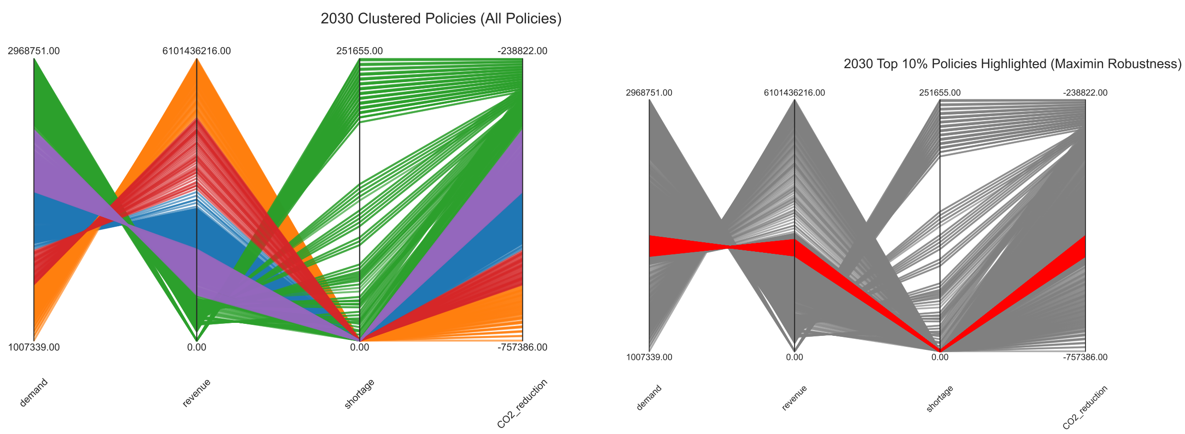
Figure 5.1: The 2030 results for the Balanced Formulation based on lever settings.

The left panel (Figure 5.1a) shows a clustering of all simulated policies based on their lever configurations. Each line represents a unique policy, and color denotes cluster membership. From this, several distinct policy archetypes emerge. For instance, one cluster is characterized by high levels of fare subsidy (e.g., free student transit or free travel tickets), while others emphasize pricing levers such as tariff increases or rush-hour surcharges. These groupings reveal that policies naturally fall into a limited number of strategic categories, each employing different combinations of interventions to address the shared objectives.

The right panel (Figure 5.1b) displays the top 10% of 2030 policy sets by Wald robustness score (highlighted in red). These high-performing policies exhibit consistent lever-setting patterns. None of the top policies offer free transit for students, and all apply a moderate base fare reduction of approximately €0.10 per travel unit. A rush-hour surcharge is applied in every case, typically set around €0.15 per travel unit, indicating a widespread use of temporal price differentiation to manage peak demand.

In addition, all of the top-performing policies activate the free travel ticket lever, offering a flat-rate monthly ticket. The price of this ticket consistently clusters around €30, suggesting that robust policies tend to make multi-ride or subscription options available but still require partial cost recovery.

These lever-setting patterns indicate a strategic blend of moderate fare incentives and targeted pricing mechanisms. Rather than adopting extreme or populist options—like entirely free public transit—robust strategies favor subtle reductions in marginal trip costs, supplemented by optional flat-rate products and congestion pricing. This balanced approach supports ridership growth while maintaining financial and operational viability under capacity constraints and long-term uncertainty.



(a) Clustered outcomes for the 2030 Balanced Formulation.

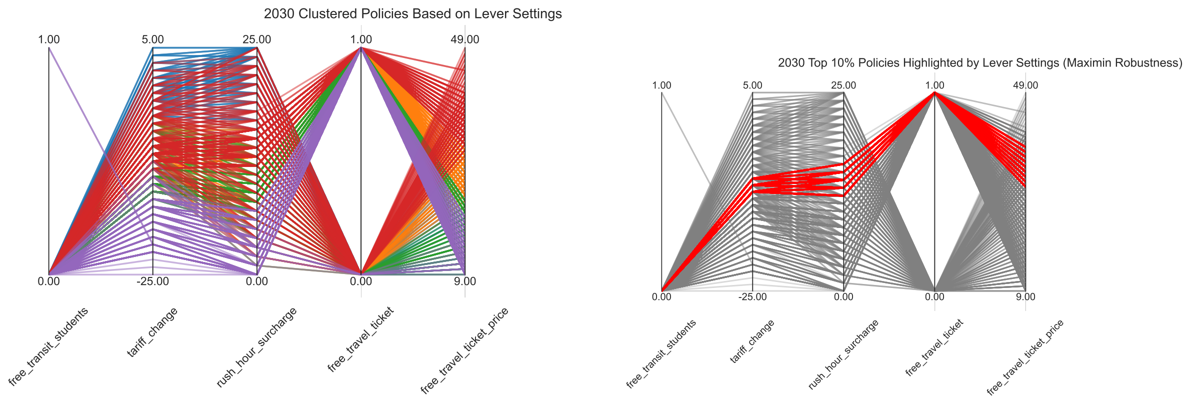
(b) Outcomes associated with the top 10% performing policies in 2030 for the Balanced Formulation.

Figure 5.2: The 2030 results for the Balanced Formulation based on outcomes.

Figure 5.2 shows the outcomes associated with the levers. The right panel isolates the top 10% of policies based on their Wald's maximin criterion. These robust policies demonstrate markedly consistent outcomes: they cluster tightly in the mid-to-high range of demand, revenue, and CO_2 reduction while minimizing shortage. These results show a balancing act between fiscal sustainability and transit accessibility. Notably, none of these top-performing policies accept severe trade-offs on any single dimension, which highlights the conservative nature of the robustness metric.

5.2. Unrestrained Balanced Filter 2030

Figure 5.3 presents two visualizations of policy lever settings for the Unrestrained Balanced Filter in 2030. Unlike the previous "Balanced" case, this filter removes capacity constraints, allowing demand to grow without triggering seat shortages. Figure 5.3 does not show model outcomes directly, but instead focuses on the underlying lever configurations to reveal which emerged as most effective.



(a) Clustered policies for the 2030 Unrestrained Balanced Filter.

(b) Top 10% performing policies based on lever settings in 2030 for the Unrestrained Balanced Filter.

Figure 5.3: The 2030 results for the Unrestrained Balanced Filter.

In Figure 5.3a, the full set of simulated policies under the Unrestrained Balanced Filter is clustered by lever similarity. Surprisingly, the resulting clusters are nearly identical in structure to those of the capacity-constrained (balanced) formulation. The same basic lever-setting archetypes reappear, including policies with modest fare changes, consistent activation of the monthly free travel ticket, and moderate use of peak-period surcharges.

Figure 5.3b highlights the top 10% of policies based on their combined ridership and revenue scores, again using Wald's maximin robustness criterion. Their lever settings closely mirror those seen in the Balanced Formulation: free transit for students is avoided, base fares are reduced slightly, rush-hour surcharges are applied consistently, and monthly free travel tickets are priced around €30. These patterns underscore a key finding: relaxing the capacity constraint by removing the shortage penalty did not significantly change which policies were most robust in this model.

Together, these results suggest that the model's sensitivity to capacity constraints was relatively limited in this experiment. While one might expect the absence of capacity penalties to encourage more aggressive demand stimulation, the most robust policies remained cautious and balanced. This implies that, at least in the 2030 horizon explored here, infrastructure expansion alone may not dramatically alter the structure of optimal transport policies. Instead, targeted, hybrid strategies continue to perform best, even when physical limits are relaxed.

5.3. Max Revenue Filter 2030

Figure 5.4 presents the policy lever configurations for the Max Revenue Filter in 2030. Unlike previous problem formulations that balanced multiple objectives, this case is focused solely on maximizing fare revenue.

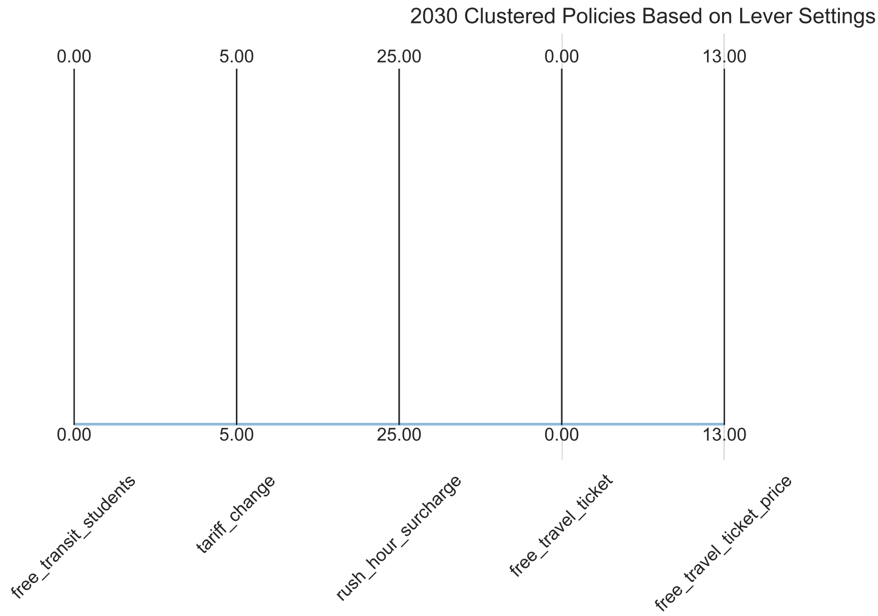


Figure 5.4: Outcome for the 2030 Max Revenue Filter. This figure shows that the Max Revenue Filter has one optimal solution, which is to slightly increase ticket prices by 0.05 EUR per travel unit and implement an aggressive rush hour surcharge of 0.25 EUR per travel unit. Since the Max Revenue Filter has only one optimal solution, the range of optimal outcomes, as indicated by the numbers at the top and bottom of the y-axes, is the same.

Figure 5.4 shows the result of solely maximizing fare revenue. Unlike previous problem formulations that yielded diverse policy clusters, here all simulations converge on the same lever configuration where ticket prices are slightly increased and an aggressive rush hour surcharge is implemented. This means the Max Revenue Filter suggests:

1. Not offering free travel for all (non-Dutch) students.
2. Increasing ticket cost by 5 cents per travel unit, which is approximately a 20% increase in ticket prices for the average distance travelled.
3. Implementing a steep rush hour surcharge of 25 cents per travel unit. This is effectively a 100% increase in ticket price during the rush hour.
4. Not offering an unlimited travel ticket. Since the travel ticket is not offered, the price of the travel ticket on the far right axis is irrelevant.

5.4. Max Demand Filter 2030

The Max Demand Filter focuses exclusively on maximizing passenger volume, without consideration for fare revenue. In practice, the model identifies a single optimal strategy: the complete elimination of fares across all user groups. By removing all price barriers, the model achieves the highest possible level of ridership within its defined constraints.

Figure 5.5 shows the result of this policy experiment. Unlike the Balanced Formulations that yielded diverse policy clusters, here all simulations converge on the same lever configuration. Every top-performing policy sets fares to zero (or the lowest allowed values), offers full travel ticket subsidies, and eliminates rush-hour surcharges. This reflects the logical outcome of a ridership-maximization objective: when revenue is not a constraint, the most effective way to boost ridership is to make travel free for everyone.

All top policies share the same settings, confirming that under this objective, there is little room for variation: any reintroduction of fares would reduce ridership and thus be suboptimal.

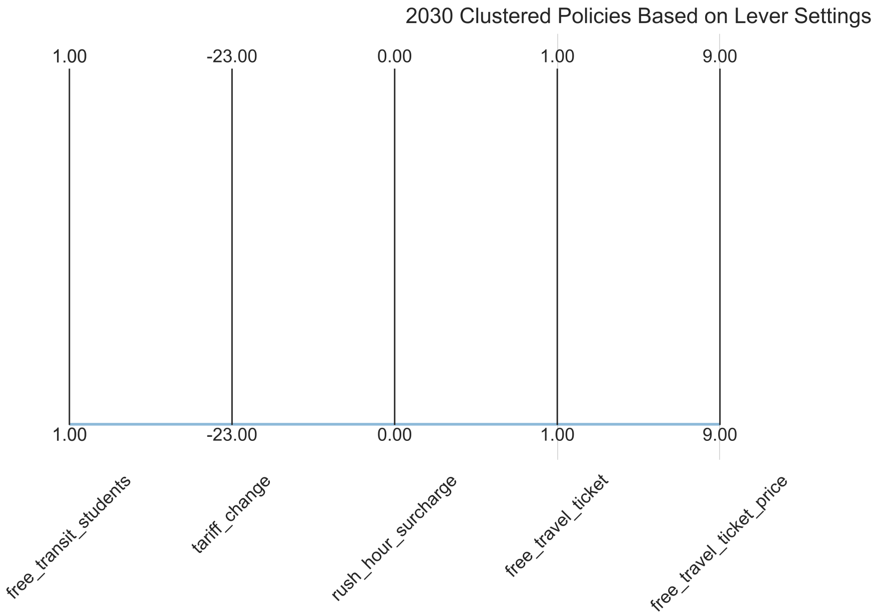


Figure 5.5: Clustered policies for the 2030 Max Demand Filter. This figure shows that the Max Demand Filter has one optimal solution, which is to make all public transit free for everyone. Since the Max Demand Filter has only one optimal solution, the range of optimal outcomes, as indicated by the numbers at the top and bottom of the y-axes, is the same.

This filter highlights an important trade-off. While extremely high ridership can be achieved through fare elimination, this strategy generates no fare revenue and would require significant external subsidy to be financially viable. The Max Demand Filter therefore illustrates the upper bound of what is possible in terms of mode shift, but also underscores the fiscal limitations of such an approach in the absence of alternative funding streams.

Additionally, this scenario would almost certainly result in severe overcrowding on existing infrastructure, particularly during peak hours. In the real world, such crowding would likely reduce demand due to discomfort, delays, or unmet service expectations. However, a limitation of the current model is that it does not capture this type of feedback: demand remains unaffected by seat shortages or congestion. As such, the demand estimates presented here should be interpreted as an idealized upper bound, rather than a fully realistic forecast under capacity-constrained conditions.

6 Balanced Policy Pathways (2024–2070)

Thus far, the analysis has treated the year 2030 as a static end-point for evaluating policy impacts. However, mobility policies have consequences that unfold over decades, and the uncertainties themselves evolve over time. This section extends the exploration to the 2024–2070 period to examine how robust policy strategies can be designed as dynamic pathways rather than one-off decisions. Instead of implementing a fixed policy in 2030 and holding it constant, consideration is given to how policies might adapt or shift over time in response to changing conditions, and what implications this has for long-term performance.

The investigation begins with how an optimal or balanced policy mix might shift as the timeline progresses. Using multi-objective analyses at future time slices, it is found that while the general shape of the ridership-revenue trade-off persists in each period, the composition of Pareto-efficient policies can change over time. In the near term (around 2030), policies that aggressively boost ridership stand out as Pareto-efficient because they capitalize on latent demand early. Over the longer term, however, if such policies are maintained indefinitely, they will likely be unsustainable without adequate infrastructural investment to match the growing population.

These shifts do not suggest that every strategy should follow the same path. Instead, they highlight the value of staying flexible and adjusting fare policy as conditions change. The idea aligns with Dynamic Adaptive Policy Pathways, which help planners prepare for different possible futures by identifying signs that a policy may need to change.

This chapter examines the evolution of balanced policy strategies over the long term (2024–2070), under capacity-constrained conditions (the “With Shortage” case). The goal is to understand how successful policies adapt over time to maintain a viable balance between ridership and revenue in response to shifting external conditions—such as demographic growth, fiscal pressures, and evolving user behavior. Since the results of the Unrestrained Balanced Filter were so similar to the original problem formulation, pathways are only calculated for the Balanced Formulation.

6.1. Ticket Price Adjustment (2024-2070)

To visualize these dynamics, Figure 6.1 shows the evolution of ticket price adjustments (tariff change) over time for the 100 sampled policy pathways in the Balanced Formulation. Each line represents one Monte Carlo-generated trajectory, showing how fare levels are adapted across decades under a different sequence of lever changes.

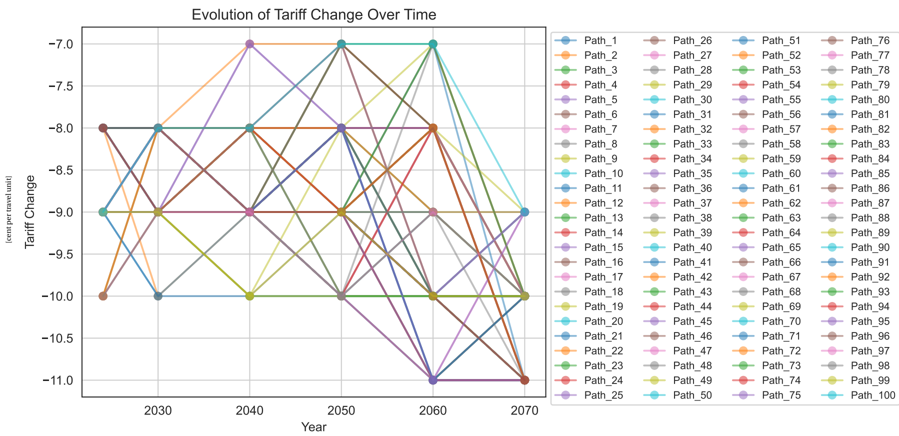


Figure 6.1: Policy pathways for ticket price change in the Balanced Formulation. This figure illustrates how much ticket prices are adjusted per distance travelled over the years.

As seen in Figure 6.1, all 100 policy pathways begin with significant fare reductions, with most simulations implementing a drop of between 8 and 10 cents per travel unit by 2030. These reductions remain largely consistent across the following decades. While some fluctuations occur, especially between 2050 and 2070, the majority of strategies hover in a relatively narrow band, typically between −8 and −10 cents, indicating long-term fare reductions are a stable and recurring feature of robust policies.

The lack of strong upward trends suggests that increasing base fares is rarely chosen, even as demographic or fiscal conditions change. Notably, no pathway returns to neutral or positive fare levels by 2070, reinforcing the interpretation that maintaining affordability is central to long-term success under capacity constraints.

Nevertheless, while base fares remain low, this does not mean pricing is static. As explored in the next section, many strategies introduce peak pricing through rush-hour surcharges as a complementary measure. This allows for differentiated pricing without reversing the broader commitment to affordable baseline travel.

6.2. Rush-Hour Surcharge (2024–2070)

Figure 6.2 illustrates the evolution of rush-hour surcharge policies across balanced pathways from 2024 to 2070. Each line represents a distinct policy trajectory, showing how surcharges during peak periods are introduced, adjusted, or sustained over time.

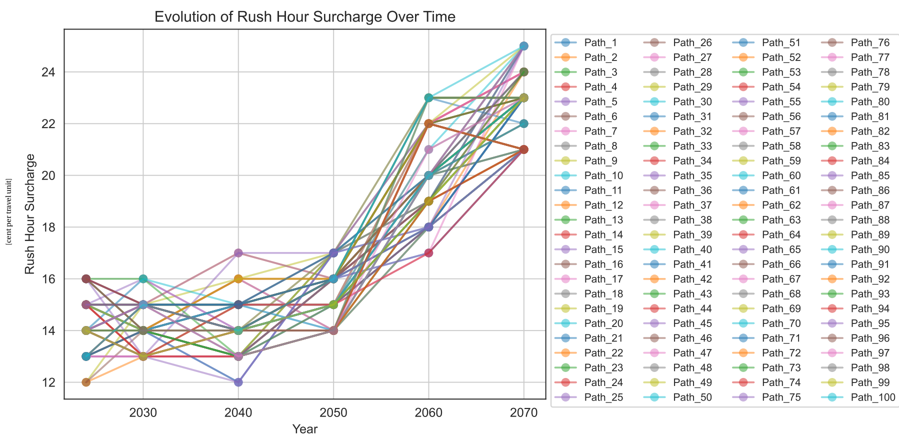


Figure 6.2: Policy pathways for rush hour surcharge in the Balanced Formulation. This figure illustrates how much of a surcharge is imposed per distance travelled during peak hours.

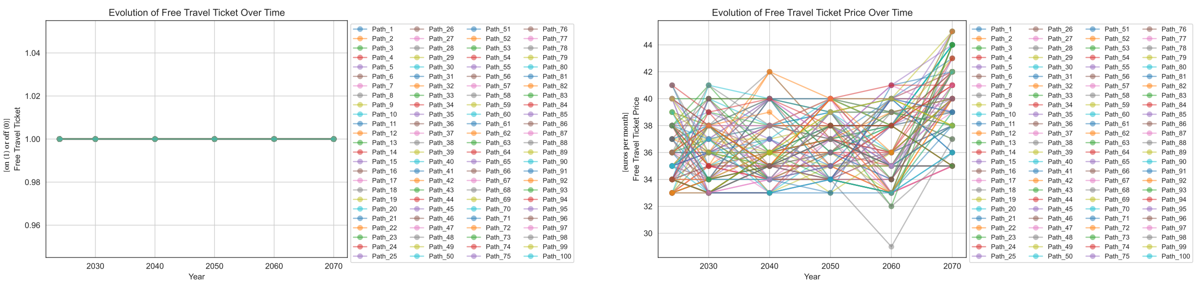
As shown in Figure 6.2, all 100 balanced policy pathways implement a rush-hour surcharge by 2024. The initial values cluster between 12 and 16 cents per travel unit, indicating a general consensus around modest peak-period pricing from the outset. This early adoption may reflect a shared recognition of the potential to manage congestion and raise revenue without politically sensitive increases to base fares.

From 2040 onward, a consistent upward trend emerges across most pathways. By 2060, nearly all strategies impose surcharges above 18 cents, with several exceeding 22 cents. This suggests a gradual but persistent escalation in peak pricing, likely driven by growing demand pressures and fiscal needs.

The uniform direction of surcharge adjustment implies that, in contrast to more volatile or reversible levers, rush-hour surcharges function as a ratcheting policy mechanism. Once introduced, they tend to be intensified rather than reversed. This result highlights rush-hour pricing as a central, adaptable component of robust fare design. It complements stable base fares by targeting periods of peak demand, providing a mechanism to balance affordability, revenue generation, and capacity management over time.

6.3. Free Transit Incentives (2024–2070)

Figure 6.3 depicts how free travel ticket policies evolve over time within the balanced strategy set. These tickets typically represent incentives aimed at boosting ridership through the provision of unlimited monthly travel at a fixed price.



(a) Policy pathways for free transit tickets in the Balanced Formulation.

(b) Policy pathways for free transit ticket price in the Balanced Formulation.

Figure 6.3: The Unlimited Transit Ticket policy lever vs price in the Balanced Formulation.

In Figure 6.3a, the graph remains at 1.00 across the policy horizon. This means that the unlimited transit ticket is activated in all 100 policy pathways by 2024 and remains consistently enabled through 2070. This unbroken activation suggests a strong consensus across balanced strategies regarding the long-term value of offering an unlimited-use monthly travel pass. Unlike more reactive levers that are toggled in response to external conditions, this incentive appears to be treated as a foundational component of fare policy design.

However, Figure 6.3b reveals that while the policy is universally active, the monthly price charged for the ticket varies substantially across pathways. Initial prices in 2024 cluster around €32–€42, but diverge over time. Some strategies gradually raise the price by 2070, but the range of prices remains relatively consistent until 2070, which would keep the incentive affordable and attractive for frequent travelers.

The stability in policy activation, combined with flexibility in pricing, points to a deliberate strategy: rather than removing or suspending the policy in response to changing conditions, planners can instead fine-tune its generosity by adjusting its cost. This approach allows the unlimited ticket to serve as a persistent and adaptable ridership tool to balance accessibility and revenue sustainability without undermining the predictability of the fare structure.

Figure 6.4 shows how policies granting free public transit to students evolve over time in the Balanced Formulation. Unlike Dutch nationals, who already receive full travel subsidies through the national student travel scheme, this policy lever likely reflects the extension of similar benefits to EU and international students, who are currently excluded from the existing arrangement.

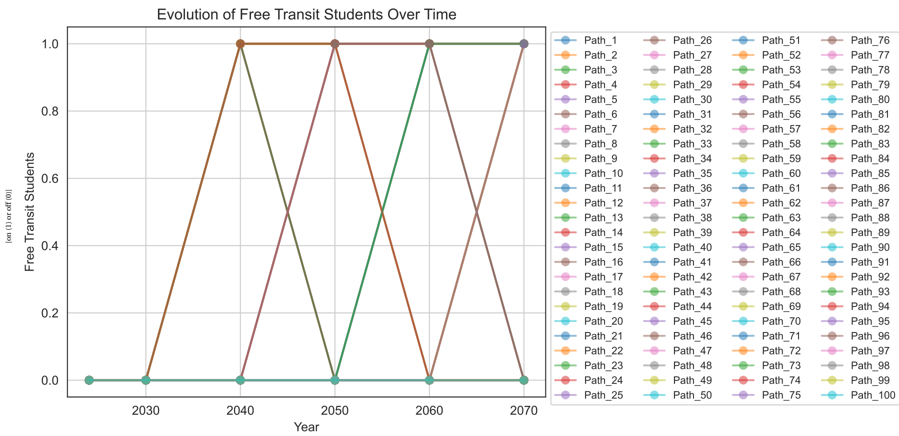


Figure 6.4: Policy pathways for providing free transit to students in the Balanced Formulation.

As Figure 6.4 illustrates, free transit for students is implemented in a minority of balanced policy pathways. While most strategies refrain from activating this lever altogether, a small subset introduces the subsidy intermittently, typically for one or two decades at most, before discontinuing it. Only a handful of trajectories sustain the policy for the full simulation period from 2030 onward.

This sparse and temporary activation pattern contrasts sharply with the consistent adoption seen in policies such as the unlimited transit ticket. It suggests that student fare exemptions are not regarded as a core component of long-term fare design under capacity-constrained conditions. The episodic nature of the student subsidy may reflect tensions between equity objectives and cost-effectiveness. While the policy aligns with goals of inclusion and long-term ridership development, the budgetary implications of expanding subsidization from Dutch students to all students may be deemed less justifiable when alternative, revenue-generating strategies are available.

In short, the student transit policy is not central to the majority of balanced strategies. When used, it serves as a temporary measure rather than a permanent fixture, highlighting its secondary role in the broader fare policy mix.

7 Discussion

This thesis applied a Multi-Objective Robust Optimization (MORO) framework to the problem of long-term passenger rail forecasting under deep uncertainty. The approach was implemented using a simplified elasticity-based model of Dutch passenger rail demand, calibrated to current conditions and historical trends.

7.1. Model Evaluation

The structural simplicity of the model was a deliberate design choice, made to enable rapid evaluation of thousands of scenarios, which may be infeasible with a more complex model like the full-scale Landelijk Model Systeem (LMS). This simplification sacrifices granular realism in exchange for feasibility within an exploratory modelling context. However, this approach had limitations on the outcomes as described in Section 7.5.

MORO was used to explore and optimize policy levers within this model. A multi-objective evolutionary algorithm (via the EMA Workbench) searched the policy space. Each candidate policy was evaluated across an ensemble of future scenarios in each generation. Instead of optimizing for a single forecast, policies were assessed on their performance over a broad range of plausible futures simultaneously. Over successive iterations, the evolutionary search identified a set of non-dominated solutions, yielding an approximate robust Pareto front of policy options. The output of the MORO analysis thus consists of fare policy strategies where no single strategy is strictly superior on all objectives, highlighting the inherent trade-offs.

This outcome provides a basis for evaluations with a menu of robust policies balancing objectives differently. This enables decision-makers to apply preferences or risk tolerance when selecting from the Pareto-optimal set. Critically, the use of MORO allows robustness to be integrated directly into the forecasting and policy design process. Traditional forecasting modeling alone often calibrate to a single best-estimate scenario or a small set of what-if cases. In contrast, this model's evaluation spans thousands of futures, helping to avoid the pitfall of designing policies that perform optimally in one scenario but poorly in others.

From a model evaluation perspective, this methodology is appropriate for the thesis objectives. The MORO framework is well-suited to exploratory policy problems requiring balance across multiple performance criteria under uncertainty. It enabled a proof-of-concept demonstration that even a simplified model, when applied in an exploratory fashion, can reveal insights that a traditional single-scenario forecast might miss. The model's structure, based on elasticities and scenario inputs, captured first-order effects of policy levers without the overhead of a full demand model. While this meant some nuances were omitted, calibration and validation against historical data provided confidence that the model's responses remained within a reasonable range.

7.2. Simulation Outcomes over 2024–2070

Using the MORO from the EMA Workbench, passenger rail outcomes were simulated under thousands of scenarios from 2024 to 2070, optimizing fare policy levers for robustness. The key patterns emerging from these simulations highlight both the potential and the challenges of long-term rail policy under deep uncertainty. One key insight is that no single static policy dominates across the entire simulation horizon.

Instead, effective strategies adapt to evolving conditions, balancing multiple objectives such as ridership, revenue, and emissions.

The simulations consistently revealed a core trade-off between maximizing ridership and preserving revenue. This tension was particularly visible in the extreme filters. For instance, in the 2030 Max Demand filter, policies that maximized ridership typically involved aggressive fare reductions or free unlimited travel passes. These approaches drove sharp increases in passenger volumes and led to considerable reductions in projected CO_2 emissions by facilitating mode shift from car travel—assuming rail's lower emissions per passenger-kilometre. However, these same strategies produced steep declines in fare revenue, occasionally approaching zero under full-subsidy conditions. At the other end of the Pareto front, revenue-maximizing strategies introduced higher base fares and peak-period surcharges. In 2030, for example, the Max Revenue filter recommended a 20% increase in base fares and a peak surcharge of approximately 100%. While these strategies improved financial returns, they tended to suppress demand and eroded associated environmental benefits.

Neither extreme strategy appeared desirable on its own. This reinforces the analytical value of the Balanced Formulation, which explicitly targeted high ridership, high revenue, and low emissions while also avoiding capacity shortages. Within this formulation, the most robust policies repeatedly combined moderate fare reductions with selective incentives. A recurring feature was the use of unlimited travel tickets priced around €32–€42 per month, which is likely high enough to retain meaningful revenue, yet low enough to encourage uptake and stimulate ridership. These were often coupled with modest reductions in base fares and the addition of peak-hour surcharges to smooth demand. Rather than relying on a single lever, the most effective strategies consistently employed a hybrid configuration of incentives and controls.

The presence of moderate peak surcharges in robust solutions suggests the importance of managing peak demand. Without such measures, extremely cheap fares led to capacity shortages during peak periods, with demand exceeding available seats in many futures. Introducing even a small additional fee for peak-hour travel tempered excessive rush-hour demand, reducing overcrowding, while generating extra revenue for reinvestment.

Policy robustness was not limited to the Balanced Formulation. A key finding is that similar combinations of levers appeared among the top solutions in both the Balanced and Unrestrained formulations. This suggests that hybrid strategies are not simply artifacts of capacity constraints, but reflect generally high-performing fare designs under uncertainty. Notably, policies built around full fare elimination were not robust, even when infrastructure limitations were removed. This outcome underscores the limitations of blunt instruments and points to the broader advantages of mixed, flexible fare structures.

Simulation outcomes also indicated how optimal policies evolved over time in response to growing demand. In the near term (2020s–2030s), most robust strategies emphasized ridership growth through fare reductions and travel passes, taking advantage of initial spare capacity. However, over longer timelines, cumulative high ridership began to strain the system in many scenarios. By the 2040s and 2050s, if demand growth continued, previously slack capacity became fully utilized. This is likely due to the fact that capacity was constant in the model. As discussed in Section 7.5, this meant that the increased population in future years struggled when using 2019 baseline capacity numbers. To address rising pressure, many robust policies gradually increased the rush-hour surcharge—holding steady through 2040, then rising to €0.20–€0.25 per travel unit by 2070 in most pathways (Figure 6.2).

7.3. Policy Implications for Long-Term Fare Strategies

The results of this MORO-based analysis carry several important implications for long-term transportation policy, particularly regarding fare instruments (such as low-cost travel passes) and the management of peak demand. Firstly, the analysis provides evidence that fare policy can be a powerful tool to influence ridership and environmental outcomes. Large-scale fare reductions or subsidies—such as hypothetical €9 or €49 monthly unlimited travel tickets—have the potential to substantially increase rail ridership and contribute to climate goals by shifting travelers from cars to trains. Policymakers aiming to reduce transport sector CO_2 emissions or boost public transit use can interpret these findings, reinforced by real-world examples like Germany's €9 ticket trial, as proof-of-concept that pricing interventions can induce major behavioral change.

One clear insight is that fare reductions can be used to increase ridership and reduce emissions, particularly in the near term. Policies involving monthly unlimited travel passes priced between €32 and €42 emerged repeatedly in the top-performing policies for the Balanced Formulation in 2030. These passes appeared to enable significant ridership gains while avoiding the extreme revenue losses associated with completely free travel. The results suggest that it is possible to increase demand substantially without fully eliminating fares, thereby maintaining a stable revenue base.

However, such interventions are not silver bullets; they come with trade-offs and temporal considerations. Over the long term, sustaining extreme discounts could strain public budgets or rail operator finances unless accompanied by economic growth or cost reductions elsewhere. Additionally, system capacity would need to keep pace with increased demand to fully realize environmental benefits. Otherwise, overcrowding could erode service quality and deter the very ridership that such policies aim to encourage.

One concrete implication is the value of targeted fare policies rather than blunt, across-the-board measures. For Dutch rail planners, this implies that future fare strategies might involve a menu of products: a moderately priced "Deutschlandticket"-style pass valid on off-peak services, combined with normal fares (or a rush hour surcharge) during peak times, for example, could incentivize travel when and where capacity exists and disincentivize it when the system is strained.

The prominence of the rush-hour surcharge lever in the analysis carries its own policy message: managing peak demand through pricing should be seriously considered as part of long-term strategy. The findings support this, as the rush hour surcharge was shown to be effective at mitigating capacity strain during peak hours, as some travelers shift their trips or forgo marginal peak journeys. Nevertheless, these findings must be interpreted in light of real-world implementation constraints. The model does not represent differentiated user groups or institutional arrangements such as employer-funded travel cards. As noted in Section 7.5, Dutch business commuters with NS Business Cards may be less sensitive to peak pricing, which could weaken the effectiveness of the rush hour surcharge. There are also distributional concerns. If not accompanied by compensatory measures, peak surcharges may place disproportionate burdens on low-income travelers who lack flexibility in travel times. To address these challenges, policymakers may need to design exemptions, to earmark revenue for reinvestment, or to frame fare changes as part of broader service improvements.

7.4. Reflections on Problem Formulation and Pathway Construction

Although MORO was rerun for each of the four problem formulations, the process effectively boiled down to a single underlying optimization: the Balanced Formulation. The results for the other formulations could have been obtained by applying post hoc filters to the Balanced Pareto set, such as selecting solutions that maximized ridership, revenue, or assumed unrestrained capacity. While rerunning MORO under different objective combinations added formal structure, from a methodological standpoint, these alternate formulations functioned as filtered views of the same core results, and filtering the Balanced Pareto set would've yielded the same result with much less computational time.

The construction of adaptive policy pathways remains a more fundamental methodological challenge. In this study, policy pathways were built heuristically: after selecting the top-performing policies for each year based on a set of robustness metrics, a penalty-based transition graph was constructed to capture the difficulty of moving between policy settings over time. Monte Carlo sampling was then used to generate plausible sequences of policies by traversing this graph with probabilistic transitions that favored smoother changes. While this approach reflects current practice in adaptive pathway literature, it remains an ad hoc process that lacks a formal optimization of pathway-level robustness. That is, although individual policies may be Pareto-efficient in isolation, the resulting sequences are not guaranteed to be globally optimal or robust across the full time horizon.

This reflects a broader gap in the literature: the identification of robust, adaptive policy pathways over time is still an open research problem. There is no consensus on how to define or operationalize pathway-level optimality when multiple objectives, deep uncertainty, and policy inertia must all be taken into account. Many studies, including this one, rely on rule-based or stochastic sampling approaches to approximate plausible adaptation sequences, but these methods do not optimize transitions jointly with policy outcomes.

7.5. Analysis Limitations

While the findings offer valuable insights, several limitations must be acknowledged, stemming from both model assumptions and the scope of the study. Firstly, the model structure is a simplification of reality. Demand responses to fare changes were modeled using constant elasticities and aggregate relationships. In practice, traveler behavior is more complex, with different market segments (commuters, occasional travelers, tourists) exhibiting varying sensitivities, and extreme fare changes potentially inducing qualitatively different behaviors. The assumption of static elasticity across the exploration range may over- or under-estimate responses to large policy shifts. For example, offering a €9 monthly ticket might generate effects that an elasticity-based model cannot capture.

A second limitation lies in the treatment of modal competition and emissions. The model assumes that increased rail ridership results in a proportional reduction in car travel, thereby decreasing CO_2 emissions. This substitution effect is governed by the car substitution rate uncertainty, which varies between 0.1 and 0.5 based on estimates from the Victoria Transport Policy Institute (Litman, 2024). While this provides a flexible parameter to capture potential mode shift, it remains a stylized simplification. In practice, mode choice depends on complex behavioral factors such as trip purpose, convenience, travel time, and access to alternative modes. Moreover, the model assumes fixed emissions factors for avoided car trips, ignoring possible changes in vehicle technology or energy systems, such as increased adoption of electric vehicles, which could alter the climate impact of mode shift in later decades. Consequently, the CO_2 outcomes in the model should be interpreted as indicative rather than precise.

Limitations also apply to the policy levers modeled. The focus was on fare price instruments (monthly flat fares and peak/off-peak price differences), holding other system attributes constant. In reality, service frequency, network expansion, capacity improvements, and operational changes co-evolve with fare policy. While a scenario variant with unrestrained capacity was examined, the model did not determine capacity expansions as an internal outcome of the system. Therefore, capacity was either fixed to 2019 values or assumed infinite. This means that in later time horizons, especially in the Balanced Formulation, the optimization effectively attempts to minimize shortage using outdated capacity assumptions, artificially constraining the system. In reality, sustained demand growth would likely trigger infrastructure investment, operational adjustments, or behavioral responses, creating an endogenous feedback loop between demand and capacity. The model's inability to simulate this feedback loop limits the realism of long-term results and forces reliance on the Unrestrained Balanced Filter variant, which artificially removes capacity constraints to explore potential outcomes without shortage penalties. Due to the absence of a dynamic feedback loop between capacity and demand, the "maximum demand" filter yields only one unrealistic endpoint: offering 100% free travel. In practice, demand growth would likely lead to congestion effects and declining service quality which would have a negative feedback on demand. Additionally, the model's treatment of the rush-hour surcharge relies on simplified elasticities that do not account for institutional and behavioral realities. A substantial portion of Dutch rush-hour travelers are business commuters whose tickets are covered by employers via NS Business Cards, limiting their price sensitivity. Consequently, the model likely overestimates the ability of peak pricing alone to shift demand.

Equity considerations were also not explicitly modeled. While targeted policies were discussed qualitatively, the model lacked differentiated passenger classes to assess distributional impacts (e.g., effects on low-income versus high-income travelers). This omission is noteworthy, as peak surcharges could negatively affect commuters with no schedule flexibility, while ultra-low fares might disproportionately benefit frequent travelers. A more comprehensive analysis would include equity as an explicit objective or at least disaggregate outcomes by group.

In summary, the results should be viewed as insight-generating rather than decision-finalizing. While this thesis demonstrates the promise of MORO for informing robust rail policies under uncertainty, it also highlights the need for further modeling and research to address aspects beyond its current scope.

8 Conclusions

8.1. Research Questions and Key Findings

At the outset of this research, the following research questions were posed to guide the inquiry into improving passenger rail forecasting under deep uncertainty using the MORO framework:

1. How can Multi-Objective Robust Optimization be applied to enhance long-term passenger rail demand forecasting under deep uncertainty, particularly in evaluating fare policy levers?

2. What are the potential impacts of implementing extreme fare interventions on rail ridership, revenue, and CO_2 emissions across a wide range of uncertain future scenarios?

3. How can fare policies be structured or adapted over the 2024–2070 horizon to remain effective in achieving transportation objectives despite deep uncertainty in future mobility trends?

These questions were addressed through an exploratory modeling and MORO approach, and the findings of the thesis can be summarized as follows:

(1) MORO's Role in Improving Forecasting Under Deep Uncertainty

The study demonstrated that a MORO framework can enhance long-term rail demand forecasting and policy analysis by shifting the focus from point prediction to robust decision exploration. Rather than producing a single forecast of passenger volumes, the MORO approach generated a rich ensemble of possible futures and identified fare policy strategies performing well across this ensemble. By incorporating multiple objectives (ridership, revenue, emissions, etc.) directly into the optimization, the framework provided a more nuanced picture of potential futures and how various policies might perform under divergent conditions.

MORO enhanced forecasting not by improving precision or predictive accuracy but by broadening the scope and resilience of planning. It identified which policies were likely to succeed across multiple plausible futures. This represents a fundamentally different and valuable contribution to planning under deep uncertainty. Rather than relying on a single scenario, planners can prepare for many. The analysis revealed, for example, that moderate fare reductions combined with peak management tend to provide robust strategies across scenarios, whereas policies optimized for a single future can lead to major shortfalls if reality diverges.

The answer to Research Question 1 is that applying MORO transforms the forecasting exercise into a robust planning exercise. This can yield insights that improve the ability of decision-makers to craft policies resilient to a range of uncertainties. This approach complements traditional models like the LMS by covering a much larger scenario space and highlighting trade-offs, thereby enhancing the adaptability and defensibility of forecasts used in policy development.

(2) Impacts of Ultra-Low Fares and Peak-Hour Surcharges Under Uncertainty

The analysis found that ultra-low-cost travel passes (such as a €9 or €49 monthly ticket) and peak-hour surcharges exert profound but contrasting impacts on the rail system, with their effectiveness strongly dependent on scenario context, though some general patterns were observed.

A nationwide ultra-low fare ticket can substantially increase ridership, often leading to record-high passenger-kilometers and significant CO_2 emissions reductions by drawing travelers from cars to trains. This effect appeared robust across almost all futures, with cheaper fares consistently boosting rail usage relative to baseline. For climate and mobility objectives, this finding is encouraging as a dramatic fare cut increases rail use.

However, the financial impact of such a policy is substantial as fare revenue drops significantly across most simulations. Although in some futures, the lost revenue may be partially offset by increased ridership volumes and a rush hour surcharge. Furthermore, capacity constraints become a limiting factor; under high-demand scenarios, the model showed that unmet demand would arise without parallel investments in service expansion. Thus, the ultra-low fare strategy achieves ridership and emissions goals but challenges revenue stability and capacity management.

By contrast, a rush-hour surcharge policy primarily flattens demand peaks and increases revenue per trip during peak periods. Simulations indicated that a surcharge reduced peak-period ridership growth (with some travelers shifting to off-peak or foregoing trips) while modestly increasing daily revenue. By tempering peak loads, such a surcharge prevents extreme overcrowding scenarios, thereby enhancing system reliability. The trade-off is that overall ridership is slightly lower than in no-surcharge cases, and the climate benefit from mode shift is modestly reduced. However, the revenue gain can support service improvements or expansions, potentially offsetting long-term ridership losses. Additionally, in many simulations, a rush hour surcharge was supplemented with an equal tariff reduction during off peak hours. This lessens the economic burden of the rush hour surcharge by further incentivizing people to travel off-peak.

In summary, the answer to Research Question 2 is that a €9/€49-type low fare scheme robustly maximizes rail usage and environmental benefits across scenarios but undermines financial sustainability, whereas a peak-hour surcharge bolsters financial and operational sustainability but modestly constrains ridership growth. Optimal policies may combine elements of both: the analysis suggests coupling a generally low fare price with a targeted peak charge delivers strong performance. This combined strategy was observed to maintain high ridership, sustain healthier revenues, and significantly reduce capacity failures, providing a more balanced outcome under uncertainty.

(3) Designing Adaptive Fare Policies for Effectiveness Over 2024–2070

The thesis findings underscore that fare policies must be adaptive over time to remain effective amid changing conditions. In response to Research Question 3, the research shows that one-time policy changes are likely to overshoot or undershoot objectives as external conditions evolve.

Instead, the recommendation is to structure fare policy as a sequence of interventions or as an adaptable instrument. For instance, the MORO analysis identified that an effective approach for the 2020s might involve introducing a low-cost travel pass alongside mild peak pricing. Approaching 2030 and beyond, policies can be re-optimized using emerging data on ridership responses and external trends. By 2060, high demand might warrant increased rush-hour surcharges to manage crowding and fund expansions. The thesis advocates for a Dynamic Adaptive Policy Pathways approach, beginning with an initial robust policy and establishing regular checkpoints for policy review and adjustment.

The MORO results across different decades (2030, 2050, 2070) provide guidance on potential adaptations under varied scenarios. In practical terms, the answer to Research Question 3 is that fare policies can remain effective by being flexible and responsive. This approach ensures that as objectives or external circumstances shift, fare policies can adjust accordingly. Robustness is therefore not a one-time achievement but an ongoing process. By designing adaptive policies with political and institutional support, Dutch rail planners can maintain a sustained balance of ridership growth, revenue adequacy, and emissions reduction throughout 2024–2070, even as uncertainties manifest in unexpected ways.

In summary, the thesis answers Research Question 3 by highlighting that a static fare policy is poorly suited for a 50-year horizon. Instead, an adaptive, feedback-informed strategy is required, and MORO serves as a valuable tool for guiding those adaptations at each stage.

8.2. Policy Implementation Insights

Based on the exploratory modeling and MORO analysis presented in this thesis, several strategic insights emerge that may inform fare policy deliberations in the Dutch passenger rail context. These insights are not intended as fixed prescriptions but rather as evidence-based considerations to support robust, adaptive policymaking:

Implement Low-Cost Unlimited Travel Ticket

The model suggests that introducing affordable flat-fare transit passes (in the spirit of Germany's €49 "Deutschlandticket") could stimulate ridership and support a shift from car to train travel. A possible approach would be to pilot such a scheme on a limited-time basis, similar to the German trial, and evaluate its impacts on ridership, revenue, and crowding. If the benefits prove robust and costs remain within acceptable bounds, policymakers could consider expanding or institutionalizing the program over time.

Introduce a Moderate Peak-Hour Surcharge as Part of Demand Management

To address capacity constraints and provide funding for improvements, policymakers could explore pricing structures that differentiate between peak and off-peak travel. Simulation results indicate that implementing a modest rush-hour surcharge may help mitigate peak capacity pressures while improving financial sustainability (e.g., +50% on base fares for trips starting or ending during weekday peaks). This measure should be accompanied by clear public communication emphasizing its purpose and revenue generated from peak pricing should be transparently earmarked for capacity investments, such as additional trains, staff, or infrastructure upgrades. Many simulations suggest reducing off-peak ticket pricing at the same time as implementing a rush-hour surcharge. Doing so would lessen the economic burden of the surcharge and likely increase public acceptability.

Ensure Equity and Accessibility Measures Accompany Fare Changes

Any major fare policy should be evaluated for equity impacts and accompanied by measures protecting vulnerable groups. Although this research did not explicitly model equity, precedent suggests the necessity of targeted mitigation. Examples such as Vienna's discounted annual passes for residents or the UK's railcards for youth, seniors, and disabled travelers provide instructive cases. Proactively integrating equity measures would reduce political backlash and ensure broad-based ridership gains, making fare policies more sustainable by maintaining public support.

Coordinate Fare Policy with Broader Transport and Climate Policy

Finally, fare policy could be more explicitly linked to overarching transport and climate strategies. If model results showing CO_2 reductions from increased rail ridership hold in practice, it may be appropriate for climate finance mechanisms to subsidize fare policy reforms. Policymakers could therefore explore synergies between public transport pricing, modal shift goals, and national or EU-level decarbonization funding instruments.

8.3. Policy Analyst Insights

While this thesis provides empirical insights into fare policy design, a key contribution lies in demonstrating how the MORO framework can support the work of policy analysts operating under deep uncertainty. MORO does not prescribe singular solutions; rather, it enables analysts to structure uncertainty, reveal trade-offs, and communicate robust yet flexible strategies that remain valid across a range of plausible futures.

By generating policy sets that perform well under diverse scenarios, MORO helps analysts shift the conversation from prediction to preparation. Instead of asking "What will happen?" the focus becomes "What actions could perform well, regardless of what happens?" This shift aligns well with the analyst's role as a translator between technical findings and decision-making under uncertainty.

The MORO framework also highlights trade-offs that might otherwise remain hidden. In this study, it became evident that policies promoting ridership and emissions reduction—such as ultra-low fares—can undermine revenue and overburden capacity unless balanced with complementary measures like peak-hour surcharges. Exposing such tensions is a valuable step toward more transparent and inclusive policymaking, allowing decision-makers to weigh competing goals explicitly rather than pursuing single-objective optimization.

In addition, MORO supports the development of adaptive strategies rather than static policy recommendations. The results suggest that a fare policy effective in 2030 may not remain so by 2040. MORO enables analysts to identify robust starting points—such as low fares with mild peak pricing—while also providing insight into when and how these strategies might need adjustment. This supports the use of adaptive policy pathways, where policies evolve in response to observed developments rather than being fixed in advance.

The use of MORO enhances the legitimacy of policy advice by making the assumptions, uncertainties, and trade-offs embedded in modeling more visible. Analysts can demonstrate not just what is optimal under one future, but what performs reasonably well across many. This transparency supports more credible and democratic decision-making, especially in contested domains like public transport pricing.

In sum, the value of MORO lies not only in identifying robust strategies but in supporting the deliberative processes that underpin good policy. It strengthens the analyst's capacity to inform rather than dictate—to guide decision-making by revealing what is possible, plausible, and prudent given the uncertainties ahead.

8.4. Future Research Directions

Building on the limitations identified in this study, several future research directions are recommended to improve the robustness, realism, and policy relevance of exploratory rail policy modeling under deep uncertainty.

First, future models should incorporate more sophisticated representations of traveler behavior, particularly regarding heterogeneous demand elasticities. Rather than assuming static, aggregate elasticities across all passenger segments, models should differentiate between key user groups such as commuters, tourists, and occasional travelers, capturing their distinct price sensitivities and travel purposes. Special attention should be paid to how extreme fare changes might induce behavioral responses that depart from historical trends.

Second, future work should improve the treatment of modal competition and environmental impacts. Rather than relying on fixed assumptions about mode shift and CO_2 reduction, future studies could explicitly simulate competition between rail, car, and emerging mobility options, accounting for differences in service attributes such as door-to-door time, cost, convenience, and reliability. Incorporating dynamic assumptions about technological change (such as the usage of electric vehicles) would also improve the credibility of long-term emissions assessments.

Third, a key priority for future research should be the integration of dynamic capacity modeling. This study fixed capacity either to 2019 levels or to an idealized, unbounded state, ignoring the feedback between demand, overcrowding, and necessary infrastructure investment. Future research should allow capacity to adjust endogenously over time. This would enable more realistic exploration of how fare policies interact with system growth, and it would avoid unrealistic endpoint scenarios like those seen in the maximum demand case, where 100% free travel drives demand indefinitely without triggering any capacity limitations or congestion effects. Explicitly modeling how congestion degrades service quality and dampens demand would provide a more credible depiction of long-term dynamics.

Fourth, institutional and behavioral realism should be strengthened, particularly concerning rush-hour pricing strategies. Current assumptions about price sensitivity do not account for the fact that a large share of Dutch peak-hour travelers use NS Business Cards provided by employers, making them relatively insensitive to direct fare changes. Future studies should incorporate differentiated demand responses for business and non-business travelers, potentially modeling the interactions between corporate travel policies, employee preferences, and public fare structures. Without this, the effectiveness of peak pricing measures may be systematically overestimated.

Fifth, equity considerations should be elevated from qualitative discussion to quantitative analysis. Future work should incorporate explicit disaggregation by income group, geographic area, or travel purpose to examine the distributional impacts of fare policies. Doing so would allow equity to be treated as an additional optimization objective alongside ridership, revenue, and emissions to support more socially balanced policy recommendations.

Finally, improvements in uncertainty treatment are warranted. While this study explored deep uncertainty using large scenario ensembles, the selection of uncertainty ranges and distributions could be improved. Future work could combine historical data analysis and structured stakeholder engagement to define more robust uncertainty spaces. Additionally, extensions to the modeling framework could incorporate low-probability, high-impact disruptions to stress-test fare policy resilience.

Works Cited

Alexander, A., Walker, H., & Delabre, I. (2022). A Decision Theory Perspective on Wicked Problems, SDGs and Stakeholders: The Case of Deforestation. Journal of Business Ethics, 180(4), 975–995. https://doi.org/10.1007/s10551-022-05198-8

American Public Transportation Association. (2003). The effects of fare changes on bus ridership. https://www.apta.com/wp-content/uploads/effects_of_fare_changes.pdf

Bankes, S. (2002). Tools and Techniques for Developing Policies for Complex and Uncertain Systems. Proceedings of the National Academy of Sciences, 99(suppl_3), 7263–7266. https://doi.org/10.1073/pnas.092081399

Bankes, S. (1993). Exploratory Modeling for Policy Analysis. Operations Research, 41(3), 435–449. https://doi.org/10.1287/opre.41.3.435

Centraal Bureau voor de Statistiek. (2021, April). Inkomen nederlanders in 50 jaar meer dan verdubbeld [News article]. https://www.cbs.nl/nl-nl/nieuws/2021/15/inkomen-nederlanders-in-50-jaar-meer-dan-verdubbeld

Centraal Bureau voor de Statistiek. (2023a). Bevolking; geslacht, leeftijd, generatie en migratieachtergrond, 1 januari [CBS StatLine dataset 37220]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37220

Centraal Bureau voor de Statistiek. (2023b). Brandstofprijzen en brandstofverbruik particuliere auto's naar soort brandstof [CBS StatLine dataset 37362]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37362

Centraal Bureau voor de Statistiek. (2023c). Onderwijsdeelname naar onderwijssoort, leeftijd en geslacht [CBS StatLine dataset 81108ned]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/81108ned

Centraal Bureau voor de Statistiek. (2023d). Passagiers luchtvaart; luchthavens van nationale betekenis [CBS Visualisatie]. https://www.cbs.nl/nl-nl/visualisaties/verkeer-en-vervoer/personen/passagiers-luchtvaart

Centraal Bureau voor de Statistiek. (2023e). Personenmobiliteit in nederland; kenmerken, vervoerwijze en motief [CBS StatLine dataset 81567NED]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/81567NED

Cook, C. N., Mascia, M. B., Schwartz, M. W., Possingham, H. P., & Fuller, R. A. (2013). Achieving Conservation Science that Bridges the Knowledge–Action Boundary. https://doi.org/10.1111/cobi.12050

DutchNews.nl. (2023a). Ns boss koolmees plans peak hour train fares to cut congestion. https://www.dutchnews.nl/2023/07/ns-boss-koolmees-plans-peak-hour-train-fares-to-cut-congestion/

DutchNews.nl. (2023b). Ns to get the green light for higher rush hour ticket prices. https://www.dutchnews.nl/2023/08/ns-to-get-the-green-light-for-higher-rush-hour-ticket-prices/

Facebook. (2017). Prophet: Tool for producing high quality forecasts for time series data. https://facebook.github.io/prophet/

Font Vivanco, D., Kemp, R., & van der Voet, E. (2016). How to Deal with the Rebound Effect? A Policy-Oriented Approach. https://doi.org/10.1016/j.enpol.2016.03.054

Führer, K., Jittrapirom, P., d'Hont, F. M., Rouwette, E. A., & Kwakkel, J. H. (2024). Modeling with a municipality: Exploring robust policies to foster climate-neutral mobility. Transportation Research Interdisciplinary Perspectives, 27, 101206.

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic Adaptive Policy Pathways: A Method for Crafting Robust Decisions for a Deeply Uncertain World. Global Environmental Change, 23(2), 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Hamarat, C., Kwakkel, J. H., & Pruyt, E. (2014). Designing adaptive policy pathways for sustainable water management under deep uncertainty. Technological Forecasting and Social Change, 79(1), 63–75. https://doi.org/10.1016/j.techfore.2011.04.004

KiM. (2019). KiM Mobiliteitsbeeld 2019. https://www.kimnet.nl/mobiliteitsbeeld/mobiliteitsbeeld-2019

KiM. (2021). KiM Mobiliteitsbeeld 2021. https://www.rijksoverheid.nl/documenten/rapporten/2021/11/18/mobiliteitsbeeld-2021

KiM. (2022). Kerncijfers Mobiliteit 2022. https://www.rijksoverheid.nl/documenten/rapporten/2022/11/15/kerncijfers-mobiliteit-2022

KiM. (2023a). KiM Mobiliteitsbeeld 2023. https://www.rijksoverheid.nl/documenten/rapporten/2023/11/14/bijlage-2-mobiliteitsbeeld-2023

KiM. (2023b). Netherlands Institute for Transport Policy Analysis (KiM) [(Accessed on 02/04/2023)]. https://english.kimnet.nl/

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An Open Source Toolkit for Exploratory Modeling, Scenario Discovery, and (Multi-Objective) Robust Decision Making. Environmental Modelling Software, 96, 239–250. https://doi.org/https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., & Haasnoot, M. (2016). Comparing robust decision-making and dynamic adaptive policy pathways for model-based decision support under deep uncertainty. Environmental Modelling & Software, 86, 168–183. https://doi.org/10.1016/j.envsoft.2016.09.017

Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2015). Developing Dynamic Adaptive Policy Pathways: a Computer-Assisted Approach for Developing Adaptive Strategies for a Deeply Uncertain World. Climatic Change, 132(3), 373–386. https://doi.org/10.1007/s10584-014-1210-4

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. (2010a). From Predictive Modeling to Exploratory Modeling: How to Use Non-Predictive Models for Decisionmaking Under Deep Uncertainty. In Carlos Henggeler Antunes, David Rios Insua, & Luis Candido Dias (Eds.), Proceedings of the 25th mini-euro conference (pp. 1–10). University of Coimbra. https://research.tudelft.nl/en/publications/from-predictive-modeling-to-exploratory-modeling-how-to-use-non-p

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. (2010b). Classifying and Communicating Uncertainties in Model-Based Policy Analysis. International Journal of Technology Policy and Management, 10, 299–315. https://doi.org/10.1504/IJTPM.2010.036918

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. Management Science, 52(4), 514–528. Retrieved September 4, 2023, from http://www.jstor.org/stable/20110530

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis (1st ed.). RAND Corporation. Retrieved September 4, 2023, from http://www.jstor.org/stable/10.7249/mr1626rpc

Litman, T. (2024, December). Understanding transport demands and elasticities: How prices and other factors affect travel behavior (tech. rep.) (Accessed July 2025). Victoria Transport Policy Institute. https://www.vtpi.org/elasticities.pdf

Loder, A., Cantner, F., Isaza, A. C., Siewert, M. B., Wurster, S., Goerg, S., & Bogenberger, K. (2022a). Insights into four months of mobility tracking. arXiv preprint. https://arxiv.org/pdf/2210.10538.pdf

Loder, A., Cantner, F., Isaza, A. C., Siewert, M. B., Wurster, S., Goerg, S., & Bogenberger, K. (2022b). A nationwide experiment: Fuel tax cuts and almost free public transport for three months in germany. arXiv preprint. https://arxiv.org/pdf/2208.14902.pdf

Macrotrends LLC. (2024). Netherlands inflation rate 1960–2024. https://www.macrotrends.net/countries/NLD/netherlands/inflation-rate-cpi

Milkovits, M., Copperman, R., Newman, J., Lemp, J., Rossi, T., & Sun, S. (2019). Exploratory Modeling and Analysis for Transportation: An Approach and Support Tool - TMIP-EMAT. Transportation Research Record, 2673(9), 407–418. https://doi.org/10.1177/0361198119844463

Moallemi, E. A., & Köhler, J. (2021). Coping With Uncertainties of Sustainability Transitions Using Exploratory Modelling: the Case of the MATISSE Model and the UK's Mobility Sector. Technological Forecasting and Social Change, 163, 120450. https://doi.org/10.1016/j.eist.2019.03.005

Nederlandse Spoorwegen. (2023a). Ns annual report 2022. https://www.nsjaarverslag.nl/

Nederlandse Spoorwegen. (2023b). Ns reizigersgedrag dashboard. https://dashboards.nsjaarverslag.nl/reizigersgedrag/

Nederlandse Spoorwegen. (2023c). Ns tarievenlijst consumenten 2023.

Phillips, R. A., & Reichart, J. (2000). The Environment as a Stakeholder? A Fairness-Based Approach. Journal of Business Ethics, 23(2), 185–197. https://www.jstor.org/stable/25074234

Rijkswaterstaat. (2023). Verkeer en Vervoer: Het Landelijk Model Systeem. https://open.rws.nl/publish/pages/34566/verkeer_en_vervoer_het_landelijk_model_sysyteem.pdf

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a General Theory of Planning. Policy Sciences, 4(2), 155–169. https://doi.org/10.1007/BF01405730

Statista Research Department. (2023). Number of international students in the netherlands from 2006 to 2022. https://www.statista.com/statistics/699754/international-students-in-the-netherlands/

Taylor, S. J., & Letham, B. (2018). Forecasting at scale. The American Statistician, 72(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

UN. (2015). Transforming Our World: The 2030 Agenda for Sustainable Development. United Nations. https://sustainabledevelopment.un.org/post2015/transformingourworld

van der Voort, H. (2022, November). MSc EPA docentvideo Haiko van der Voort - YouTube [(Accessed on 06/20/2023)]. https://www.youtube.com/watch?v=RsYjyZTuHd4&t=70s

Verband Deutscher Verkehrsunternehmen. (2022). Bilanz: 9-euro-ticket. https://www.vdv.de/bilanz-9-euro-ticket.aspx

Wald, A. (1950). Statistical decision functions [Republished by Dover Publications, 2004]. John Wiley & Sons.

Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or Perish: A Review of Planning Approaches for Adaptation under Deep Uncertainty. https://ris.utwente.nl/ws/files/148024718/Walker2013adapt.pdf

World Bank. (2022). Inflation, consumer prices (annual %) - netherlands. https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=NL

A
Model Overview

This document provides detailed documentation of the Python model code developed for the Dutch passenger rail network. The model integrates with the EMA Workbench and is organized within a single class `TrainModel`. It processes multiple data sources, computes fare prices and demand estimates, calculates emissions, and determines capacity requirements. The following sections document each component of the code.

The model is implemented in Python and leverages the following functionalities:

- **Fare Calculation:** Computes fare prices based on distance and elasticities.
- **Demand Estimation:** Estimates train demand for different population segments.
- **Emission Calculations:** Assesses the CO_2 emissions reduction associated with modal shifts.
- **Capacity Analysis:** Evaluates capacity constraints and the need for additional trains.
- **Policy Impact:** Computes the effects of free travel ticket policies.

A.1. Fare Price Calculation

Purpose: Calculates the fare price based on the average distance per trip. The method:

- Computes the average distance per trip.
- Rounds up the distance to determine the number of fare units.
- Uses a predefined fare structure to return the corresponding fare price.

One of the primary drivers of demand is the fare price. The model computes the fare based on the average distance traveled during a trip. The fare structure is predefined, allowing the model to determine the price based on this average distance. As the distance increases, the fare might adjust, reflecting longer journeys.

$$\text{avg\_distance\_per\_trip} = \frac{\text{km}}{\text{trips}} \tag{A.1}$$

$$\text{fare\_units\_per\_trip} = \lceil \text{avg\_distance\_per\_trip} \rceil \tag{A.2}$$

$$\text{fare\_price} = \text{fare\_structure}[\text{fare\_units\_per\_trip}] \tag{A.3}$$

Fare Price Calculation

```
def calculate_fare_price(self, trips, km, pop):
    avg_distance_per_trip = km / (trips * pop) / 260
    fare_units_per_trip = math.ceil(avg_distance_per_trip)  % 1 km ~ 1 fare unit
    fare_structure = {i: 2.6 if i <= 8 else 2.6 + (0.20 * (i - 8)) if i <= 75 else 2.6 + (0.14 * (i - 8)) for
    ↪  i in range(1, 201)}
    return fare_structure.get(fare_units_per_trip, max(fare_structure.values()))
```

A.2. Demand Calculation

Purpose: Estimates the daily train demand and its breakdown among Dutch and international students. The method:

- Separates the student population.
- Computes demand using provided usage percentages.
- Aggregates the demands over the year (converted to a daily estimate).

The demand for train travel is derived from various segments of the population: Dutch students, international students, and non-students. Each group has distinct travel patterns influenced by factors such as the use of OV (public transport) cards during the week and weekends.

Calculating OV Usage

Demand calculation begins with determining the real OV usage percentages during weekdays and weekends for Dutch students:

$$\text{week\_ov\_real} = \frac{\text{week\_ov}}{\frac{5}{7}} \tag{A.4}$$

$$\text{weekend\_ov\_real} = \frac{\text{weekend\_ov}}{\frac{2}{7}} \tag{A.5}$$

$$\text{avg\_dutch\_students\_usage} = \frac{\text{week\_ov\_real} + \text{weekend\_ov\_real}}{2} \tag{A.6}$$

$$\text{avg\_international\_students\_usage} = \frac{\text{non\_ov}}{100} \tag{A.7}$$

$$\text{avg\_non\_students\_usage} = \frac{\text{non\_ov}}{100} \tag{A.8}$$

Demand Calculation

The demand for each segment is then calculated. The Dutch students have a relatively straightforward demand:

$$\text{demand\_dutch\_students} = \text{dutch\_students} \times \text{avg\_dutch\_students\_usage} \tag{A.9}$$

For international students, their demand is influenced both by the average international student usage and the free transit policy levers:

$$\begin{aligned}\text{demand\_international\_students} = \text{international\_students} \times \\ \big(\text{avg\_international\_students\_usage} \times (1 - \text{free\_transit\_students}) \\ + \text{avg\_dutch\_students\_usage} \times \text{free\_transit\_students}\big)\end{aligned} \tag{A.10}$$

Non-students' demand is influenced by their usage and the free transit policy levers, which is influenced by their participation in traffic:

$$\begin{aligned}\text{demand\_non\_students} = \text{non\_students} \times \\ \big(\text{avg\_non\_students\_usage} \times (1 - \text{free\_transit}) \\ + \text{avg\_dutch\_students\_usage} \times \text{free\_transit} \times \text{traffic\_participation}\big)\end{aligned} \tag{A.11}$$

The total daily demand is the sum of the demands for all segments:

$$\begin{aligned}\text{total\_daily\_demand} = \text{demand\_dutch\_students} \\ + \text{demand\_international\_students} \\ + \text{demand\_non\_students}\end{aligned} \tag{A.12}$$

Demand Calculation

```
def calculate_demand(self, trips, km, week_ov, weekend_ov, non_ov, free_transit, free_transit_students, pop,
↪ students, international_students, traffic_participation):
    dutch_students = students - international_students
    non_students = pop - students

    week_ov_real = week_ov
    weekend_ov_real = weekend_ov
    avg_international_students_usage = traffic_participation
    avg_non_students_usage = traffic_participation

    international_students_usage = (avg_international_students_usage * (1 - free_transit_students)) +
    ↪ (week_ov_real * free_transit_students)
    non_students_usage = avg_non_students_usage

    demand_dutch_students = ((dutch_students * (week_ov_real * (52 * 5))) + (dutch_students *
    ↪ (weekend_ov_real * (52 * 2)))) / 365
    demand_international_students = (international_students * international_students_usage) / 365
    demand_non_students = (non_students * non_students_usage) / 365

    daily_demand = (demand_dutch_students + demand_international_students + demand_non_students) * 2
    return daily_demand, demand_dutch_students, demand_international_students
```

A.3. Environmental Impact and Emissions Calculation

Purpose: Calculates the reduction in CO_2 emissions due to reduced car usage and computes the net CO_2 emissions after modal shift.

A significant benefit of promoting train travel is the reduction in CO_2 emissions. Estimating the number of car trips replaced by train trips allows computation of the potential reduction in CO_2 emissions:

$$\text{avg\_car\_trips\_per\_day} = \text{car\_trips\_per\_person\_per\_day} \times \text{pop} \tag{A.13}$$

$$\text{total\_car\_distance} = \text{avg\_car\_trips\_per\_day} \times \text{distance\_per\_car\_trip} \tag{A.14}$$

$$\text{CO}_2\text{\_reduction} = \text{car\_substitution\_rate} \times \text{demand} \times \text{km} \times \text{avg\_CO}_2\text{\_emissions\_per\_km} \tag{A.15}$$

$$\text{net\_CO}_2\text{\_emissions} = \text{car\_C02\_emissions} \tag{A.16}$$

$$- \text{demand} \times \text{distance\_per\_car\_trip} \times \text{avg\_CO}_2\text{\_emissions\_per\_km} \tag{A.17}$$

Emissions Calculation

```
def calculate_emissions(self, pop, demand, km, car_trips_per_person_per_day, distance_per_car_trip,
↪ car_C02_emissions, AverageKMperTrainTrip, car_substitution_rate):
    avg_car_trips_per_day = car_trips_per_person_per_day * pop
    total_car_distance = avg_car_trips_per_day * distance_per_car_trip
    avg_C02_emissions_per_km = car_C02_emissions / total_car_distance
    C02_reduction = (car_substitution_rate * demand * 365 * (AverageKMperTrainTrip *
    ↪ avg_C02_emissions_per_km)) - (km * avg_C02_emissions_per_km)
    net_C02_emissions = car_C02_emissions - C02_reduction
    return C02_reduction, net_C02_emissions
```

A.4. Fare Price with Elasticity

Purpose: Calculates the fare price while considering demand elasticity effects. It:

- Computes the fare price based on the average trip distance.
- Retrieves tariff data and determines the price per kilometer.

Fare Price with Elasticity

```
def calculate_fare_price_with_elasticity(self, pop, trips, km, AverageKMperTrainTrip):
    trips_per_year = pop * trips * 260
    km_per_year = AverageKMperTrainTrip * trips_per_year
    avg_distance_per_trip = AverageKMperTrainTrip
    fare_units_per_trip = math.ceil(avg_distance_per_trip)
    try:
        tariff_df = pd.read_excel("/TariffList.xlsx")
        tariff_dict = dict(zip(tariff_df['Distance'], tariff_df['Price']))
    except Exception as e:
        tariff_dict = str(e)
    try:
        fare_price = tariff_dict.get(min(fare_units_per_trip, 200))
    except Exception as e:
        fare_price = 10.8
    price_per_km = fare_price / fare_units_per_trip
    return fare_price, price_per_km
```

A.5. Free Travel Ticket Impact

Purpose: Evaluates the impact of a free travel ticket policy on both demand and revenue by:

- Adjusting demand using a subscription ticket modifier.
- Calculating revenue loss due to the policy.

Free Travel Ticket Impact

```
def calculate_free_travel_ticket_impact(self, daily_demand, revenue, km, free_travel_ticket_price,
↪   fare_price, pop, nine_euro_modifier, forty_nine_euro_modifier):
    subscription_ticket_df = pd.DataFrame({'Price': np.arange(0, 50)})
    subscription_ticket_df['Modifier'] = np.nan
    subscription_ticket_df.loc[subscription_ticket_df['Price'] == 9, 'Modifier'] = nine_euro_modifier
    subscription_ticket_df.loc[subscription_ticket_df['Price'] == 49, 'Modifier'] = forty_nine_euro_modifier
    subscription_ticket_df['Modifier'] = subscription_ticket_df['Modifier'].interpolate()
    subscription_ticket_df.set_index('Price', inplace=True)

    percent_travelled_regardless = 0.44
    adjusted_total_daily_demand = daily_demand * subscription_ticket_df['Modifier'][free_travel_ticket_price]
    demand_for_free_travel_ticket = (adjusted_total_daily_demand - daily_demand) +
    ↪   (percent_travelled_regardless * daily_demand)
    free_travel_ticket_price /= (365 / 12)
    if fare_price > 0:
        free_travel_ticket_revenue = demand_for_free_travel_ticket * free_travel_ticket_price
    else:
        free_travel_ticket_revenue = 0
    revenue_loss = (demand_for_free_travel_ticket * fare_price) - free_travel_ticket_revenue
    adjusted_revenue = max(revenue - revenue_loss, 0)
    return adjusted_total_daily_demand, adjusted_revenue, revenue_loss
```

A.6. Extended Demand Calculation with Elasticity

Purpose: Extends the basic demand calculation by incorporating multiple elasticity factors (price, student population, resident population, jobs, income, etc.) and policy impacts. It:

- Adjusts fare price based on tariff changes.
- Applies several elasticity parameters to modify the baseline demand.
- Optionally adjusts demand and revenue if a free travel ticket policy is applied.

Extended Demand Calculation with Elasticity

```python
def calculate_demand_with_elasticity_extended(self, trips, km, week_ov, weekend_ov, non_ov, free_transit_students,
                                              pop, students, international_students, traffic_participation,
                                              banen, inkomen, autobezit, schiphol, brandstof,
                                              tariff_change, free_travel_ticket, free_travel_ticket_price,
                                              AverageKMperTrainTrip,
                                              nine_euro_modifier, forty_nine_euro_modifier):
    fare_price, price_per_km = self.calculate_fare_price_with_elasticity(pop, trips, km, AverageKMperTrainTrip)
    baseline_price_per_km = price_per_km
    price_per_km = max(baseline_price_per_km + tariff_change, 0)
    if price_per_km < 0.01:
        free_transit = 1
        fare_price = 0
    else:
        free_transit = 0
        fare_price = (fare_price / baseline_price_per_km) * price_per_km
    price_change_percentage = (price_per_km - baseline_price_per_km) / baseline_price_per_km
    demand_change_percentage_price = self.treintarief_elasticity * price_change_percentage
    student_change_percentage = (students - self.baseline_students) / self.baseline_students
    resident_change_percentage = (pop - self.baseline_residents) / self.baseline_residents
    demand_change_percentage_student = self.studenten_elasticity * student_change_percentage
    demand_change_percentage_resident = self.inwoners_elasticity * resident_change_percentage
    total_demand, demand_dutch_students, demand_international_students = self.calculate_demand(
        trips, km, week_ov, weekend_ov, non_ov, free_transit, free_transit_students, pop, students, international_students, traffic_participation)
    adjusted_demand = total_demand * (1 + demand_change_percentage_price)
    adjusted_demand *= (1 + demand_change_percentage_student)
    adjusted_demand *= (1 + demand_change_percentage_resident)
    demand_change_percentage_banen = self.banen_elasticity * ((banen - self.baseline_banen) / self.baseline_banen)
    demand_change_percentage_inkomen = self.inkomen_elasticity * ((inkomen - self.baseline_inkomen) / self.baseline_inkomen)
    demand_change_percentage_autobezit = self.autobezit_elasticity * ((autobezit - self.baseline_autobezit) / self.baseline_autobezit)
    demand_change_percentage_schiphol = self.schiphol_elasticity * ((schiphol - self.baseline_schiphol) / self.baseline_schiphol)
    demand_change_percentage_brandstof = self.brandstof_elasticity * ((brandstof - self.baseline_brandstof) / self.baseline_brandstof)
    adjusted_demand *= (1 + demand_change_percentage_banen)
    adjusted_demand *= (1 + demand_change_percentage_inkomen)
    adjusted_demand *= (1 + demand_change_percentage_autobezit)
    adjusted_demand *= (1 + demand_change_percentage_schiphol)
    adjusted_demand *= (1 + demand_change_percentage_brandstof)
    daily_km_per_person = AverageKMperTrainTrip
    revenue = adjusted_demand * fare_price
    adjusted_demand = max(adjusted_demand, 0)
    adjusted_revenue = max(revenue, 0)
    if free_travel_ticket == 1:
        adjusted_demand, adjusted_revenue, cost_free_travel_ticket = self.calculate_free_travel_ticket_impact(
            adjusted_demand, revenue, daily_km_per_person, free_travel_ticket_price, fare_price, pop,
            nine_euro_modifier, forty_nine_euro_modifier)
    else:
        cost_free_travel_ticket = 0
    if free_transit_students == 1:
        cost_free_international_students = math.ceil(demand_international_students * fare_price)
    else:
        cost_free_international_students = 0
    cost_free_dutch_students = math.ceil(demand_dutch_students * fare_price)
    if free_transit == 1:
        cost_free_travel_ticket = adjusted_demand * fare_price
    adjusted_revenue *= 365
    cost_free_travel_ticket *= 365
    cost_free_dutch_students *= 365
    cost_free_international_students *= 365
    adjusted_revenue = math.ceil(adjusted_revenue)
    adjusted_demand = math.ceil(adjusted_demand)
    cost_free_travel_ticket = math.ceil(cost_free_travel_ticket)
    cost_free_dutch_students = math.ceil(cost_free_dutch_students)
    cost_free_international_students = math.ceil(cost_free_international_students)
    return adjusted_demand, adjusted_revenue, cost_free_travel_ticket, cost_free_dutch_students, cost_free_international_students, price_per_km, free_transit, fare_price
```

A.7. Main Rail Model Function

Purpose: Serves as the central function that integrates the demand, revenue, capacity, and emissions calculations. The method:

- Adjusts tariff change values.
- Computes demand and revenue using the extended elasticity function.
- Evaluates capacity constraints (using a time series approach).
- Calculates CO_2 emissions impact.

Main Rail Model Function

```
def rail_model_with_elasticity_extended(self, trips, km, week_ov, weekend_ov, non_ov, free_transit_students,
                                        pop, students, international_students, traffic_participation,
                                        capacity, car_trips_per_person_per_day, distance_per_car_trip, car_CO2_emissions,
                                        banen, inkomen, autobezit, schiphol, brandstof, tariff_change,
                                        free_travel_ticket, free_travel_ticket_price,
                                        capacity_2022, trains_2022, AverageKMperTrainTrip, nine_euro_modifier, forty_nine_euro_modifier, rush_hour_surcharge, peak_pm_demand_modifier, peak_am_demand_modifier, car_substitution_rate):
    tariff_change = tariff_change / 100
    daily_demand, revenue, cost_free_travel_ticket, cost_free_dutch_students, cost_free_international_students, price_per_km, free_transit, fare_price = self.calculate_demand_with_elasticity_extended(
        trips, km, week_ov, weekend_ov, non_ov,
        free_transit_students, pop, students, international_students,
        traffic_participation, banen, inkomen,
        autobezit, schiphol, brandstof, tariff_change, free_travel_ticket,
        free_travel_ticket_price, AverageKMperTrainTrip,
        nine_euro_modifier, forty_nine_euro_modifier)
    price_per_km = round(price_per_km, 2)
    total_capacity, off_peak_demand, peak_demand, shortage, average_seats_per_train, additional_trains = self.timeSeriesCapacity(price_per_km, daily_demand, capacity, capacity_2022, trains_2022, rush_hour_surcharge, peak_pm_demand_modifier, peak_am_demand_modifier, AverageKMperTrainTrip, fare_price)
    CO2_reduction, net_CO2_emissions = self.calculate_emissions(pop, daily_demand, km, car_trips_per_person_per_day,
                                                                distance_per_car_trip, car_CO2_emissions, AverageKMperTrainTrip, car_substitution_rate)
    return {'demand': np.int64(daily_demand), 'revenue': np.int64(revenue), 'shortage': np.int64(shortage), 'additional_trains': np.int64(additional_trains),
            'CO2_reduction': np.int64(CO2_reduction), 'net_CO2_emissions': np.int64(net_CO2_emissions), 'free_transit': np.int64(free_transit),
            'cost_free_dutch_students': np.int64(cost_free_dutch_students),
            'cost_free_international_students': np.int64(cost_free_international_students),
            'cost_free_travel_ticket': np.int64(cost_free_travel_ticket), 'price_per_km': np.int64(price_per_km), 'fare_price': np.int64(fare_price)}
```

A.8. Capacity Calculations

Purpose: Evaluates capacity requirements over different time periods (peak and off-peak). It:

- Splits the daily demand into off-peak, peak AM, and peak PM.
- Adjusts demand based on a rush hour surcharge.
- Determines the overall shortage and additional trains needed.

Time Series Capacity Calculation

```python
def timeSeriesCapacity(self, price_per_km, daily_demand, capacity, capacity_2022, trains_2022, rush_hour_surcharge, peak_pm_demand_modifier, peak_am_demand_modifier, AverageKMperTrainTrip, fare_price):
    if fare_price <= 0:
        return capacity, 0, 0, 0, 0, 0
    if price_per_km <= 0:
        return capacity, 0, 0, 0, 0, 0

    rounds_per_day = 2  # at least there and back
    total_capacity = capacity * rounds_per_day
    capacity = total_capacity

    off_peak_demand = (1 - peak_pm_demand_modifier - peak_am_demand_modifier) * daily_demand
    peak_pm_demand = peak_pm_demand_modifier * daily_demand
    peak_am_demand = peak_am_demand_modifier * daily_demand

    rush_hour_price_per_km = max(price_per_km + rush_hour_surcharge, 0)
    price_change_percentage = (rush_hour_price_per_km - price_per_km) / price_per_km if price_per_km > 0 else rush_hour_surcharge
    demand_change_percentage_price = (self.treintarief_elasticity / 2) * price_change_percentage

    if rush_hour_surcharge == 0:
        demand_change_percentage_price = 0

    peak_pm_demand_modified = peak_pm_demand * max((1 + demand_change_percentage_price), 0)
    peak_am_demand_modified = peak_am_demand * max((1 + demand_change_percentage_price), 0)
    off_peak_demand_modified = off_peak_demand + ((peak_pm_demand - peak_pm_demand_modified) / 2) + ((peak_am_demand - peak_am_demand_modified) / 2)

    peak_am_demand = peak_am_demand_modified
    peak_pm_demand = peak_pm_demand_modified
    off_peak_demand = off_peak_demand_modified

    peak_demand = max(peak_am_demand, peak_pm_demand)
    shortage = max(peak_am_demand - capacity, 0) + max(peak_pm_demand - capacity, 0) if peak_demand > capacity else 0

    average_seats_per_train = math.ceil(capacity_2022 / trains_2022)
    additional_trains = math.ceil(shortage / (average_seats_per_train * rounds_per_day))

    surcharge_revenue = max((AverageKMperTrainTrip * rush_hour_surcharge) * (peak_pm_demand + peak_am_demand) * 365, 0)
    demand_change = max((daily_demand - peak_am_demand - peak_pm_demand - off_peak_demand) * -1, daily_demand * -1)
    revenue_change = min(fare_price * demand_change * 365, 0)

    return total_capacity, shortage, additional_trains, surcharge_revenue, demand_change, revenue_change
```

B
Model Convergence

To ensure robust optimization and reliable simulation outcomes, a systematic experimental setup was employed to determine the appropriate number of function evaluations (NFE), evaluate convergence, and calculate epsilon progress. This section details the procedures followed to establish convergence criteria, identify stopping points, and assess solution stability across different prediction years.

B.1. Optimization Setup and Convergence Detection

The optimization process was executed using the EMA Workbench framework, with the objective of identifying Pareto-efficient policies under deep uncertainty. For each prediction year (e.g., 2030, 2040, 2050, 2060, 2070), independent optimization runs were conducted. The key steps included:

1. **Function Evaluations:** Conduct multiple runs with an initial NFE of 100,000 per year, allowing the algorithm sufficient exploration space to identify promising solutions.
2. **Convergence Tracking:** Monitor the epsilon progress throughout the optimization, representing the improvement of Pareto solutions with increasing NFE.
3. **Archiving Results:** Store the results of each run, including the convergence metrics and Pareto-efficient solutions, in year-specific archive files.

B.2. Epsilon Progress and Convergence Criteria

To determine when the optimization had effectively converged, epsilon progress was analyzed by tracking changes in the objective space. The following approach was applied:

- **Epsilon Progress Calculation:** Epsilon progress was calculated as the cumulative improvement in Pareto efficiency across generations.
- **Threshold for Convergence:** Convergence was defined as the point where the absolute difference between consecutive epsilon progress values fell below a threshold of 0.01 for at least five consecutive evaluations.
- **Approximate Convergence Point:** The NFE corresponding to the first instance of the epsilon difference falling below the threshold was identified as the approximate convergence point.

Table B.1: Epsilon Values by Year for Each Outcome - Balanced Formulation

Year	demand	revenue	shortage	CO_2_reduction	net_CO_2_emissions	cost_free_travel_ticket
2024	1.325983	1.696662	1.186243	1.324434	1.324439	1.716443
2030	1.332262	1.704278	1.216093	1.326225	1.326216	1.729970
2040	1.348794	1.716169	1.269668	1.337543	1.337537	1.741817
2050	1.359177	1.727180	1.282916	1.343287	1.343288	1.752456
2060	1.367632	1.738835	1.298871	1.347379	1.347378	1.759514
2070	1.376251	1.748284	1.302992	1.350707	1.350704	1.767991

Table B.2: Epsilon Values by Year for Each Outcome - Unrestrained Balanced Filter

Year	demand	revenue	CO_2_reduction	net_CO_2_emissions	cost_free_travel_ticket
2024	1.329364	1.695990	1.327382	1.327372	1.721138
2030	1.334049	1.704806	1.328487	1.328494	1.724923
2040	1.345308	1.715687	1.334960	1.334950	1.739897
2050	1.354702	1.726309	1.338556	1.338550	1.752331
2060	1.367363	1.738973	1.346777	1.346780	1.757656
2070	1.376773	1.748506	1.352216	1.352209	1.771621

Table B.3: Epsilon Values by Year for Each Outcome - Max Revenue Scenario

Year	revenue	shortage	cost_free_international_students
2024	1.696368	1.199781	1.265859
2030	1.704591	1.222506	1.276671
2040	1.715890	1.246973	1.288115
2050	1.727935	1.280161	1.299376
2060	1.738009	1.305423	1.307754
2070	1.748241	1.302933	1.314948

Table B.4: Epsilon Values by Year for Each Outcome - Max Demand Scenario

Year	demand	shortage
2024	1.324639	1.205107
2030	1.332876	1.209795
2040	1.345288	1.236076
2050	1.355113	1.267001
2060	1.363828	1.288961
2070	1.376868	1.301529

B.3. Convergence Visualization and Interpretation

For each prediction year, convergence plots were generated to visualize the relationship between NFE and epsilon progress. The plots included:

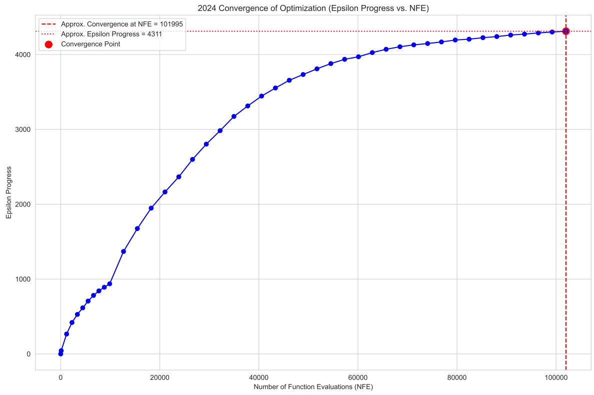
- **Epsilon Progress vs. NFE:** This plot displayed the overall convergence trajectory, with a red vertical line indicating the approximate convergence point and a green horizontal line showing the corresponding epsilon value.

- **Epsilon Difference vs. NFE:** This plot highlighted the change in epsilon progress between consecutive evaluations, with a dashed red line representing the convergence threshold.

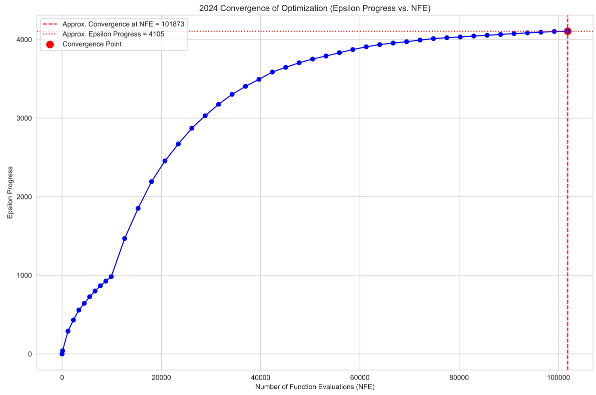
These visualizations allowed for a clear assessment of whether the optimization had plateaued, suggesting that further evaluations were unlikely to yield significant improvement.

2024 Convergence and Epsilon Difference

Convergence of Optimization



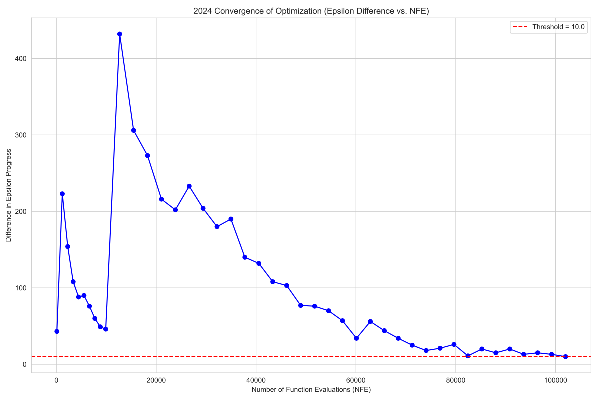
(a) 2024 Balanced Formulation



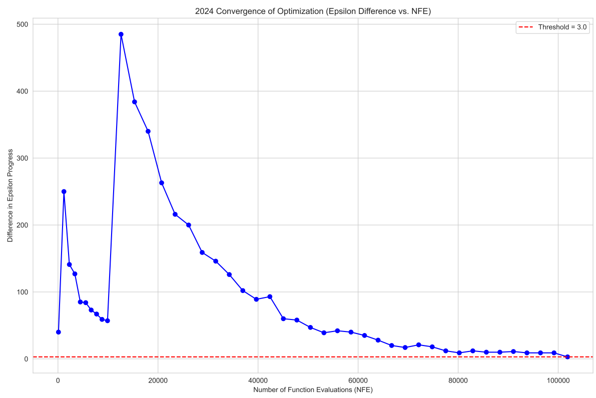
(b) 2024 Unrestrained Balanced Filter

Figure B.1: 2024 convergence across scenarios

Epsilon Difference



(a) 2024 Balanced Formulation

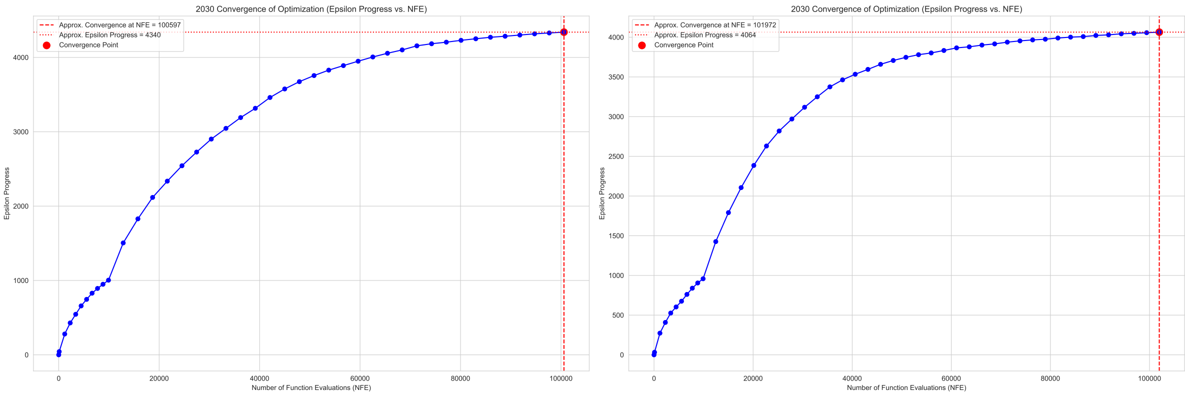


(b) 2024 Unrestrained Balanced Filter

Figure B.2: 2024 epsilon difference across scenarios

2030 Convergence and Epsilon Difference

Convergence of Optimization

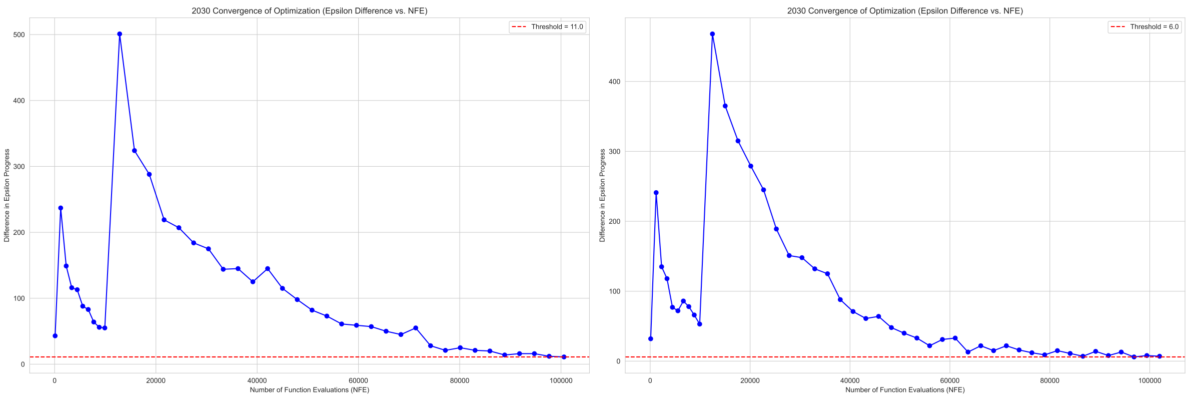


(a) 2030 Balanced Formulation

(b) 2030 Unrestrained Balanced Filter

Figure B.3: 2030 convergence across scenarios

Epsilon Difference



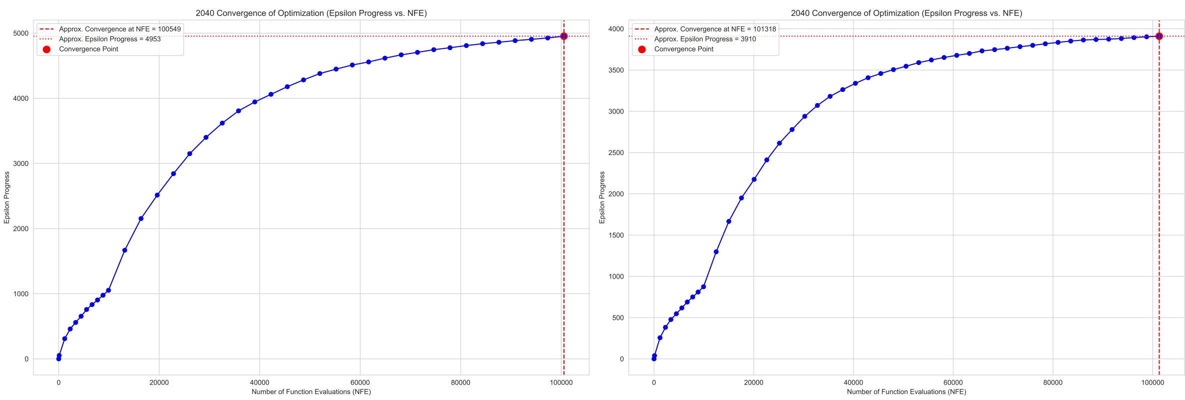
(a) 2030 Balanced Formulation

(b) 2030 Unrestrained Balanced Filter

Figure B.4: 2030 epsilon difference across scenarios

2040 Convergence and Epsilon Difference

Convergence of Optimization

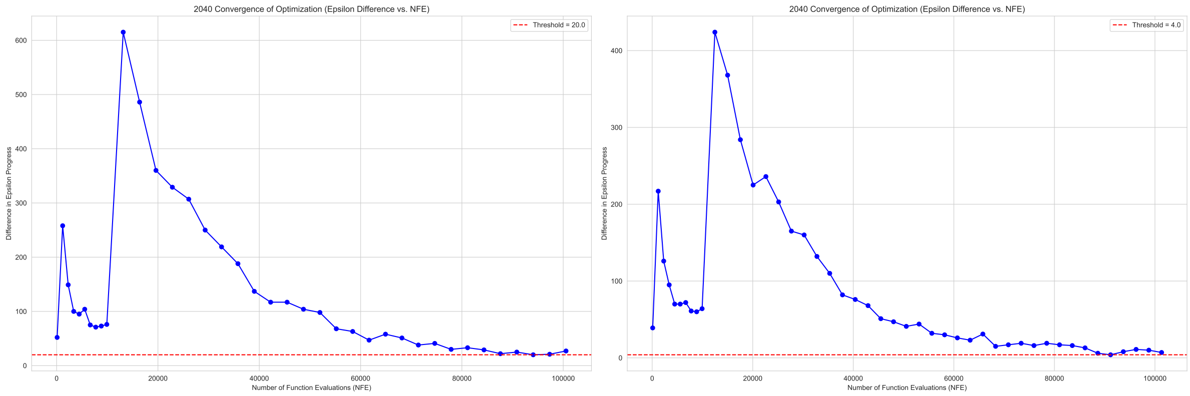


(a) 2040 Balanced Formulation

(b) 2040 Unrestrained Balanced Filter

Figure B.5: 2040 convergence across scenarios

Epsilon Difference

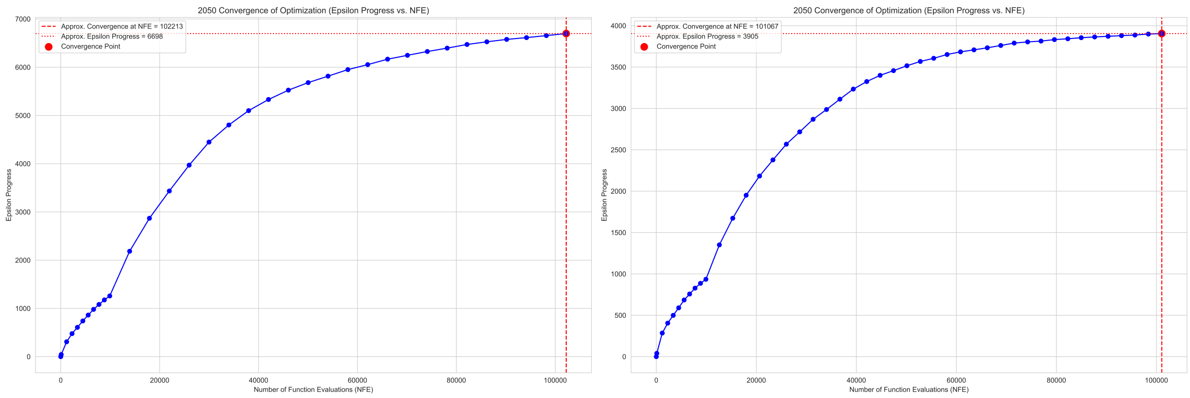


(a) 2040 Balanced Formulation (b) 2040 Unrestrained Balanced Filter

Figure B.6: 2040 epsilon difference across scenarios

2050 Convergence and Epsilon Difference

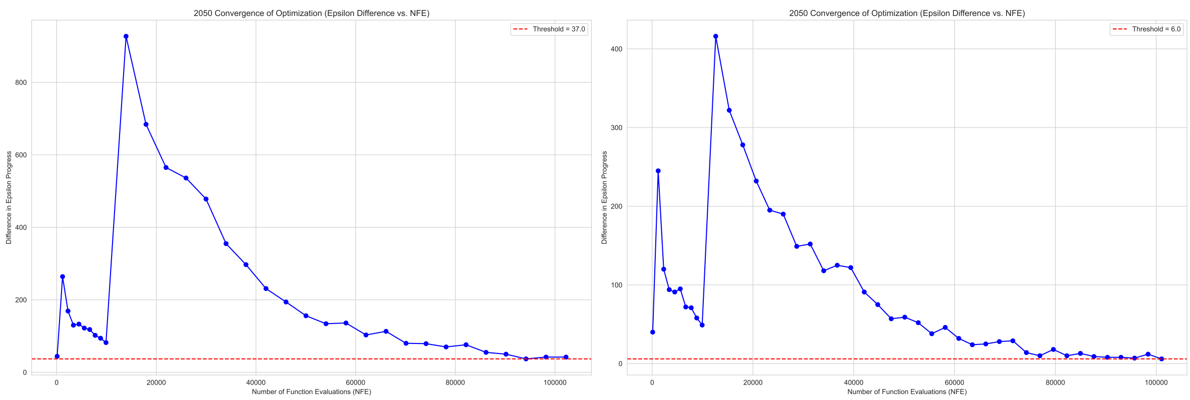
Convergence of Optimization



(a) 2050 Balanced Formulation (b) 2050 Unrestrained Balanced Filter

Figure B.7: 2050 convergence across scenarios

Epsilon Difference

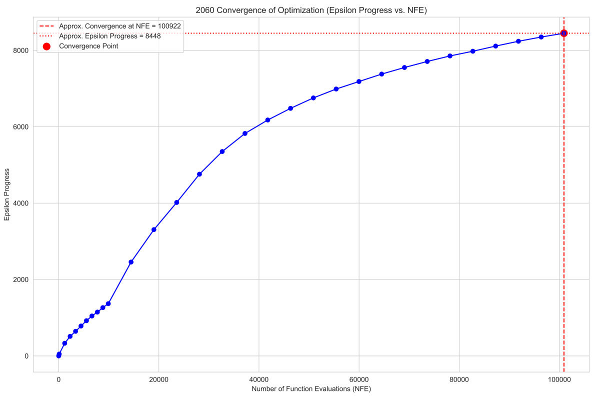


(a) 2050 Balanced Formulation (b) 2050 Unrestrained Balanced Filter

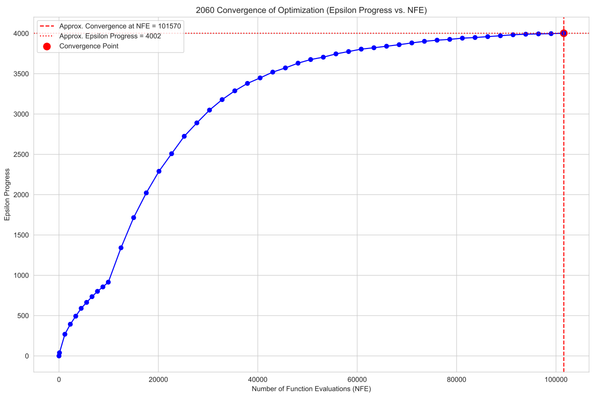
Figure B.8: 2050 epsilon difference across scenarios

2060 Convergence and Epsilon Difference

Convergence of Optimization



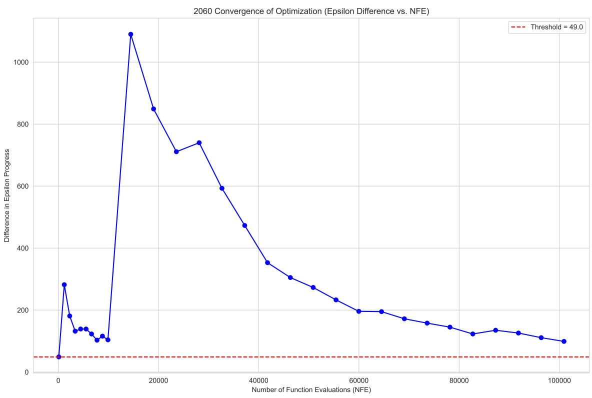
(a) 2060 Balanced Formulation



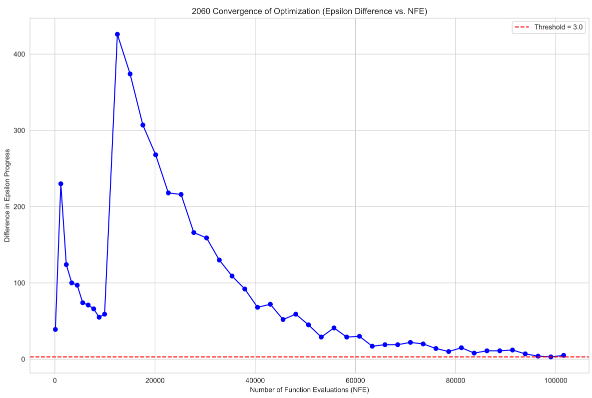
(b) 2060 Unrestrained Balanced Filter

Figure B.9: 2060 convergence across scenarios

Epsilon Difference



(a) 2060 Balanced Formulation

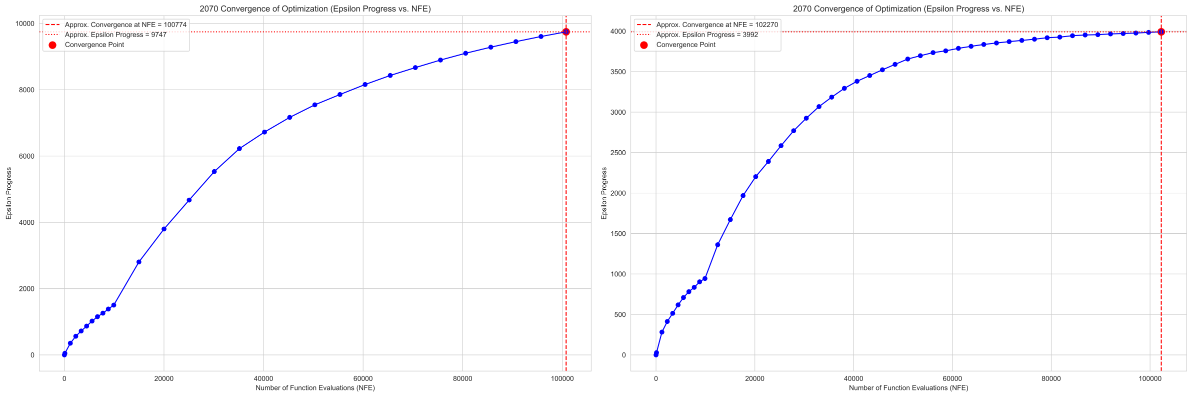


(b) 2060 Unrestrained Balanced Filter

Figure B.10: 2060 epsilon difference across scenarios

2070 Convergence and Epsilon Difference

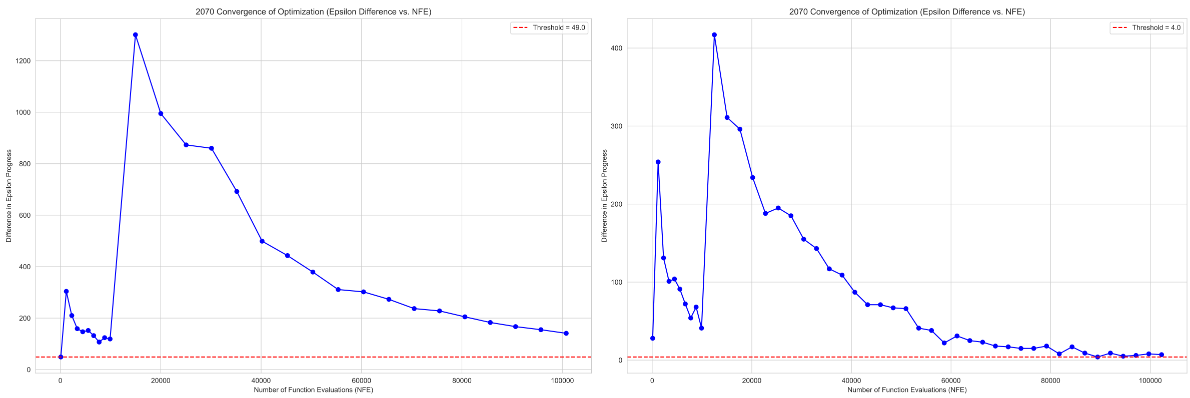
Convergence of Optimization



(a) 2070 Balanced Formulation (b) 2070 Unrestrained Balanced Filter

Figure B.11: 2070 convergence across scenarios

Epsilon Difference



(a) 2070 Balanced Formulation (b) 2070 Unrestrained Balanced Filter

Figure B.12: 2070 epsilon difference across scenarios

Dynamic NFE Adjustment

Based on the convergence analysis, the following dynamic approach was adopted for adjusting NFEs:

- **Early Convergence:** For earlier years, convergence was achieved before the maximum NFE (e.g., 2030 and 2040).
- **Extended Runs:** For higher prediction years (e.g., 2060 and 2070), convergence was slower and additional evaluations were considered, extending the NFE if the epsilon difference remained above the threshold.

This adaptive strategy ensured computational efficiency while maintaining solution robustness.

C
Scenario Discovery

This chapter explores the conditions under which rail policy strategies succeed or fail by applying formal scenario discovery techniques to the model ensemble. While previous sections evaluated outcomes across the entire policy space, the focus here is narrower: identifying the specific combinations of levers and external uncertainties that reliably lead to successful outcomes—defined as achieving both high ridership and high revenue.

Two complementary methods are used:

- **Patient Rule Induction Method (PRIM)** — A clustering algorithm that identifies bounded regions in the input space with a high density of successful cases. This method is used to highlight "boxes" of plausible futures in which certain policies consistently perform well.
- **Classification and Regression Trees (CART)** — A decision-tree approach that derives interpretable rules to classify scenarios as successes or failures based on input thresholds. This method helps surface critical tipping points in both policy and contextual conditions.

The results from these tools are reported separately for the Balanced and Unrestrained Balanced Filters, across each major planning horizon (2024, 2030, 2040, 2050, 2060, and 2070). Each section includes visualizations of the PRIM coverage-density trade-off, the conditions defining successful regions, and the CART classification tree for that year and scenario.

Together, these analyses provide insight into the deeper structure of the outcome space. Rather than evaluating policies in isolation, scenario discovery allows us to map success to specific environments—identifying when, and under what external conditions, certain strategies can be expected to thrive.

2024 Balanced Formulation

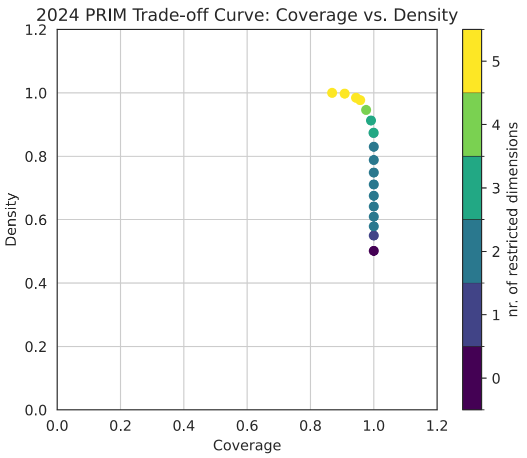


Figure C.1: 2024 PRIM trade-off: coverage vs. density - Balanced Formulation

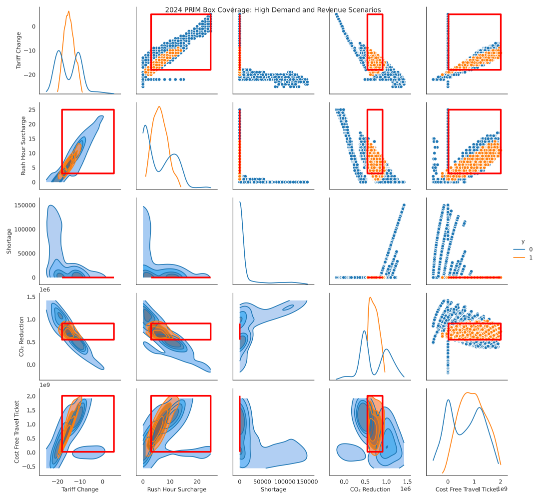


Figure C.2: 2024 Conditions defining a high-performance region (PRIM box) - Balanced Formulation

Figure C.3: Results of PRIM scenario discovery for 2024 high-demand, high-revenue outcomes. (a) Coverage-density trade-off curve: as the PRIM box grows to cover more successful scenarios, its purity (fraction of successes) declines. (b) One example of a PRIM-derived scenario "box" (range of uncertain factors and lever settings) that yields predominantly high-demand, high-revenue outcomes.

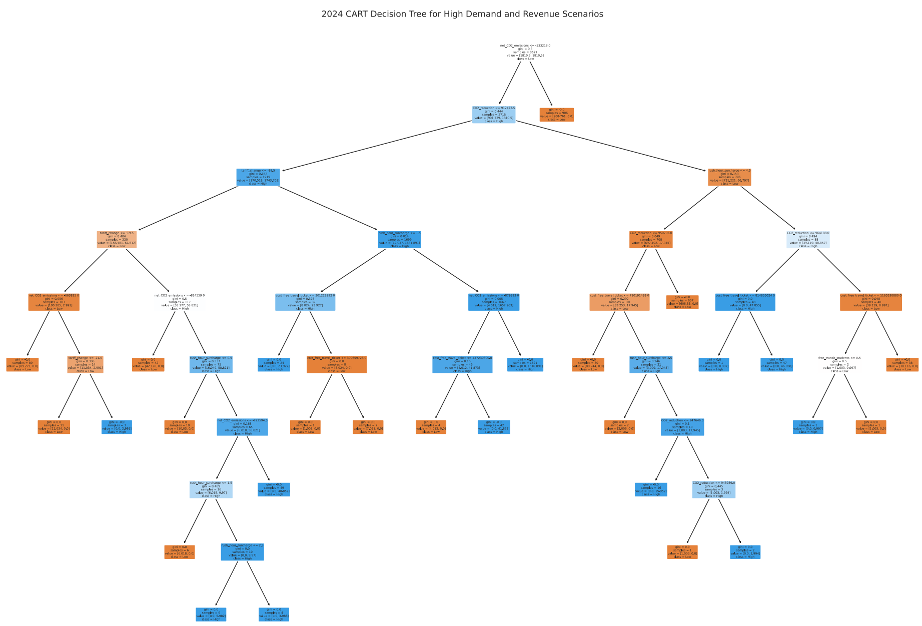


Figure C.4: Decision tree (CART) for classifying 2024 scenarios as high-demand/high-revenue successes or not. Each branch split is based on a threshold of a key input (policy or uncertainty). The terminal leaves indicate whether the condition combination leads to success (both objectives met) or failure. The top splits in the tree highlight the most influential factors (e.g., the implementation of a major fare policy, and the level of exogenous demand growth).

2024 Unrestrained Balanced Filter

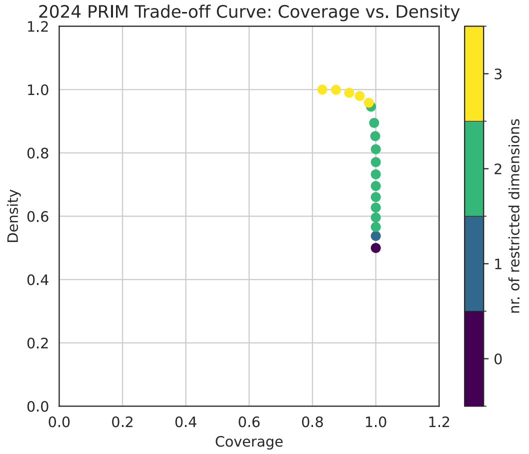


Figure C.5: 2024 PRIM trade-off: coverage vs. density - Unrestrained Balanced Filter

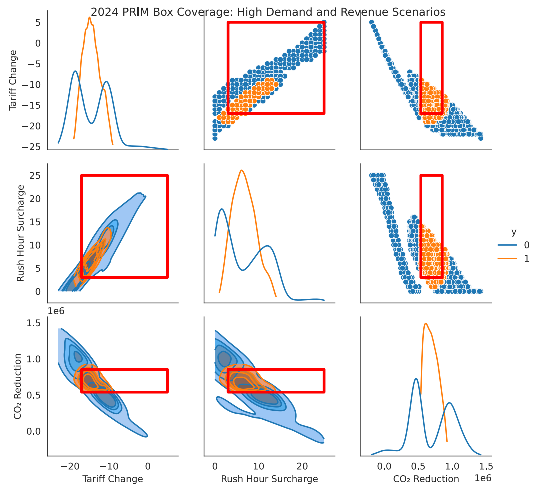


Figure C.6: 2024 Conditions defining a high-performance region (PRIM box) - Unrestrained Balanced Filter

Figure C.7: Results of PRIM scenario discovery for 2024 high-demand, high-revenue outcomes. (a) Coverage-density trade-off curve: as the PRIM box grows to cover more successful scenarios, its purity (fraction of successes) declines. (b) One example of a PRIM-derived scenario "box" (range of uncertain factors and lever settings) that yields predominantly high-demand, high-revenue outcomes.

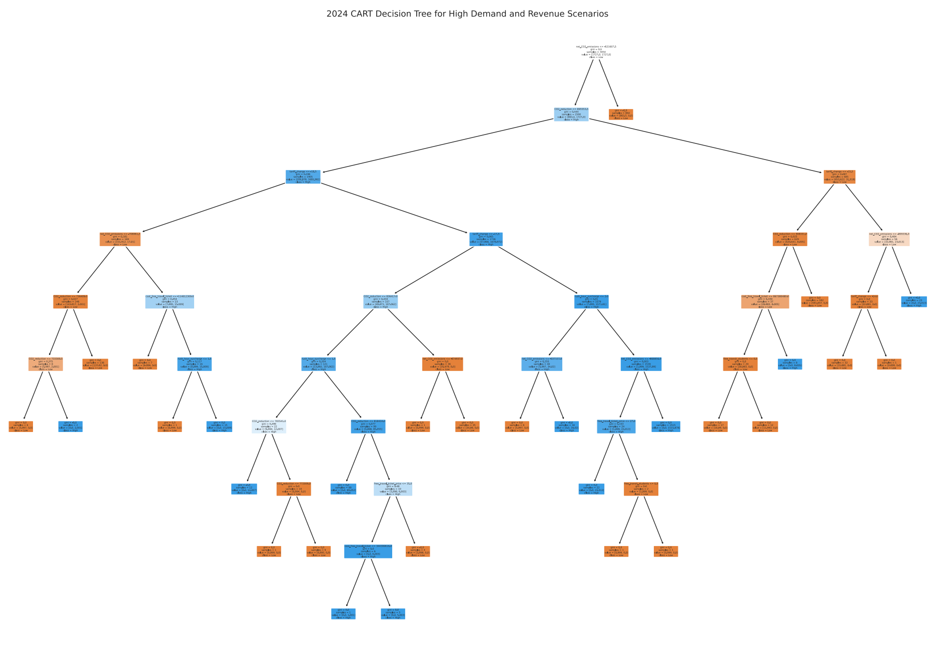


Figure C.8: Decision tree (CART) for classifying 2024 scenarios as high-demand/high-revenue successes or not. Each branch split is based on a threshold of a key input (policy or uncertainty). The terminal leaves indicate whether the condition combination leads to success (both objectives met) or failure. The top splits in the tree highlight the most influential factors (e.g., the implementation of a major fare policy, and the level of exogenous demand growth).

2030 Balanced Formulation

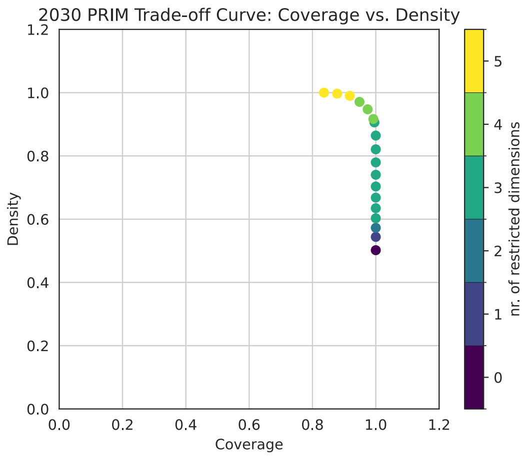


Figure C.9: 2030 PRIM trade-off: coverage vs. density - Balanced Formulation

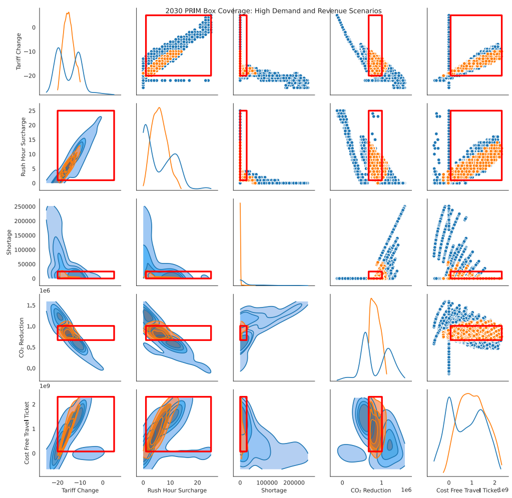


Figure C.10: 2030 Conditions defining a high-performance region (PRIM box) - Balanced Formulation

Figure C.11: PRIM results for 2030: trade-off between box coverage and purity, and example box defining a high-performance region for demand and revenue.

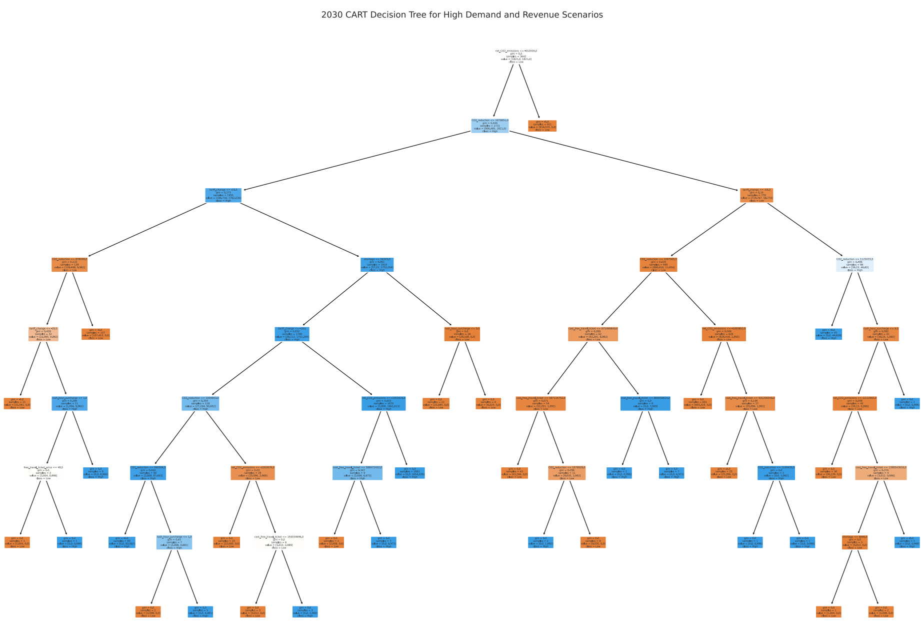


Figure C.12: CART tree for 2030 showing decision rules and key variables for high-demand and high-revenue outcomes in the Balanced Formulation.

2030 Unrestrained Balanced Filter

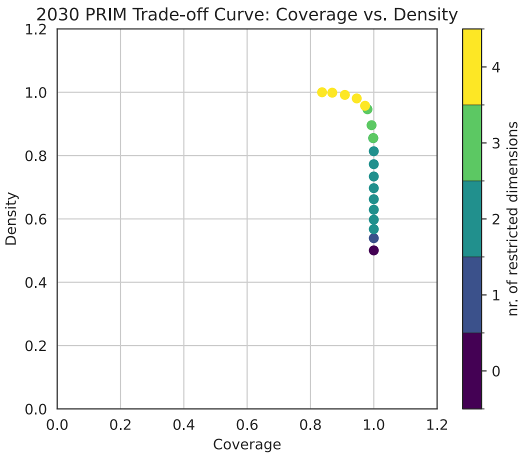


Figure C.13: 2030 PRIM trade-off: coverage vs. density - Unrestrained Balanced Filter

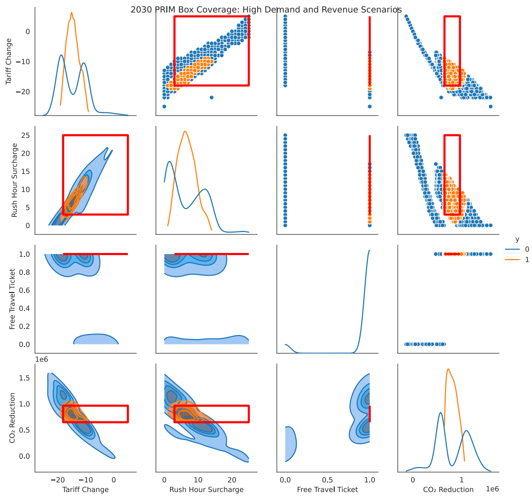


Figure C.14: 2030 Conditions defining a high-performance region (PRIM box) - Unrestrained Balanced Filter

Figure C.15: PRIM analysis for 2030 in the No Shortage scenario: coverage-density trade-off and scenario conditions leading to strong performance.

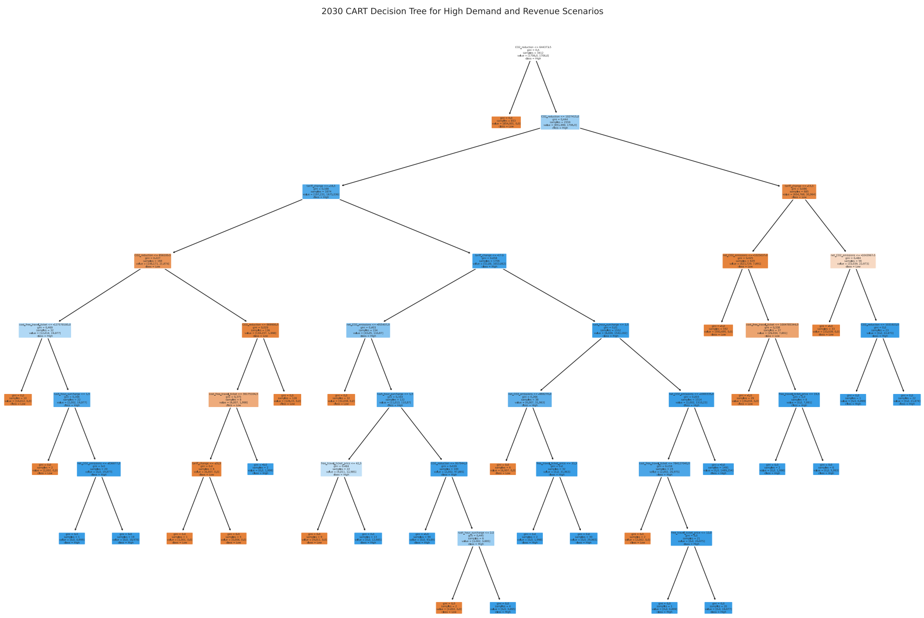


Figure C.16: CART output for 2030 under the Unrestrained Balanced Filter. The tree illustrates key threshold splits leading to successful outcomes.

2040 Balanced Formulation

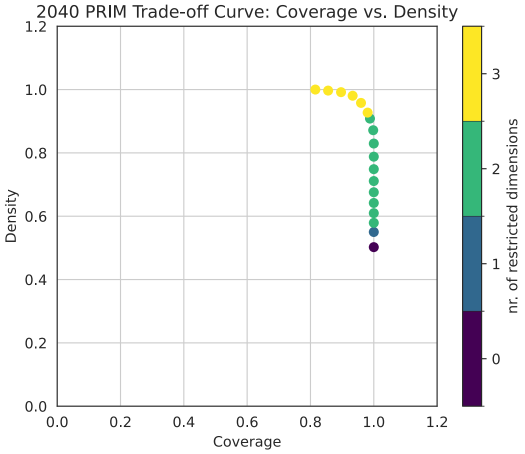


Figure C.17: 2040 PRIM trade-off: coverage vs. density - Balanced Formulation

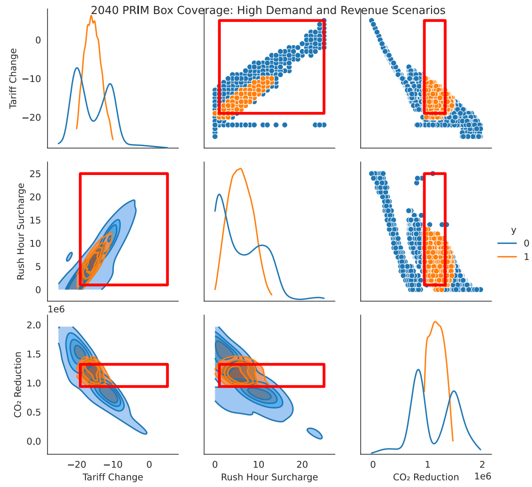


Figure C.18: 2040 Conditions defining a high-performance region (PRIM box) - Balanced Formulation

Figure C.19: PRIM results for 2040: trade-off between box coverage and density, and a PRIM box representing successful outcome conditions.

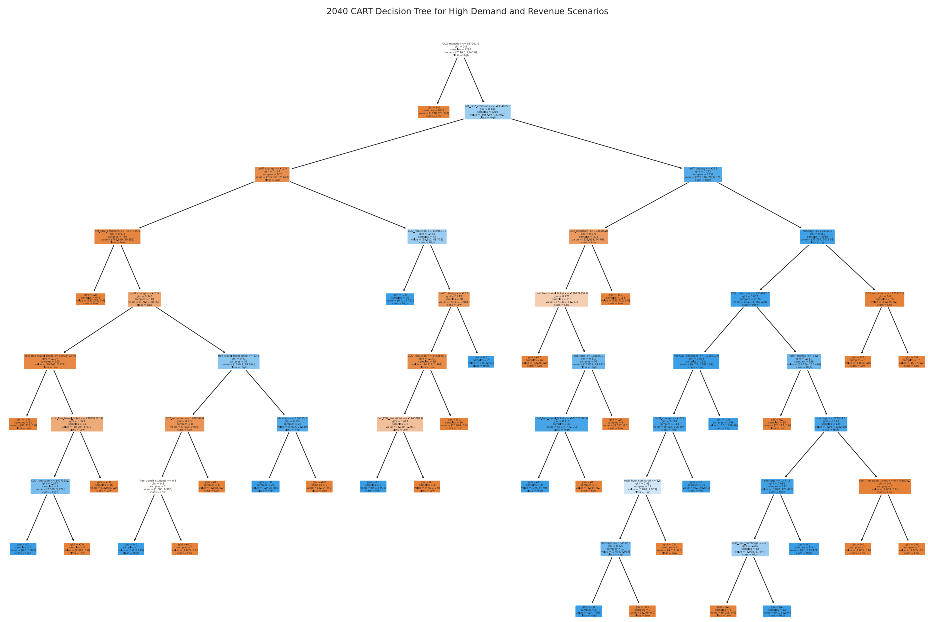


Figure C.20: CART decision tree for classifying high-performance outcomes in 2040 under the Balanced Formulation.

2040 Unrestrained Balanced Filter

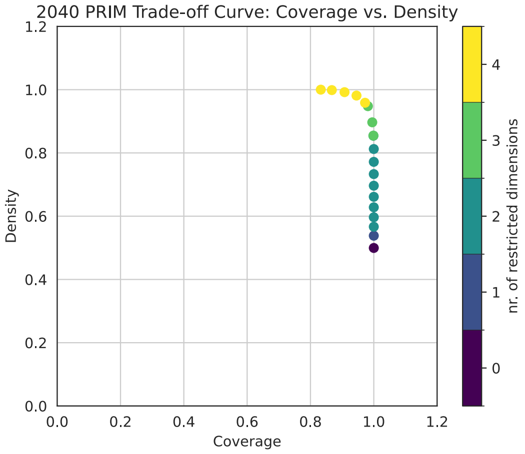


Figure C.21: 2040 PRIM trade-off: coverage vs. density - Unrestrained Balanced Filter

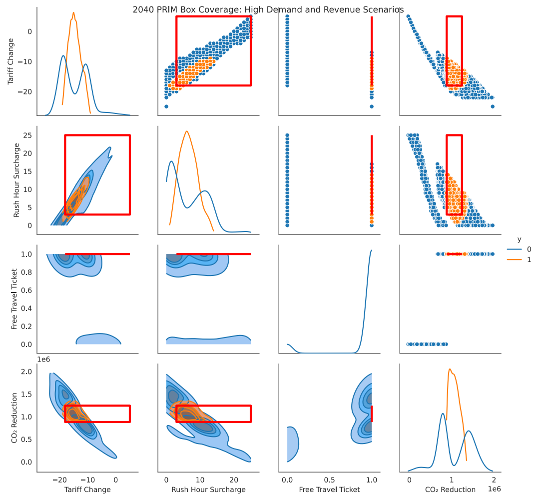


Figure C.22: 2040 Conditions defining a high-performance region (PRIM box) - Unrestrained Balanced Filter

Figure C.23: PRIM scenario discovery results for 2040 under No Shortage.

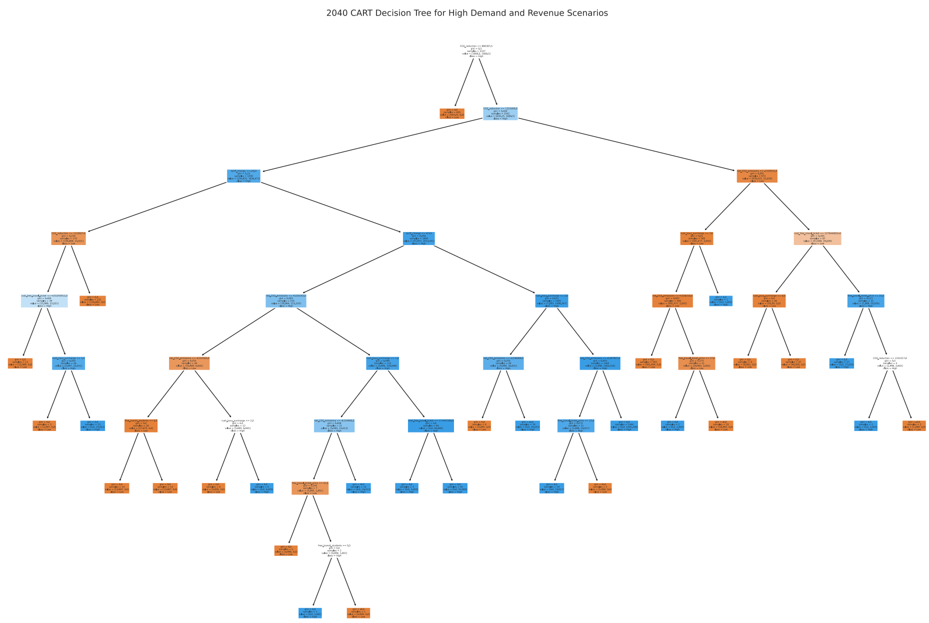


Figure C.24: CART classification tree for successful scenarios in 2040 under the Unrestrained Balanced Filter.

2050 Balanced Formulation

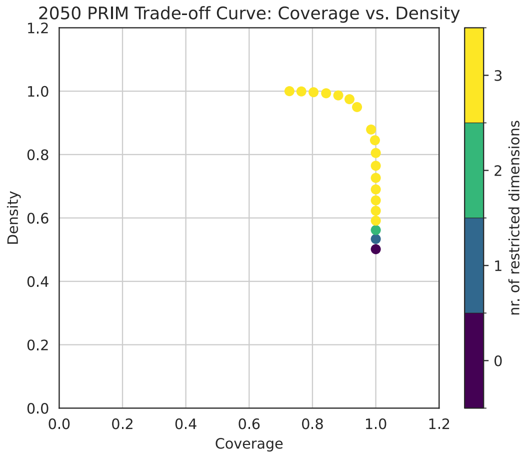


Figure C.25: 2050 PRIM trade-off: coverage vs. density - Balanced Formulation

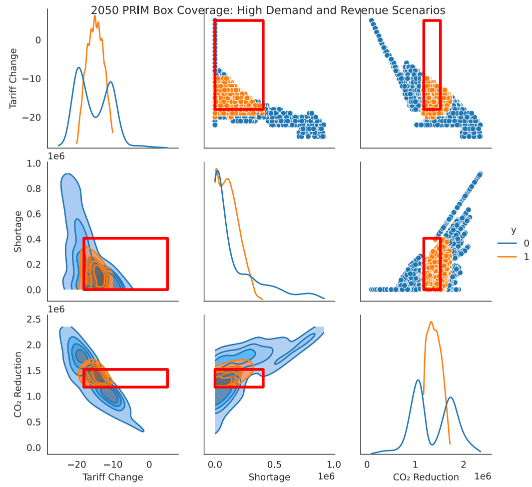


Figure C.26: 2050 Conditions defining a high-performance region (PRIM box) - Balanced Formulation

Figure C.27: PRIM results for 2050 under capacity-constrained conditions.

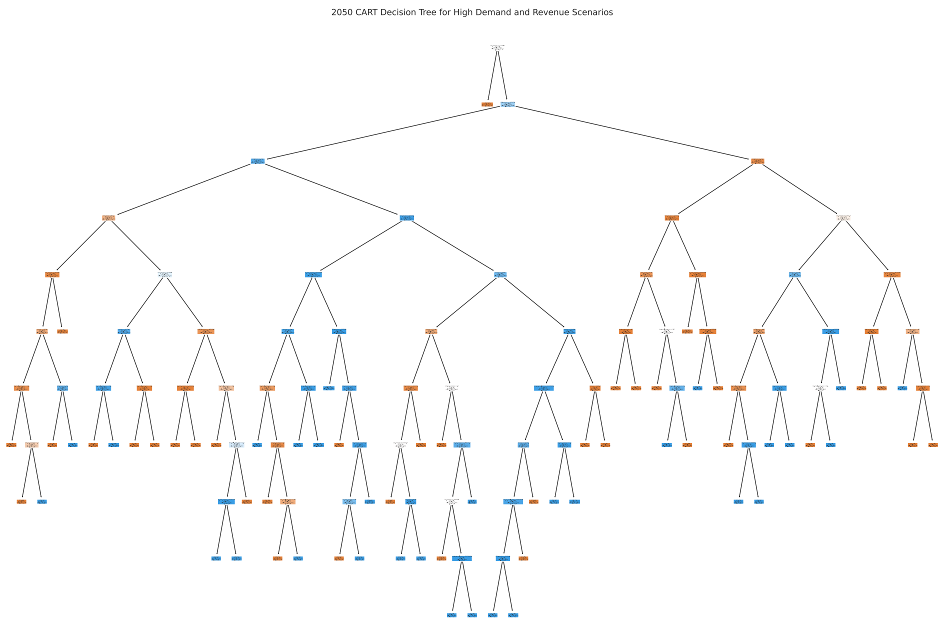


Figure C.28: CART tree showing classification paths for high-performing policies in the 2050 Balanced Formulation.

2050 Unrestrained Balanced Filter

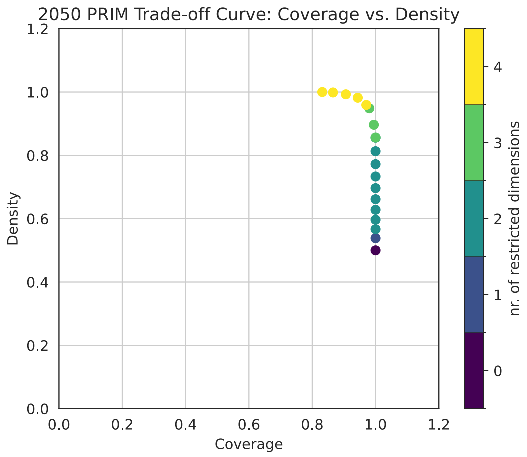


Figure C.29: 2050 PRIM trade-off: coverage vs. density - Unrestrained Balanced Filter

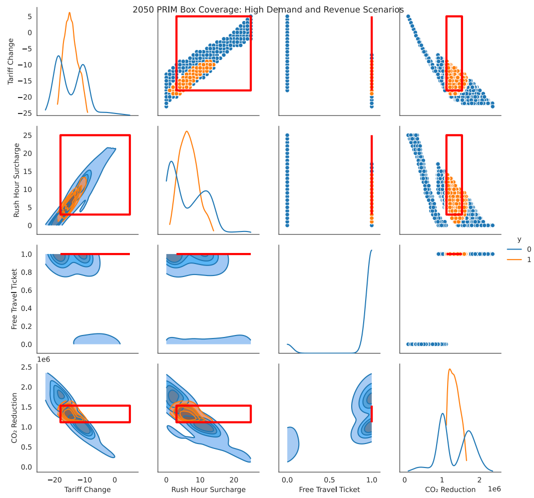


Figure C.30: 2050 Conditions defining a high-performance region (PRIM box) - Unrestrained Balanced Filter

Figure C.31: PRIM trade-offs and high-performance regions identified in the 2050 No Shortage scenario.

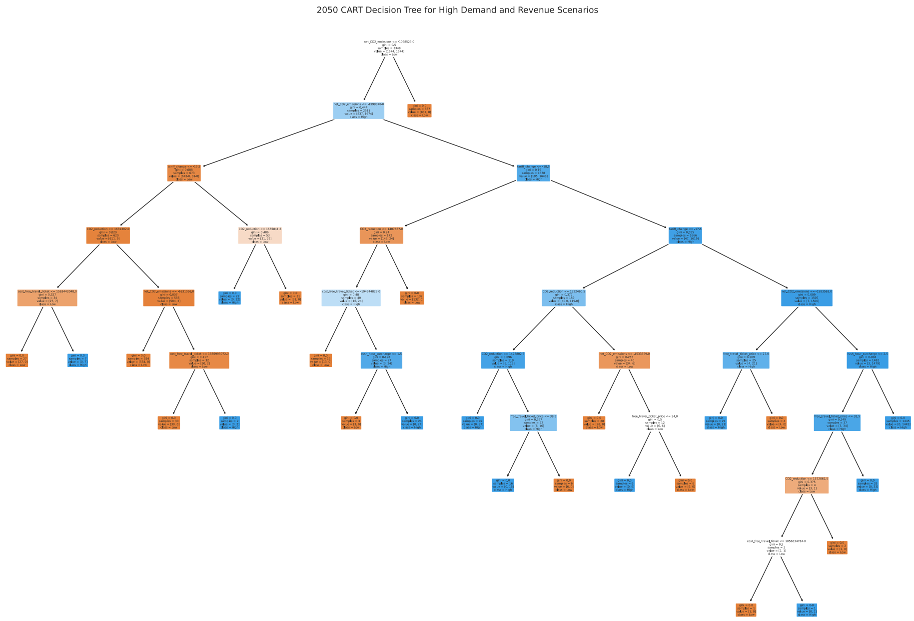


Figure C.32: CART model for outcome classification under the Unrestrained 2050 scenario.

2060 Balanced Formulation

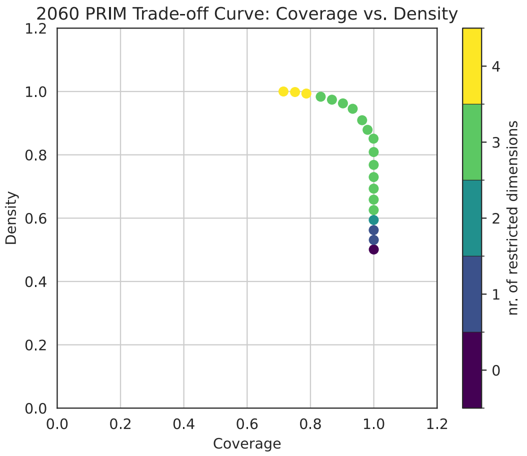


Figure C.33: 2060 PRIM trade-off: coverage vs. density - Balanced Formulation

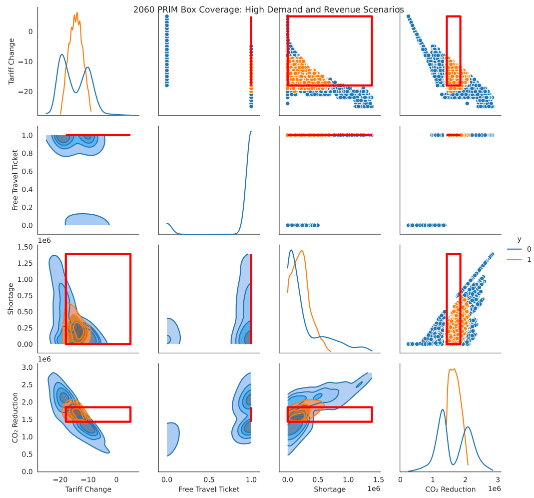


Figure C.34: 2060 Conditions defining a high-performance region (PRIM box) - Balanced Formulation

Figure C.35: PRIM analysis for identifying robust scenario configurations in 2060.

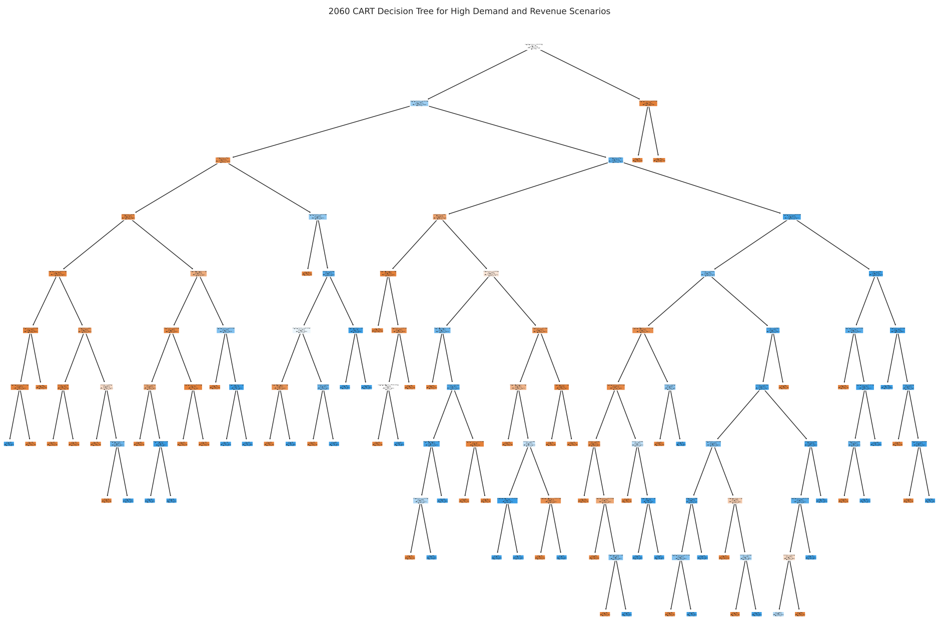


Figure C.36: CART output for 2060 showing key splits and outcome success conditions.

2060 Unrestrained Balanced Filter

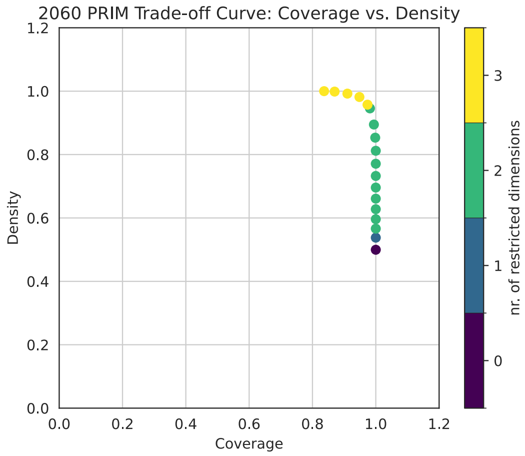


Figure C.37: 2060 PRIM trade-off: coverage vs. density - Unrestrained Balanced Filter

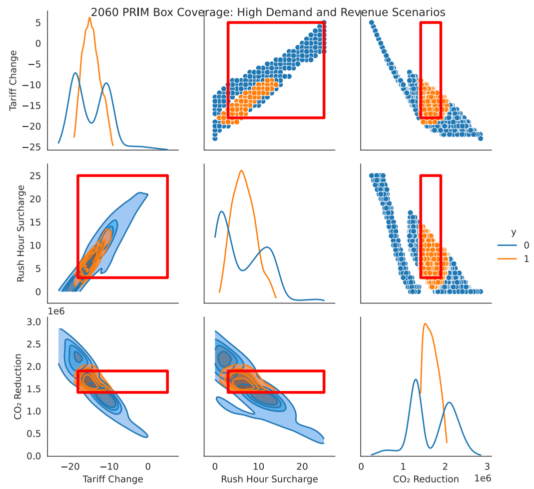


Figure C.38: 2060 Conditions defining a high-performance region (PRIM box) - Unrestrained Balanced Filter

Figure C.39: PRIM results for 2060 without capacity constraints.

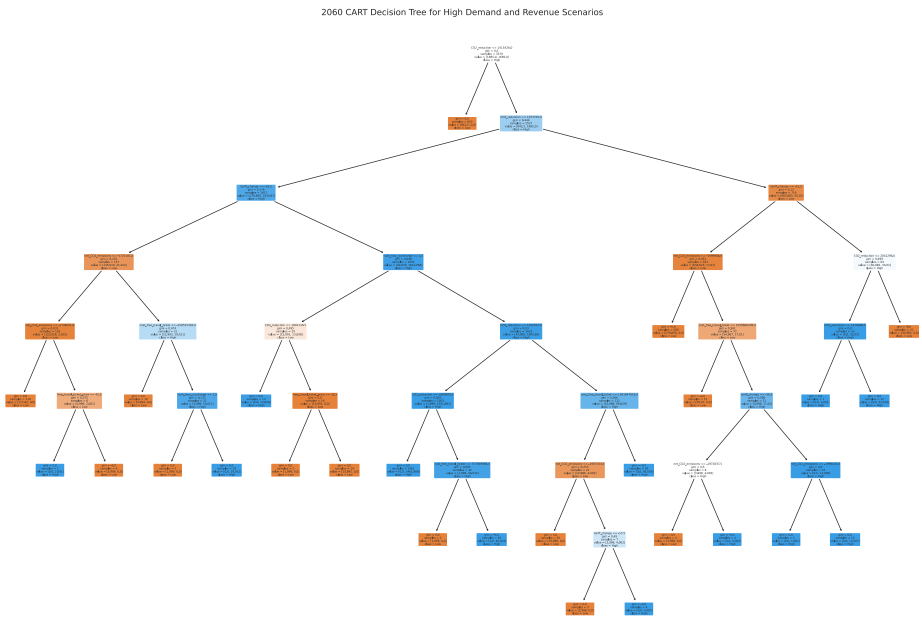


Figure C.40: CART classifier for 2060 No Shortage scenario outcomes.

2070 Balanced Formulation

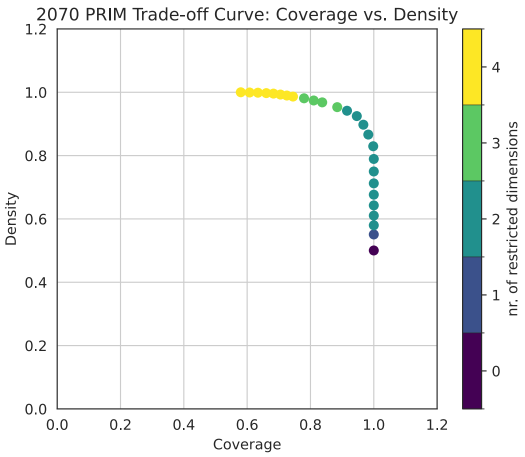


Figure C.41: 2070 PRIM trade-off: coverage vs. density - Balanced Formulation

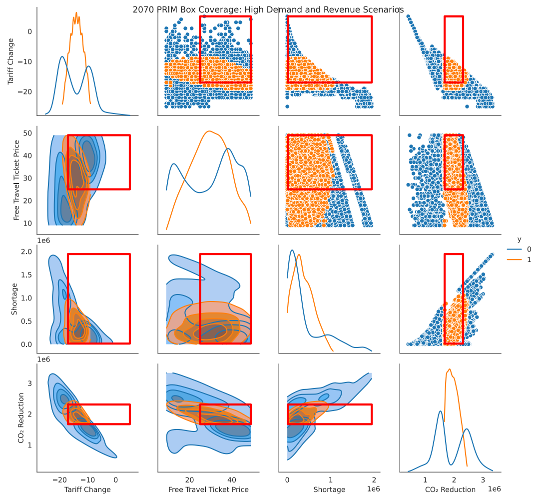


Figure C.42: 2070 Conditions defining a high-performance region (PRIM box) - Balanced Formulation

Figure C.43: PRIM trade-offs and success configurations identified in the 2070 Balanced Formulation.

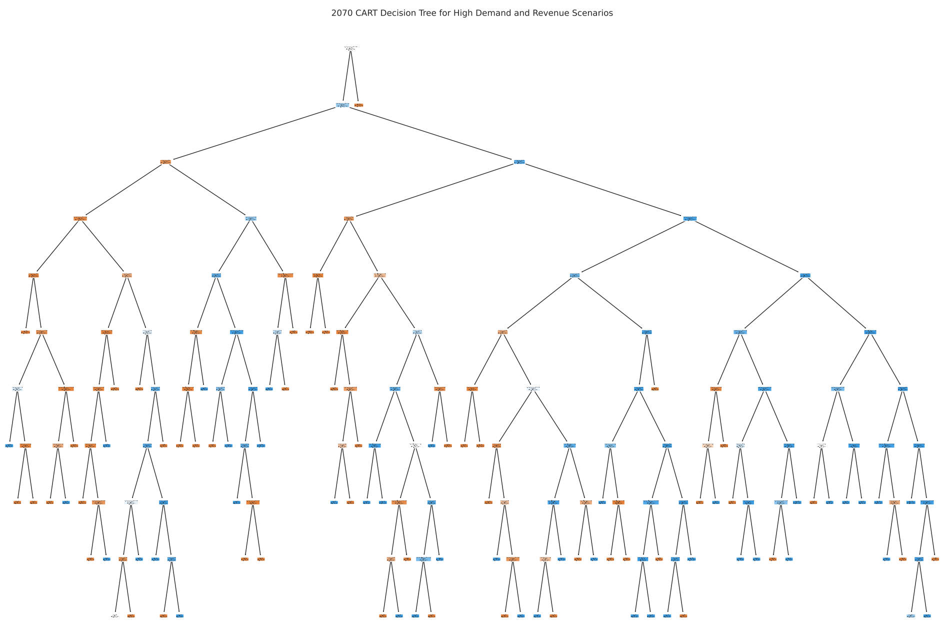


Figure C.44: CART classification structure for 2070 Balanced Formulation outcomes.

2070 Unrestrained Balanced Filter

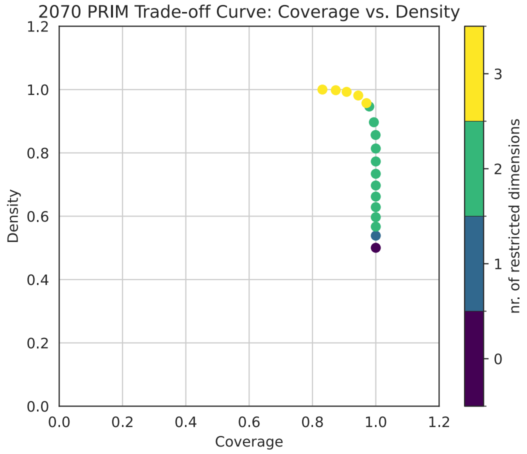


Figure C.45: 2070 PRIM trade-off: coverage vs. density - Unrestrained Balanced Filter

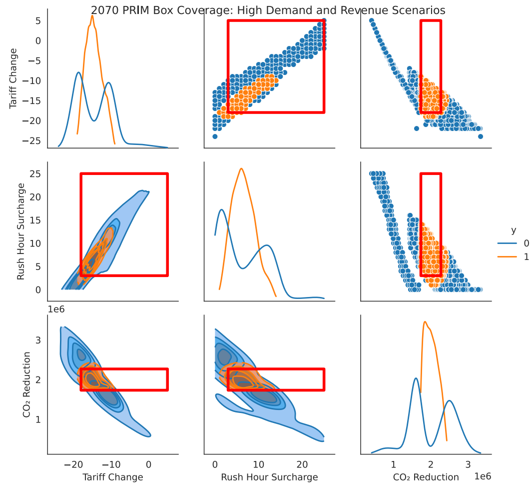


Figure C.46: 2070 Conditions defining a high-performance region (PRIM box) - Unrestrained Balanced Filter

Figure C.47: PRIM results for 2070 high-performing scenarios without capacity constraints.

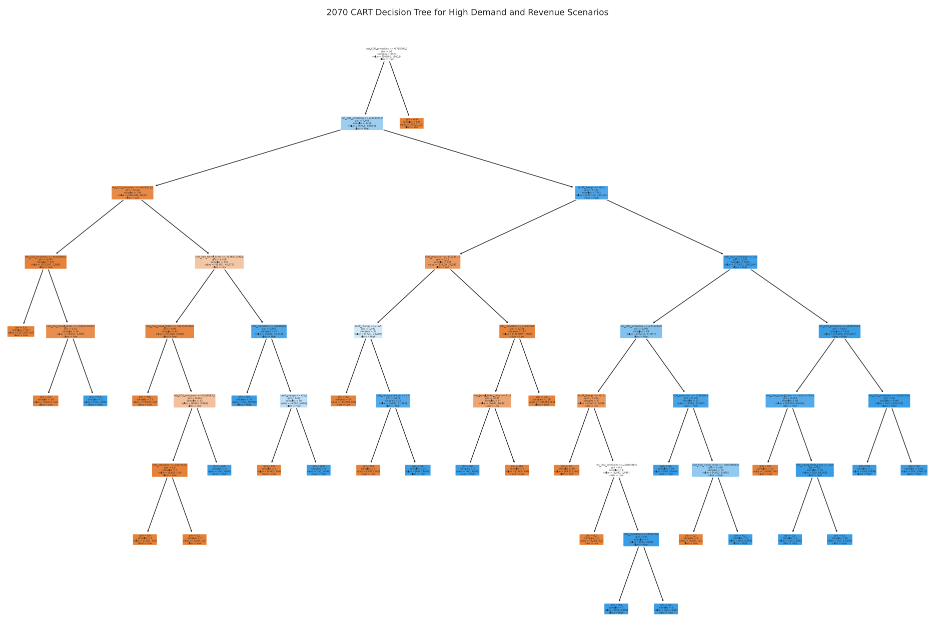


Figure C.48: CART analysis of success drivers in 2070 under the Unrestrained Balanced Filter.

D

Sensitivity Analysis and Feature Importance

This appendix presents a detailed examination of how individual policy levers and contextual uncertainties influence model outcomes across multiple time horizons. While the main chapters focused on trade-offs and scenario typologies, this section complements those insights by dissecting the marginal and global influence of each model input.

Three types of diagnostic analyses are provided for both the Balanced Scenario and Unrestrained Balanced Filter across the years 2024, 2030, 2040, 2050, 2060, and 2070:

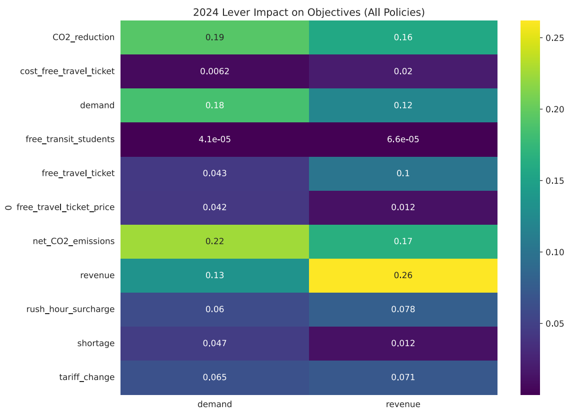
- **One-at-a-time Sensitivity Analysis** — Measures the change in demand when each policy lever is set to its extreme value, holding other inputs constant. This reveals which levers individually have the strongest effect on ridership.
- **Lever Impact Across All Policies** — Assesses each lever's overall influence across the entire simulation ensemble, reflecting both direct and interaction effects.
- **Feature Importance Rankings** — Uses a machine learning classifier to quantify which variables are most predictive of policy success, defined here as achieving both high rail demand and high revenue.

By triangulating across these methods, the analysis identifies levers that are consistently influential, as well as those that matter only under certain conditions. This can help decision-makers prioritize which levers warrant attention in strategic planning and where to expect diminishing returns.

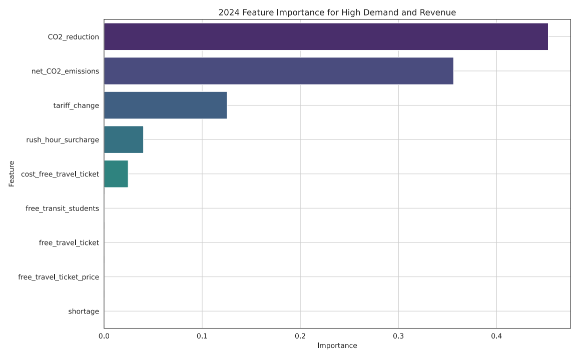
The figures that follow are grouped by year and scenario for ease of comparison.

Input Influence Analysis – 2024 Balanced Scenario

Figure D.1: One-at-a-time sensitivity of levers in 2024 Balanced Scenario.



(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.2: Lever-level influence and key predictors for high-demand/high-revenue outcomes in 2024 Balanced Scenario.

Input Influence Analysis – 2024 Unrestrained Balanced Filter

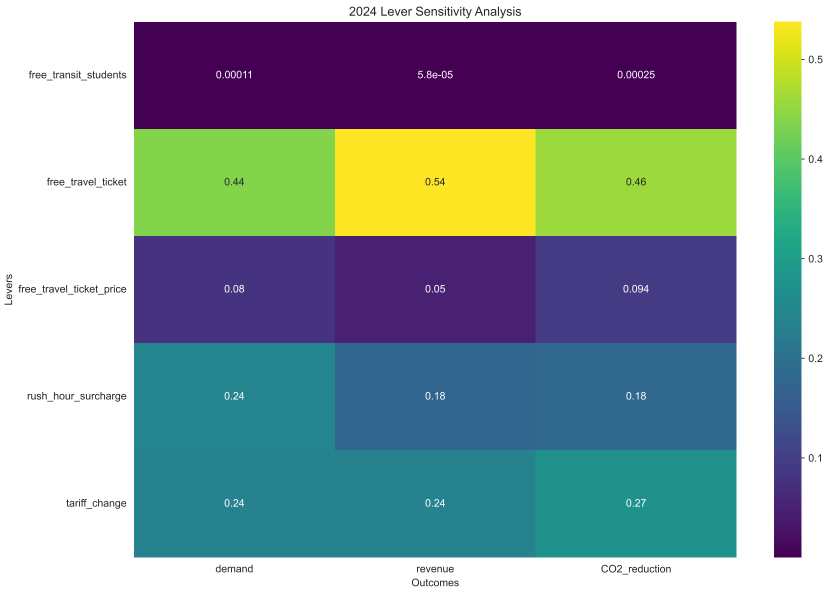
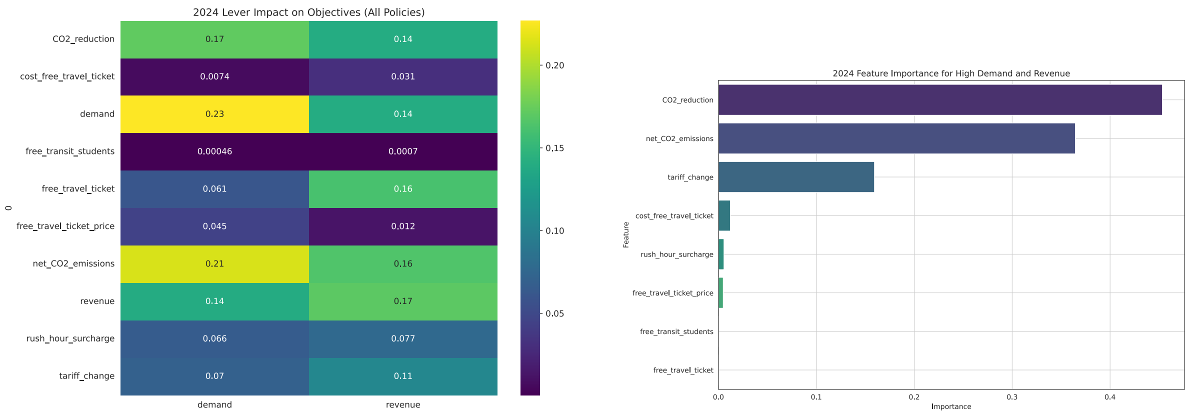


Figure D.3: Sensitivity of levers in the 2024 Unrestrained Balanced Filter.



(a) Lever impact across all policies.

(b) Feature importance for scenario success.

Figure D.4: Influence and predictiveness of inputs in 2024 Unrestrained Scenario.

Input Influence Analysis – 2024 Max Revenue Scenario

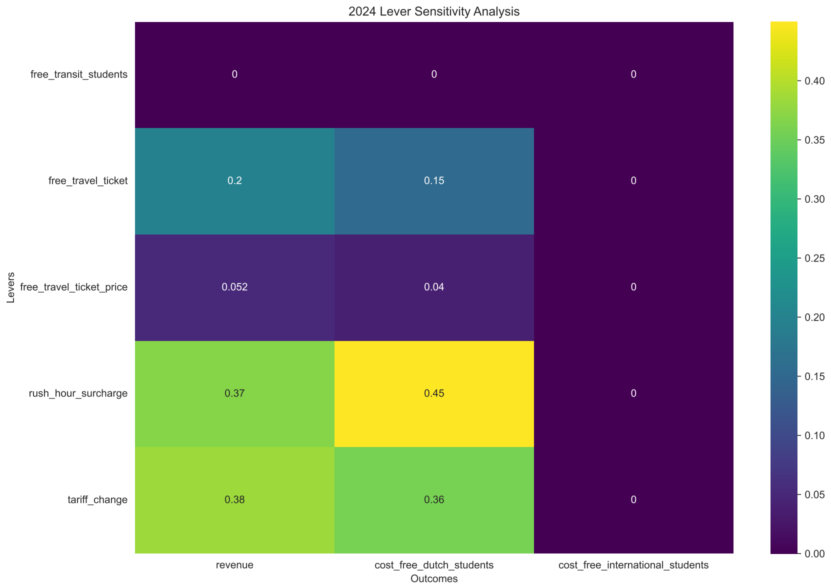
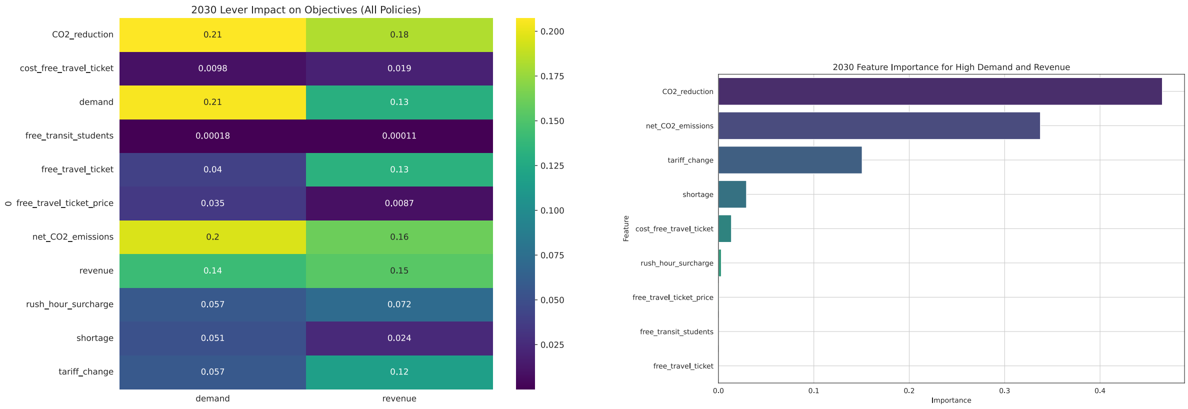


Figure D.5: One-at-a-time sensitivity of levers in 2024 Max Revenue Scenario.

Input Influence Analysis – 2030 Balanced Scenario

Figure D.6: One-at-a-time lever sensitivity in 2030 for the Balanced Scenario.



(a) Lever impact across all policies.

(b) Feature importance for scenario success.

Figure D.7: Lever influence and key predictors in the 2030 Balanced Scenario.

Input Influence Analysis – 2030 Unrestrained Balanced Filter

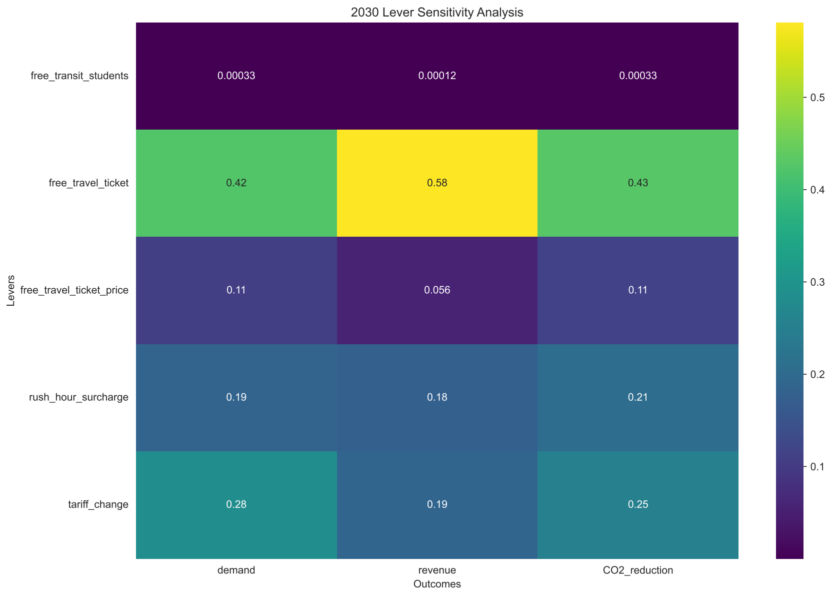
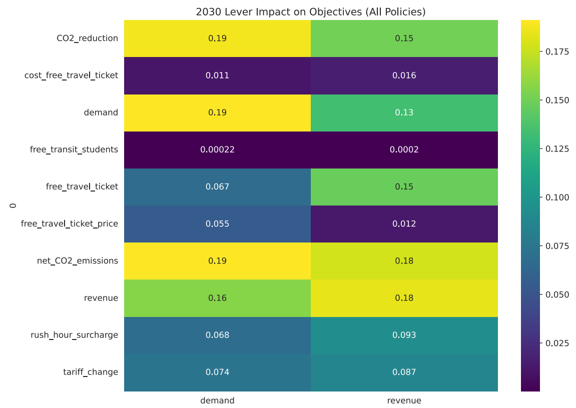
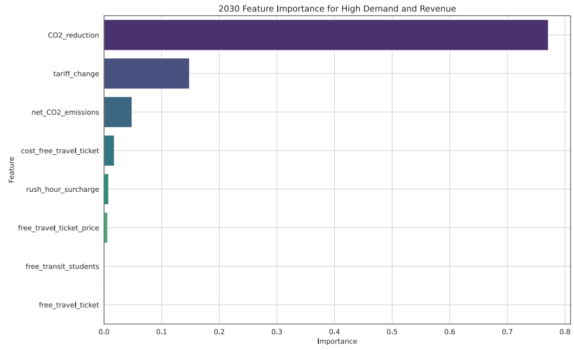


Figure D.8: Sensitivity of levers in the 2030 Unrestrained Balanced Filter.



(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.9: Influence and prediction results for 2030 in the Unrestrained Balanced Filter.

Input Influence Analysis – 2030 Max Revenue Scenario

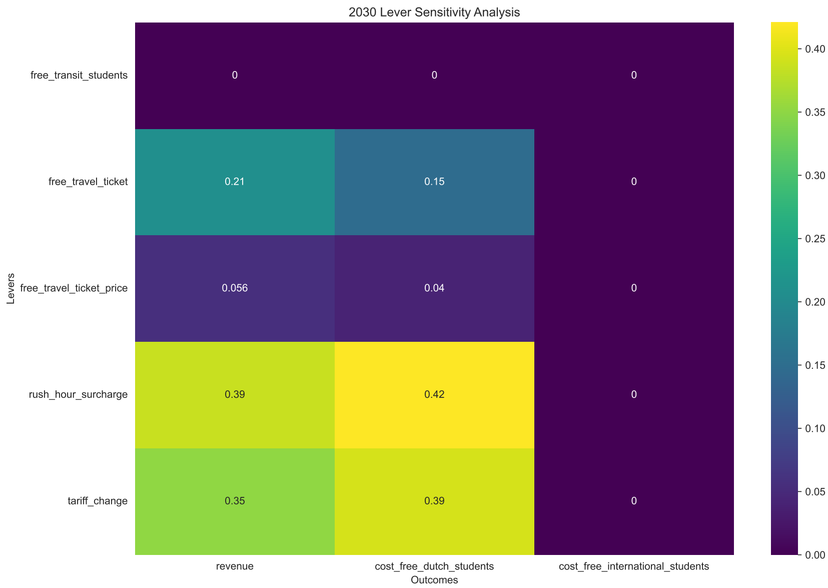


Figure D.10: One-at-a-time sensitivity of levers in 2030 Max Revenue Scenario.

Input Influence Analysis – 2040 Balanced Scenario

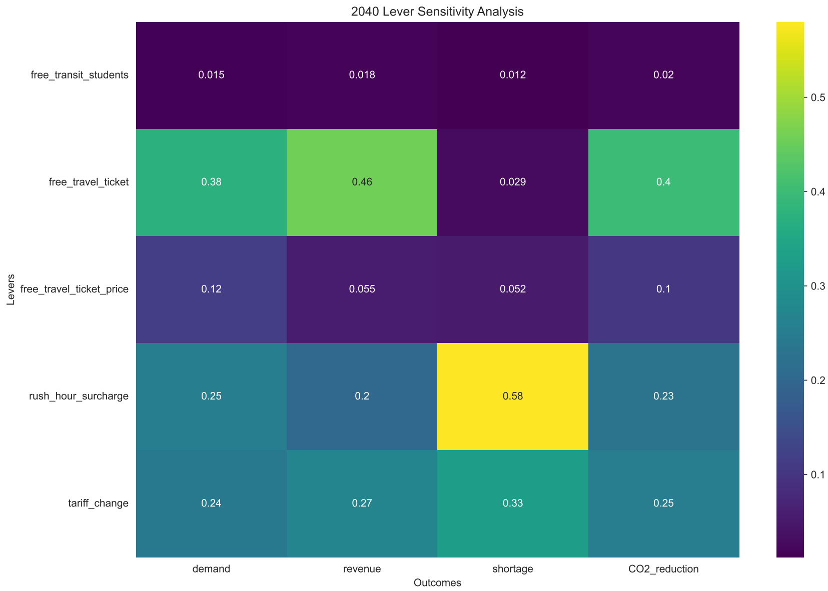
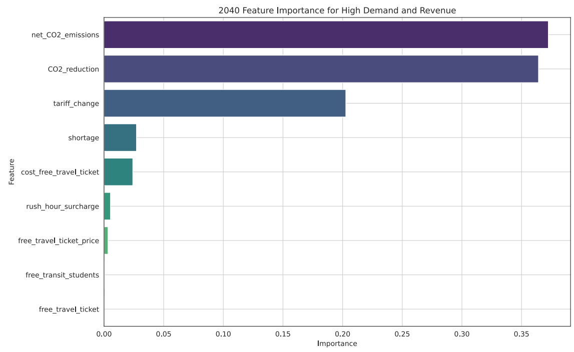


Figure D.11: One-at-a-time sensitivity of levers in 2040 Balanced Scenario.

(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.12: Lever-level influence and key predictors for high-demand/high-revenue outcomes in 2040 Balanced Scenario.

Input Influence Analysis – 2040 Unrestrained Balanced Filter

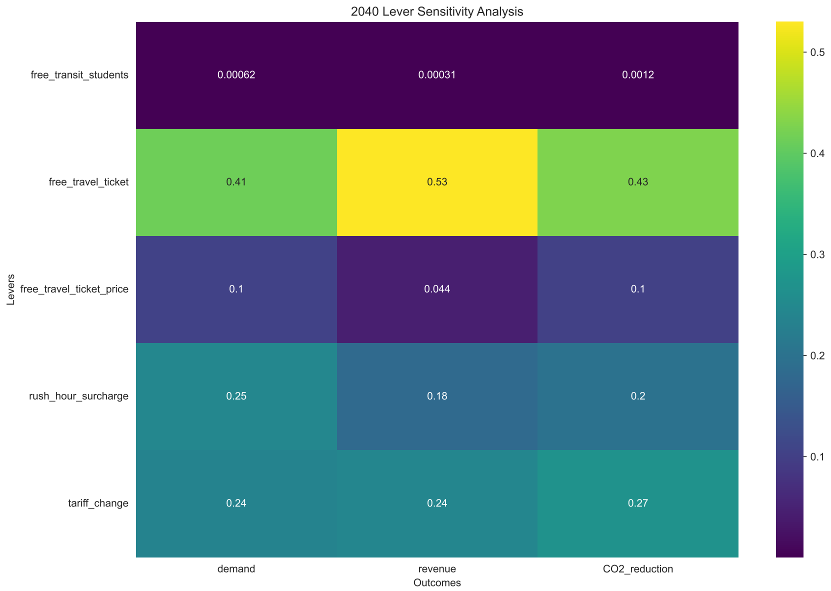
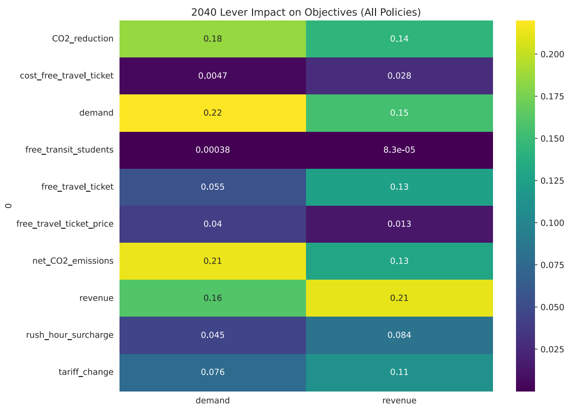
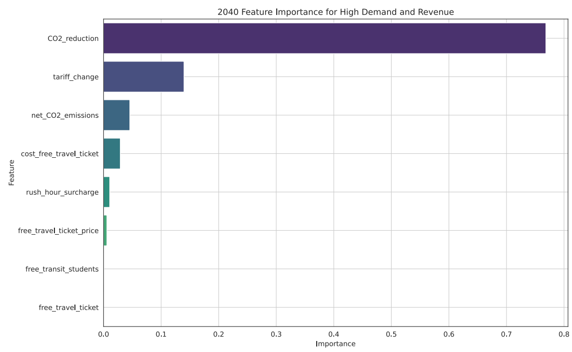


Figure D.13: Sensitivity of levers in the 2040 Unrestrained Balanced Filter.



(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.14: Influence and predictiveness of inputs in 2040 Unrestrained Scenario.

Input Influence Analysis – 2040 Max Revenue Scenario

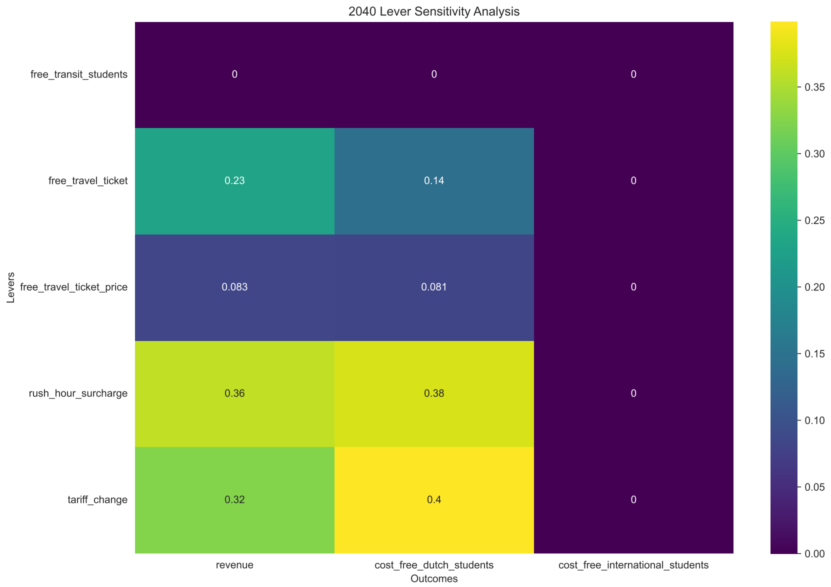
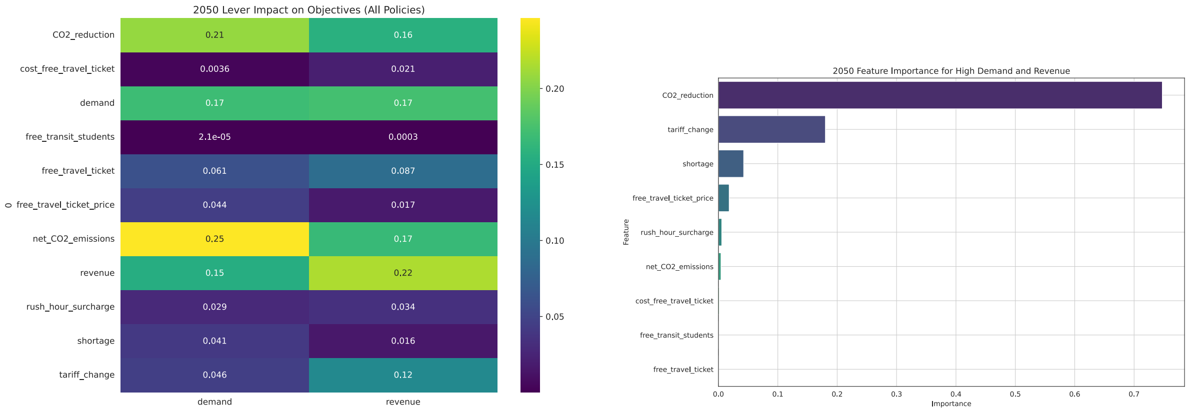


Figure D.15: One-at-a-time sensitivity of levers in 2040 Max Revenue Scenario.

Input Influence Analysis – 2050 Balanced Scenario

Figure D.16: One-at-a-time sensitivity of levers in 2050 Balanced Scenario.



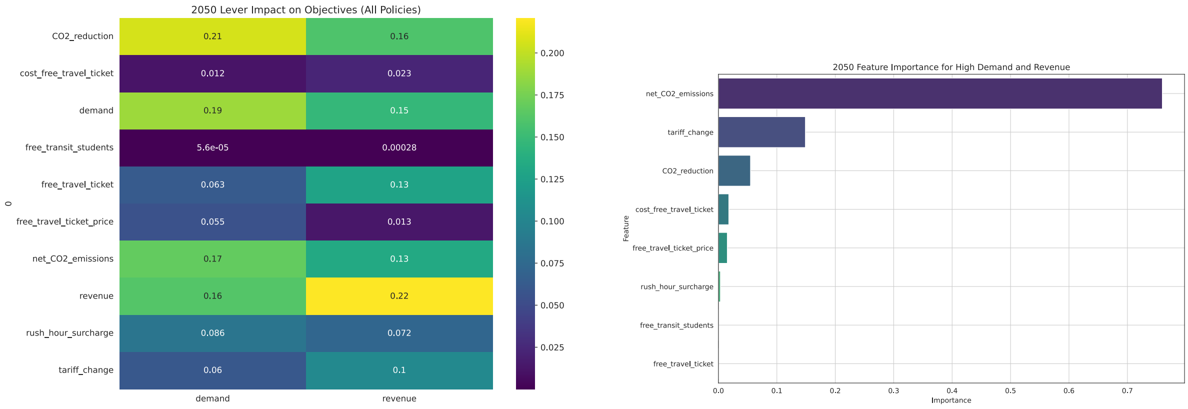
(a) Lever impact across all policies.

(b) Feature importance for scenario success.

Figure D.17: Lever-level influence and key predictors for high-demand/high-revenue outcomes in 2050 Balanced Scenario.

Input Influence Analysis – 2050 Unrestrained Balanced Filter

Figure D.18: Sensitivity of levers in the 2050 Unrestrained Balanced Filter.



(a) Lever impact across all policies.

(b) Feature importance for scenario success.

Figure D.19: Influence and predictiveness of inputs in 2050 Unrestrained Scenario.

Input Influence Analysis – 2050 Max Revenue Scenario

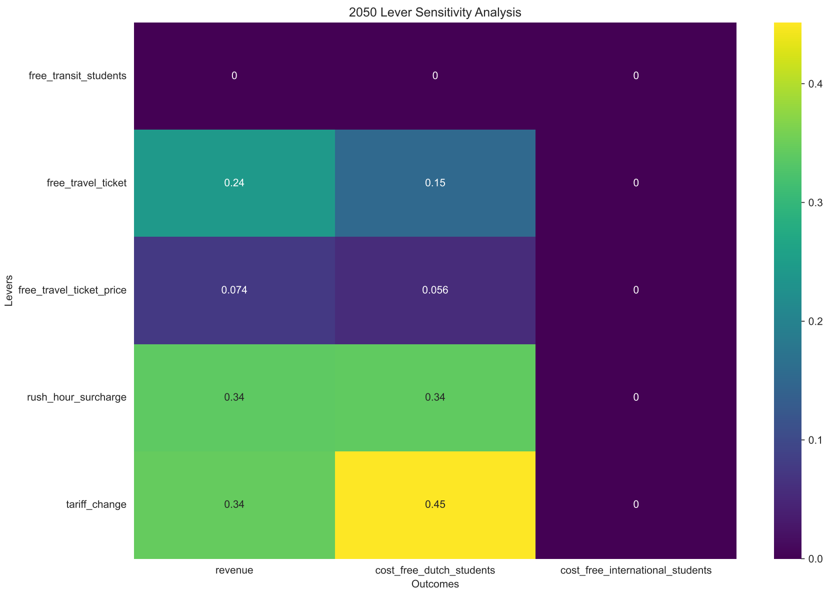
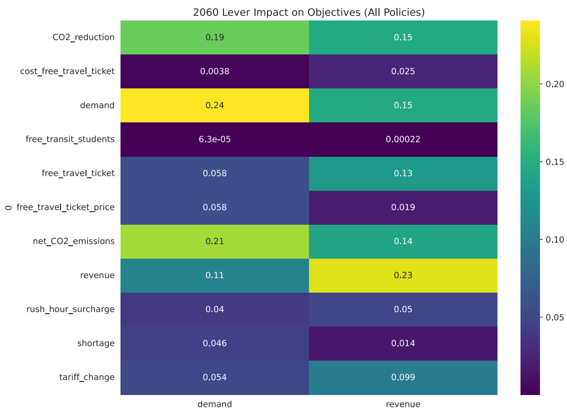


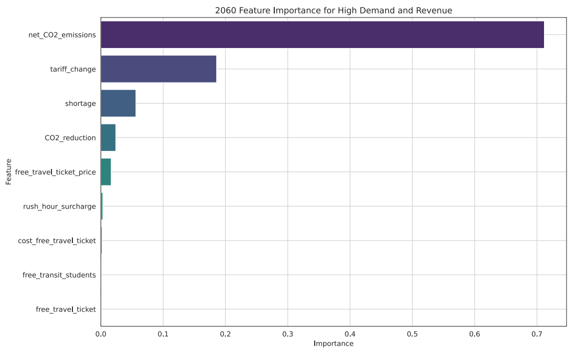
Figure D.20: One-at-a-time sensitivity of levers in 2050 Max Revenue Scenario.

Input Influence Analysis – 2060 Balanced Scenario

Figure D.21: One-at-a-time sensitivity of levers in 2060 Balanced Scenario.



(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.22: Lever-level influence and key predictors for high-demand/high-revenue outcomes in 2060 Balanced Scenario.

Input Influence Analysis – 2060 Unrestrained Balanced Filter

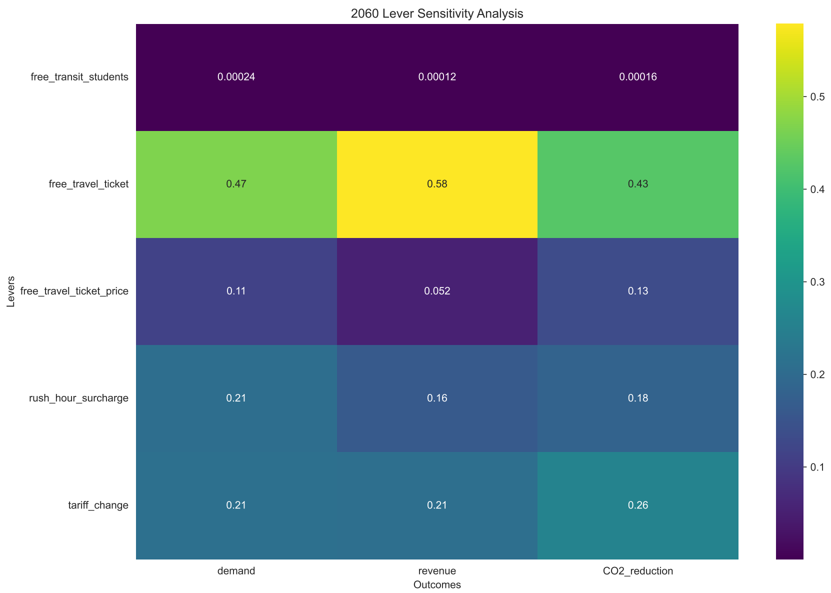
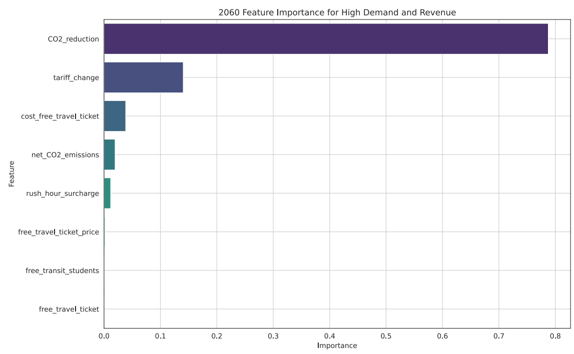


Figure D.23: Sensitivity of levers in the 2060 Unrestrained Balanced Filter.

(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.24: Influence and predictiveness of inputs in 2060 Unrestrained Scenario.

Input Influence Analysis – 2060 Max Revenue Scenario

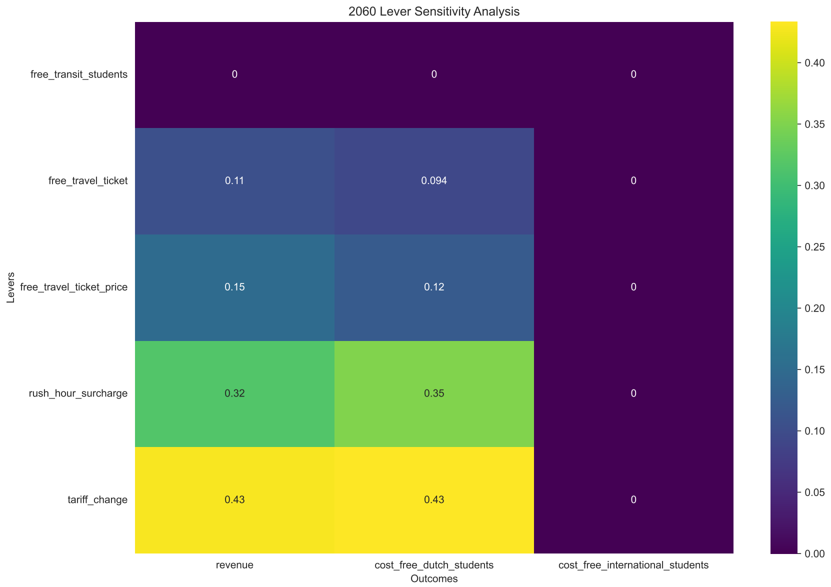
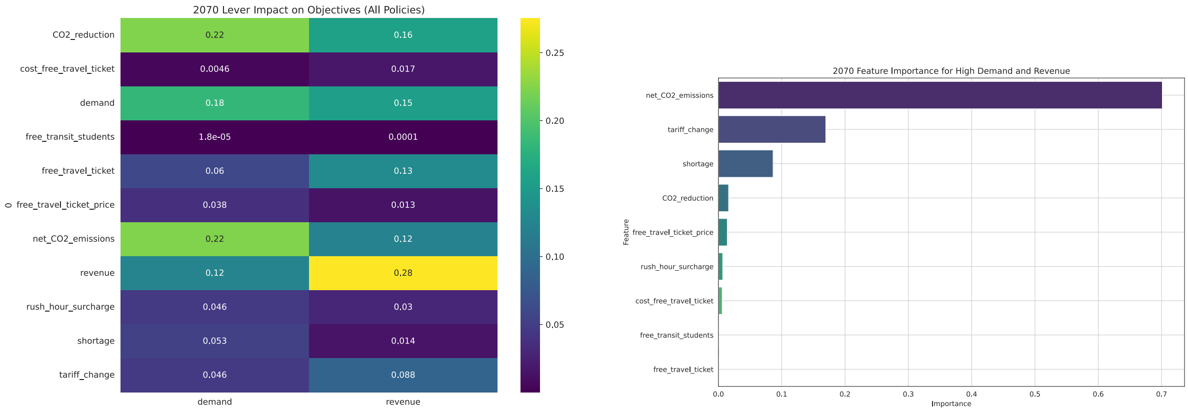


Figure D.25: One-at-a-time sensitivity of levers in 2060 Max Revenue Scenario.

Input Influence Analysis – 2070 Balanced Scenario

Figure D.26: One-at-a-time sensitivity of levers in 2070 Balanced Scenario.



(a) Lever impact across all policies.

(b) Feature importance for scenario success.

Figure D.27: Lever-level influence and key predictors for high-demand/high-revenue outcomes in 2070 Balanced Scenario.

Input Influence Analysis – 2070 Unrestrained Balanced Filter

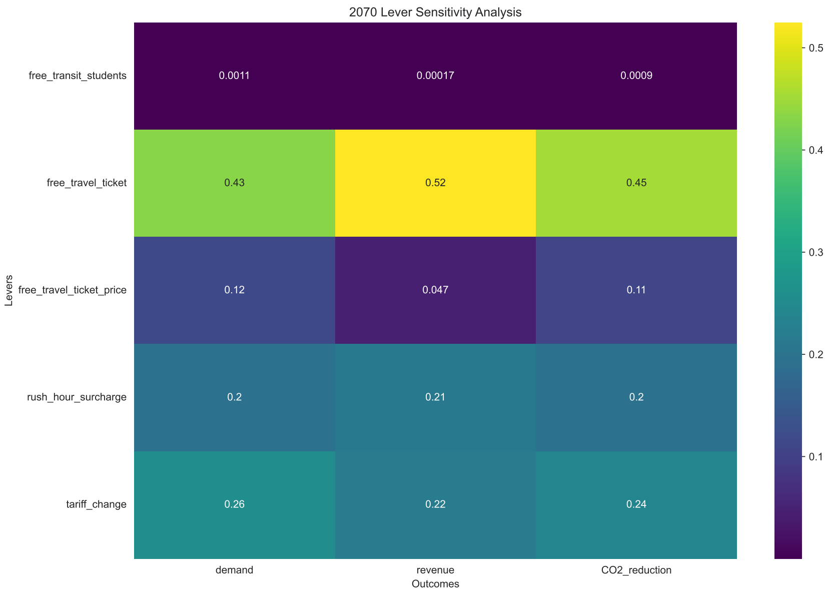
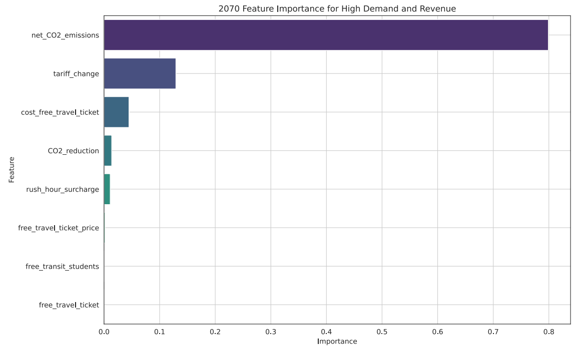


Figure D.28: Sensitivity of levers in the 2070 Unrestrained Balanced Filter.

(a) Lever impact across all policies.



(b) Feature importance for scenario success.

Figure D.29: Influence and predictiveness of inputs in 2070 Unrestrained Scenario.

Input Influence Analysis – 2070 Max Revenue Scenario

chapters/figures/2070/MaxRevenueNew/270_Lever_Sensitivity_Analysis.pdf

Figure D.30: One-at-a-time sensitivity of levers in 2070 Max Revenue Scenario.

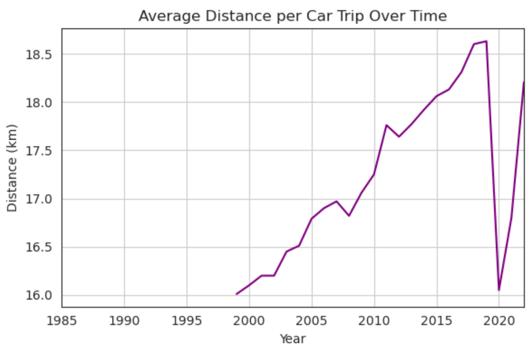
E

Exploratory Data Analysis

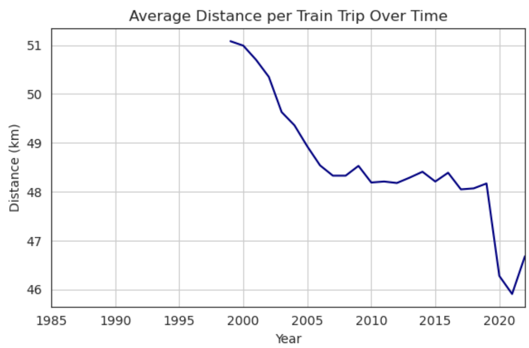
This appendix presents exploratory plots of key input variables used in the modeling framework. These figures help contextualize the assumptions behind passenger behavior, vehicle usage, economic activity, and energy costs. They also provide a basis for understanding the uncertainty ranges applied to model inputs.

E.1. Variables Related to Elasticities

Figure E.1a and Figure E.1b show trends in average trip distance by car and train, respectively. These values inform the estimation of emissions, travel time, and stitution potential between modes.

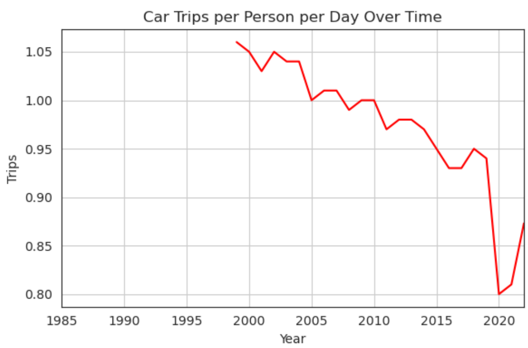


(a) Average distance per car trip over time, reflecting personal travel behavior and its evolution.

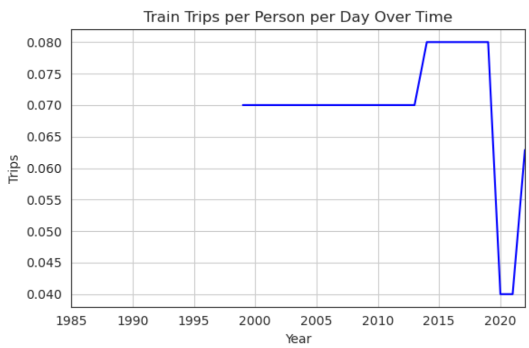


(b) Average train trip length, indicative of long-distance and intercity travel preferences.

Figure E.1: Average distance per car and train trip in the Netherlands.



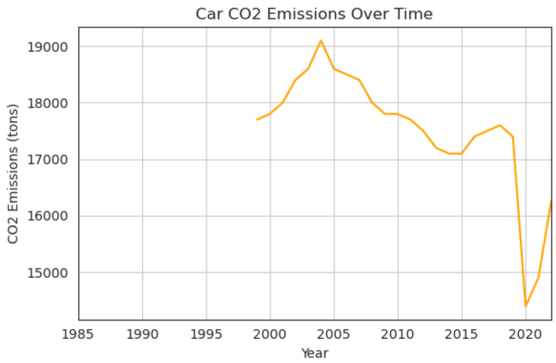
(a) Daily trip frequency by car in the Netherlands.



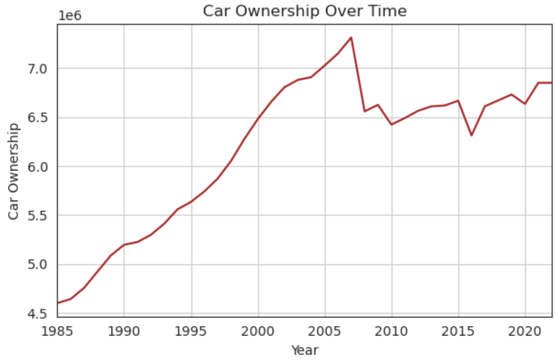
(b) Daily trip frequency by train in the Netherlands.

Figure E.2: Average number of trips by car and train per person in the Netherlands.

Figures E.3a to E.2b relate to environmental and behavioral baselines for private car use. These are especially relevant for modeling the emissions impact of modal shifts toward or away from rail.



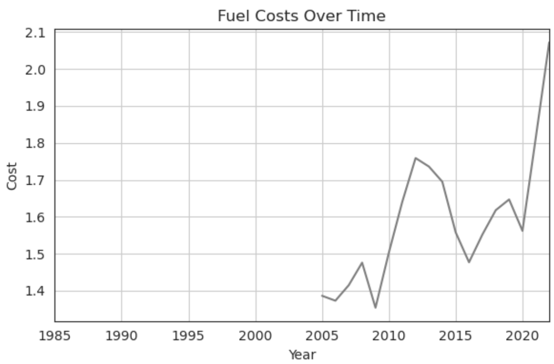
(a) Estimated CO2 emissions from car usage, showing long-term trends and impacts from external shocks such as COVID-19.



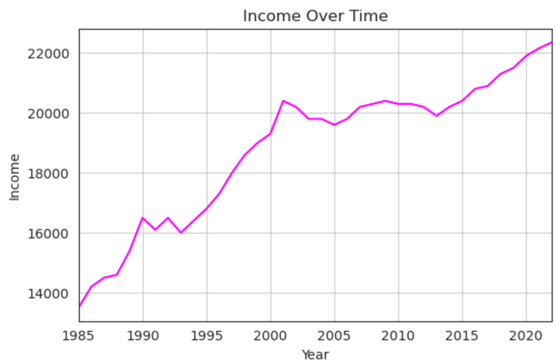
(b) Trends in car ownership, which influence baseline demand for rail alternatives.

Figure E.3: Comparison of car ownership and car CO_2 emissions in the Netherlands.

The following figures relate to observed demand changes and cost structures. Figure **??** captures a generalized demand increase under policy shifts. Figures E.4a to E.5a provide insight into cost sensitivity and socioeconomic conditions affecting mode choice.

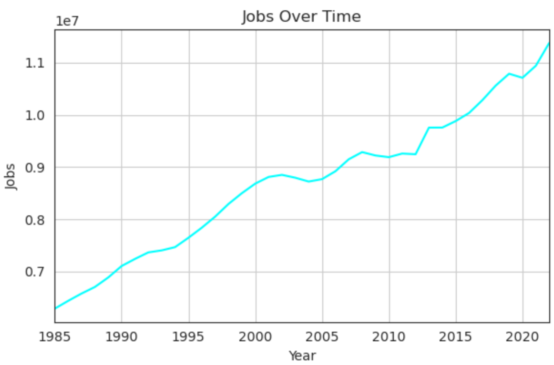


(a) Fluctuations in fuel prices, which may influence decisions to use private vehicles versus public transport.

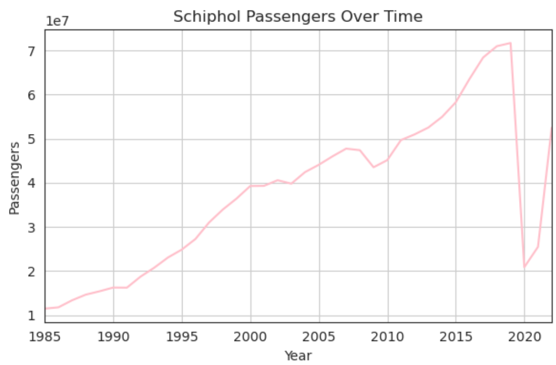


(b) Income trends, which affect fare affordability and elasticities in transport demand.

Figure E.4: Comparison of fuel costs and average disposable income in the Netherlands.



(a) Workforce dynamics, which contribute to commuting patterns and transport system demand.



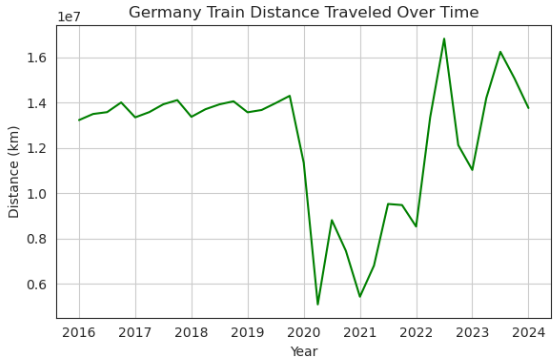
(b) Annual passenger volume at Schiphol Airport, representing tourism and potential for long-distance rail.

Figure E.5: Comparison of jobs in the Netherlands and passengers traveling through Schiphol Airport.

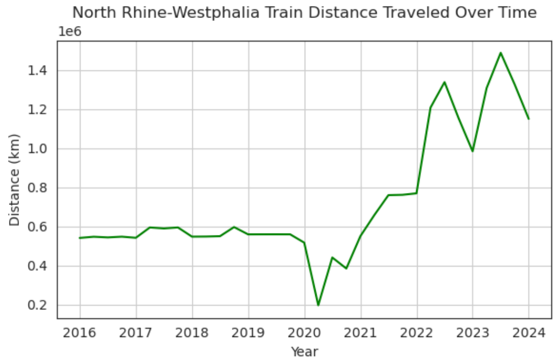
E.2. Data from Germany and North Rhine-Westphalia

The following figures show rail usage trends in Germany and North Rhine-Westphalia between 2016 and 2024. These data were used to estimate the potential effects of unlimited travel ticket policies on ridership in the Dutch context.

Figures E.6a and E.6b display the total annual train distance traveled in Germany and NRW, respectively. Both regions show a sharp decline in 2020 due to the COVID-19 pandemic, followed by strong recovery post-2022, especially during the €9 and €49 unlimited ticket periods.



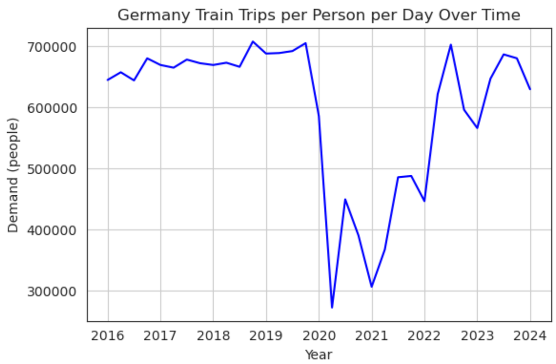
(a) Germany: Total annual train distance traveled (2016–2024).



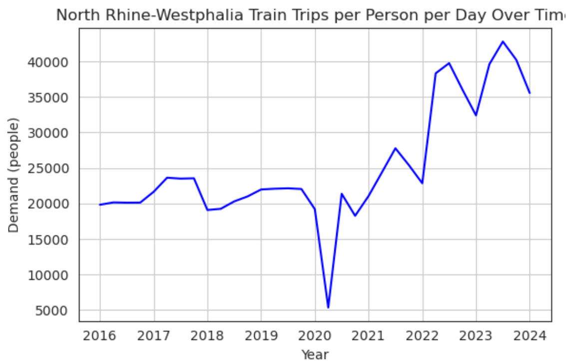
(b) North Rhine-Westphalia: Total train kilometers traveled per year.

Figure E.6: Annual train distance traveled in Germany and NRW. The trends reflect COVID-19 impacts and recovery following fare reform policies.

Figures E.7a and E.7b show train trips per person per day. These figures are particularly relevant for estimating demand elasticity and were used to set the upper and lower bounds of the unlimited travel ticket policy levers in the model.



(a) Germany: Train trips per person per day (2016–2024).



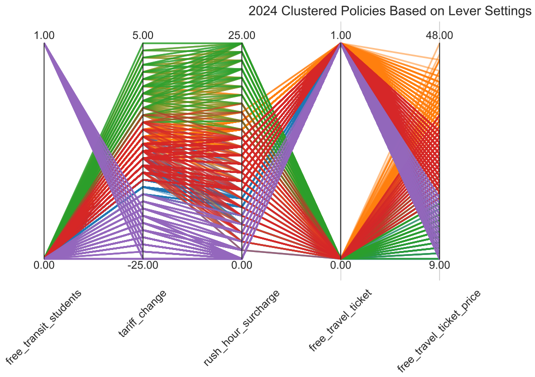
(b) North Rhine-Westphalia: Train trips per person per day.

Figure E.7: Train trips per person per day in Germany and NRW. NRW shows a steeper increase post-2022, possibly due to greater urban density and local policy responsiveness.

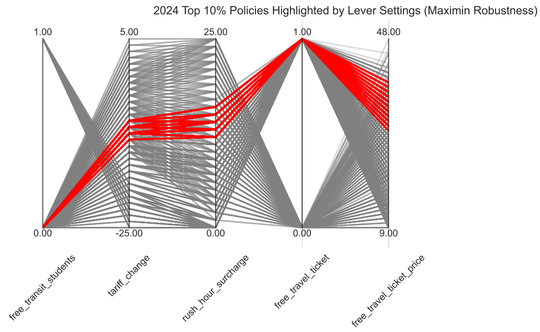
F
MORO Results by Year

This appendix presents the full set of simulation results for each evaluation year in the model: 2024, 2040, 2050, 2060, and 2070. For each year, figures are grouped by scenario and include the top-performing policies and the policy clusters derived from lever settings.

2024 Results Balanced Formulation

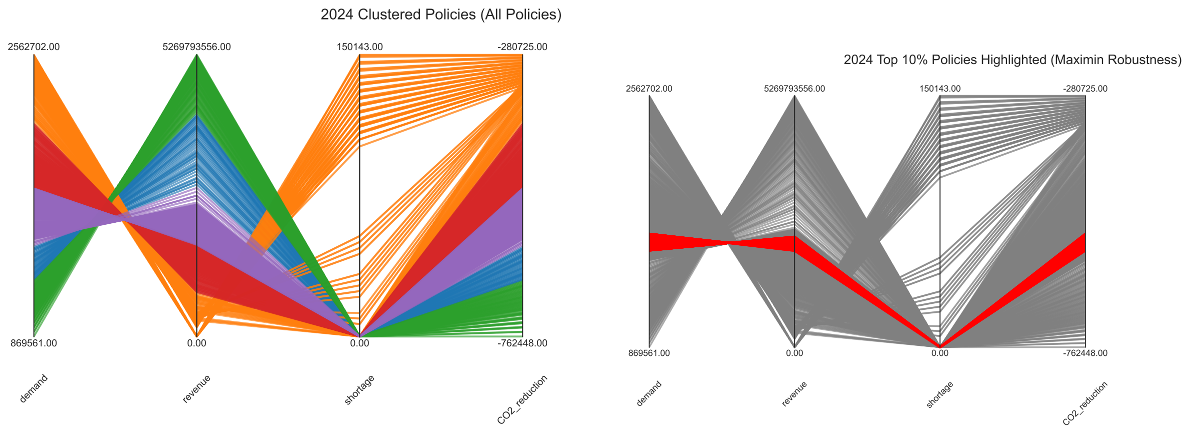


(a) Clustered policies in 2024 (With Shortage)



(b) Top 10% policies in 2024 (With Shortage)

Figure F.1: Clustered policies and top-performing strategies in 2024 under the Balanced Formulation.

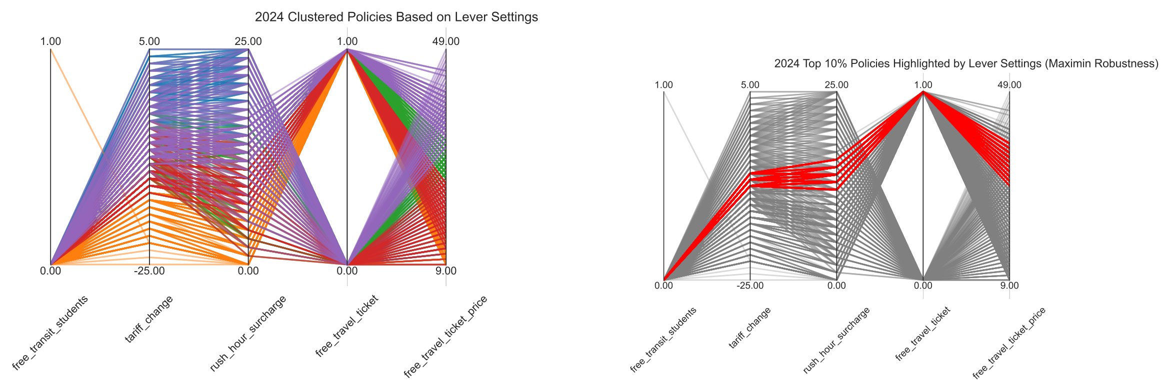


(a) Clustered outcomes for the 2024 Balanced Formulation.

(b) Outcomes associated with the top 10% performing policies in 2024 for the Balanced Formulation.

Figure F.2: The 2024 results for the Balanced Formulation based on outcomes.

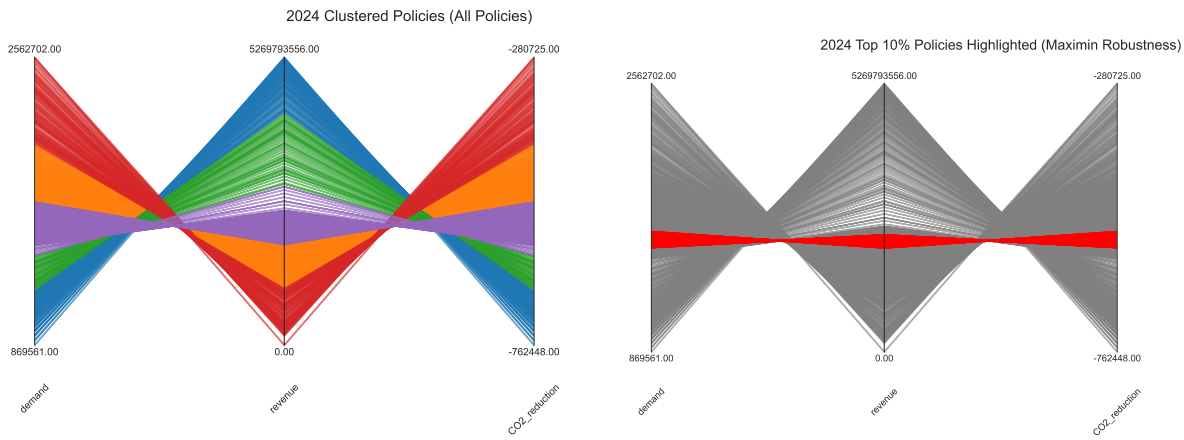
2024 Results Unrestrained Balanced Filter



(a) Clustered policies in 2024 (No Shortage)

(b) Top 10% policies in 2024 (No Shortage)

Figure F.3: Clustered policies and top-performing strategies in 2024 under the Unrestrained Balanced Filter.

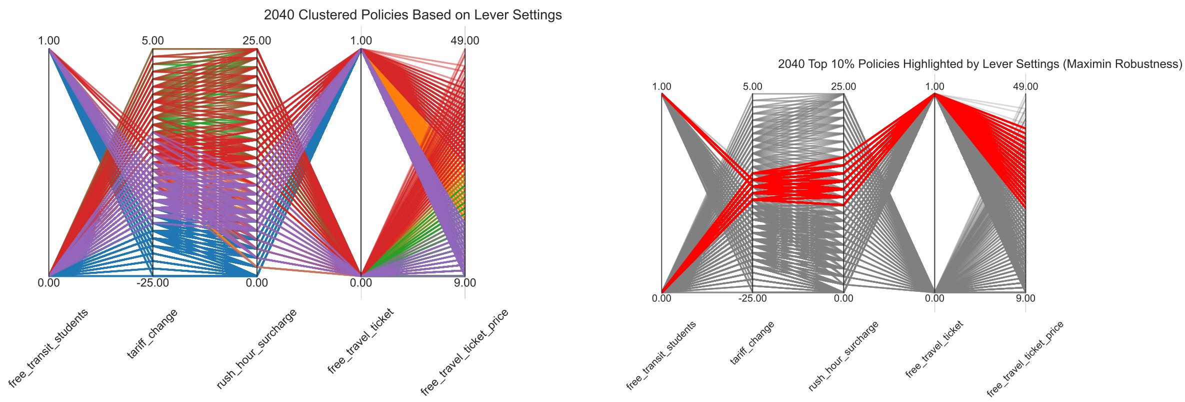


(a) Clustered outcomes for the 2024 Unrestrained Balanced Filter.

(b) Outcomes associated with the top 10% performing policies in 2024 for the Unrestrained Balanced Filter.

Figure F.4: The 2024 results for the Unrestrained Balanced Filter based on outcomes.

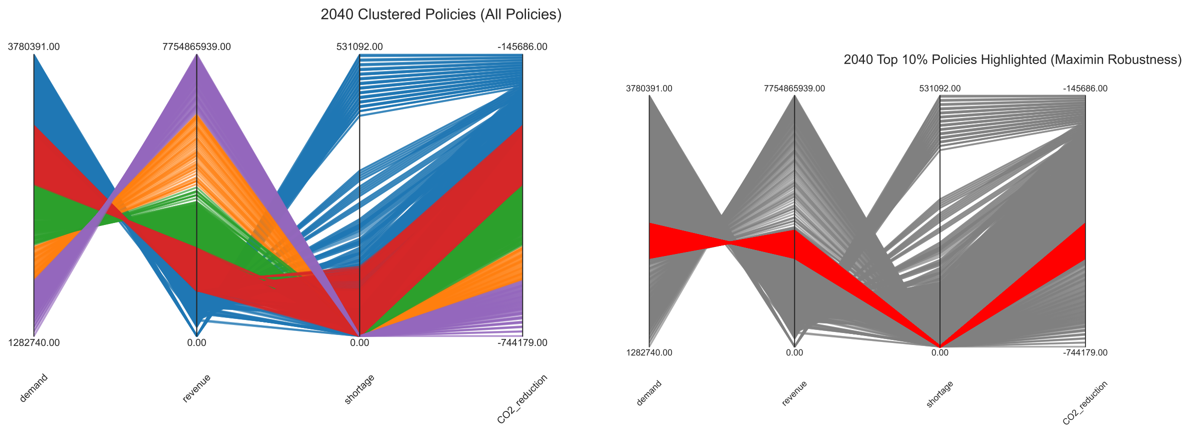
2040 Results Balanced Formulation



(a) Clustered policies in 2040 (With Shortage)

(b) Top 10% policies in 2040 (With Shortage)

Figure F.5: Clustered policies and top-performing strategies in 2040 under the Balanced Formulation.

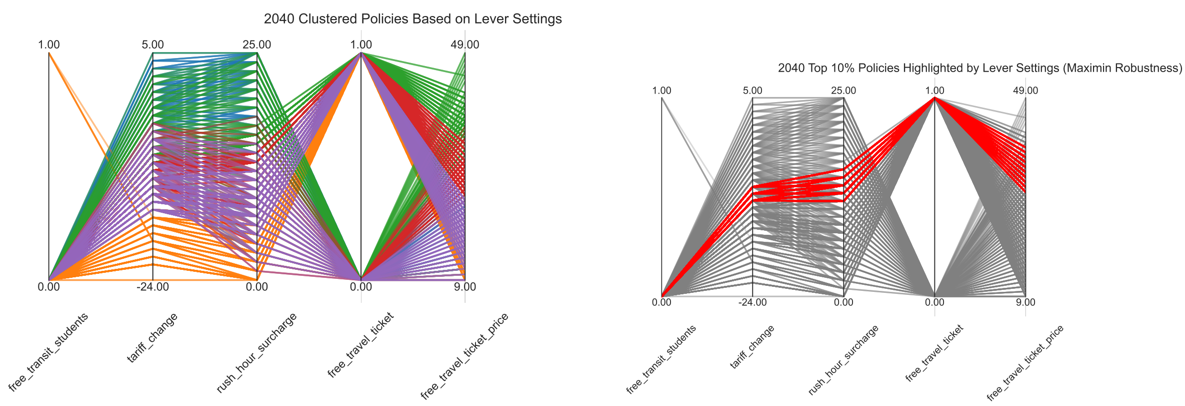


(a) Clustered outcomes for the 2040 Balanced Formulation.

(b) Outcomes associated with the top 10% performing policies in 2040 for the Balanced Formulation.

Figure F.6: The 2040 results for the Balanced Formulation based on outcomes.

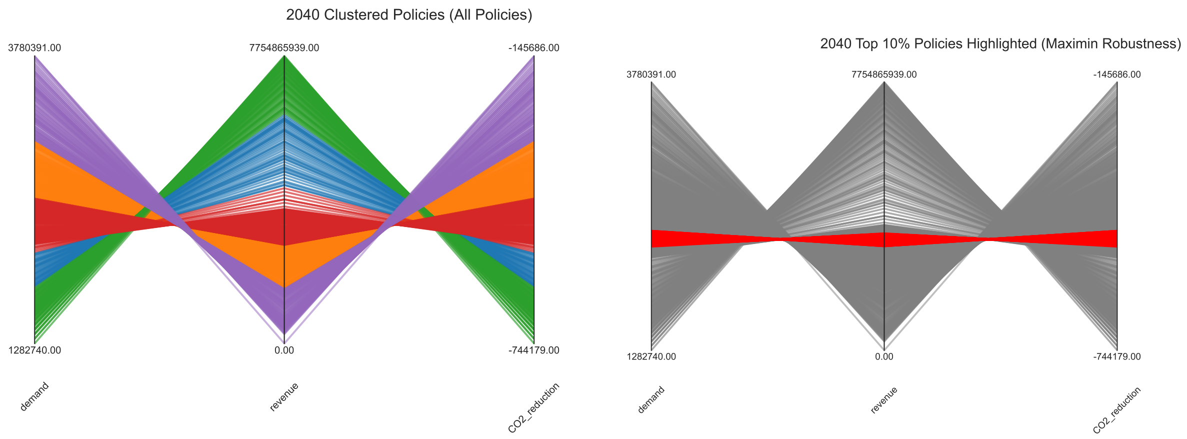
2040 Results Unrestrained Balanced Filter



(a) Clustered policies in 2040 (No Shortage)

(b) Top 10% policies in 2040 (No Shortage)

Figure F.7: Clustered policies and top-performing strategies in 2040 under the Unrestrained Balanced Filter.

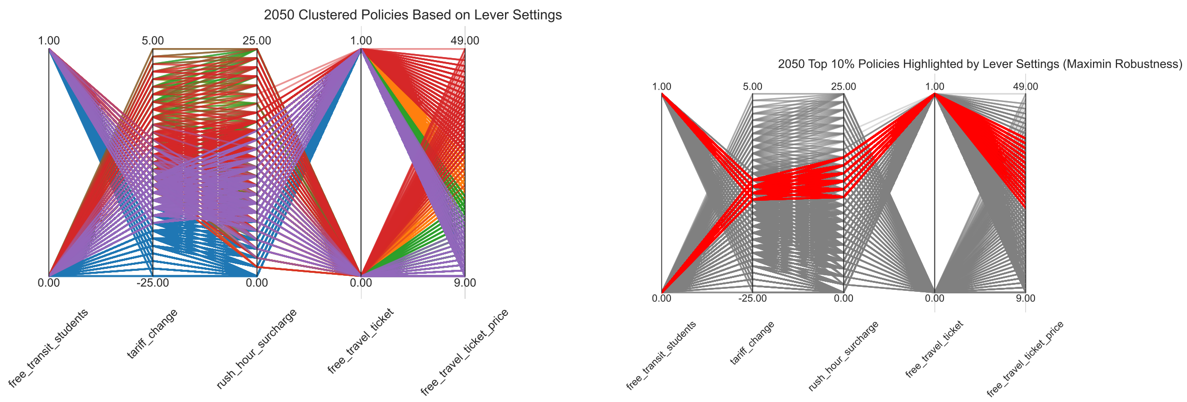


(a) Clustered outcomes for the 2040 Unrestrained Balanced Filter.

(b) Outcomes associated with the top 10% performing policies in 2040 for the Unrestrained Balanced Filter.

Figure F.8: The 2040 results for the Unrestrained Balanced Filter based on outcomes.

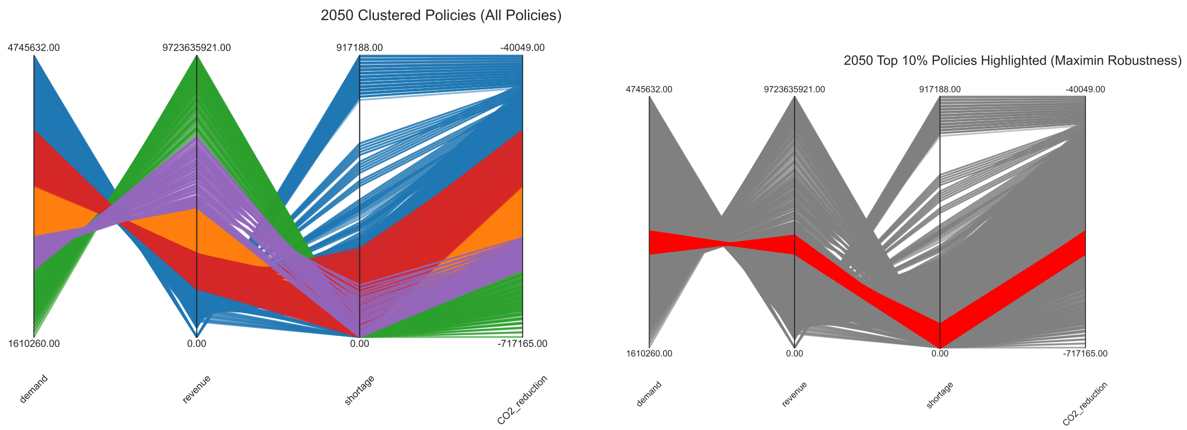
2050 Results Balanced Formulation



(a) Clustered policies in 2050 (With Shortage)

(b) Top 10% policies in 2050 (With Shortage)

Figure F.9: Clustered policies and top-performing strategies in 2050 under the Balanced Formulation.

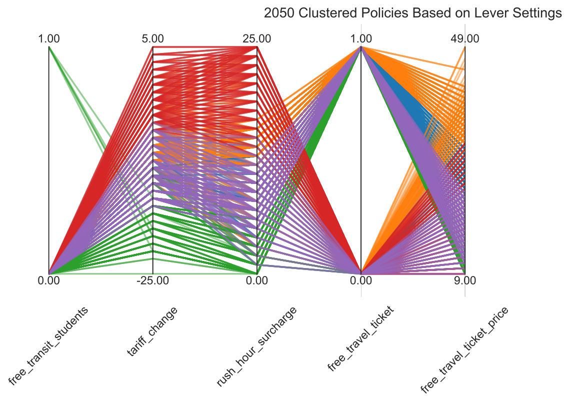


(a) Clustered outcomes for the 2050 Balanced Formulation.

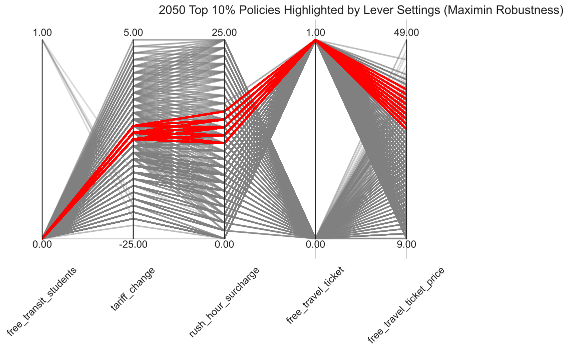
(b) Outcomes associated with the top 10% performing policies in 2050 for the Balanced Formulation.

Figure F.10: The 2050 results for the Balanced Formulation based on outcomes.

2050 Results Unrestrained Balanced Filter

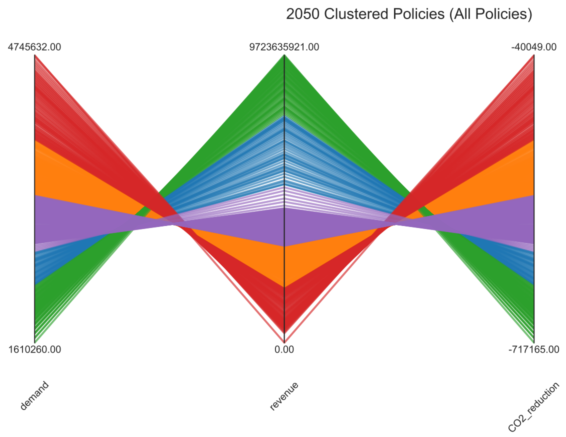


(a) Clustered policies in 2050 (No Shortage)

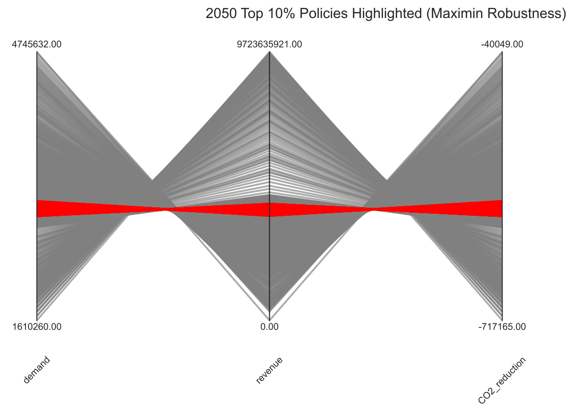


(b) Top 10% policies in 2050 (No Shortage)

Figure F.11: Clustered policies and top-performing strategies in 2050 under the Unrestrained Balanced Filter.



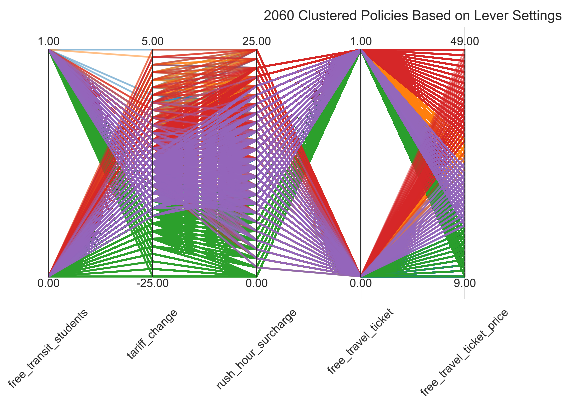
(a) Clustered outcomes for the 2050 Unrestrained Balanced Filter.



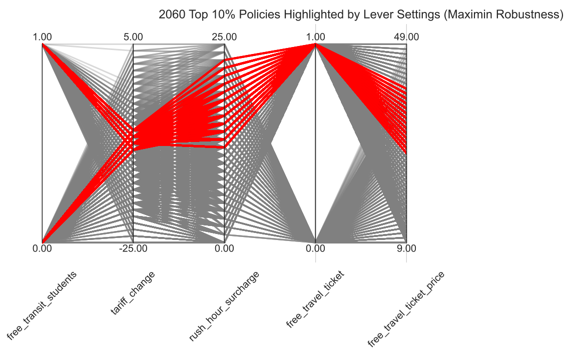
(b) Outcomes associated with the top 10% performing policies in 2050 for the Unrestrained Balanced Filter.

Figure F.12: The 2050 results for the Unrestrained Balanced Filter based on outcomes.

2060 Results Balanced Formulation

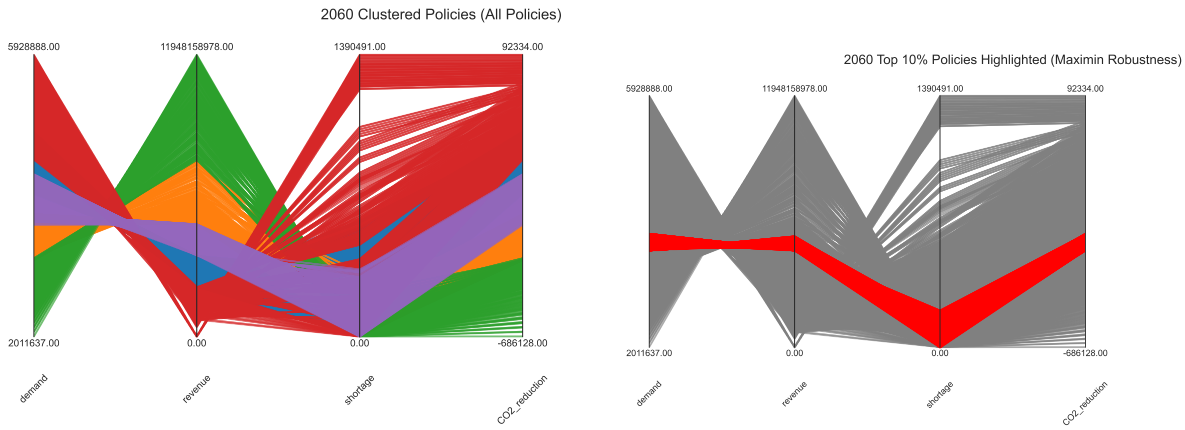


(a) Clustered policies in 2060 (With Shortage)



(b) Top 10% policies in 2060 (With Shortage)

Figure F.13: Clustered policies and top-performing strategies in 2060 under the Balanced Formulation.

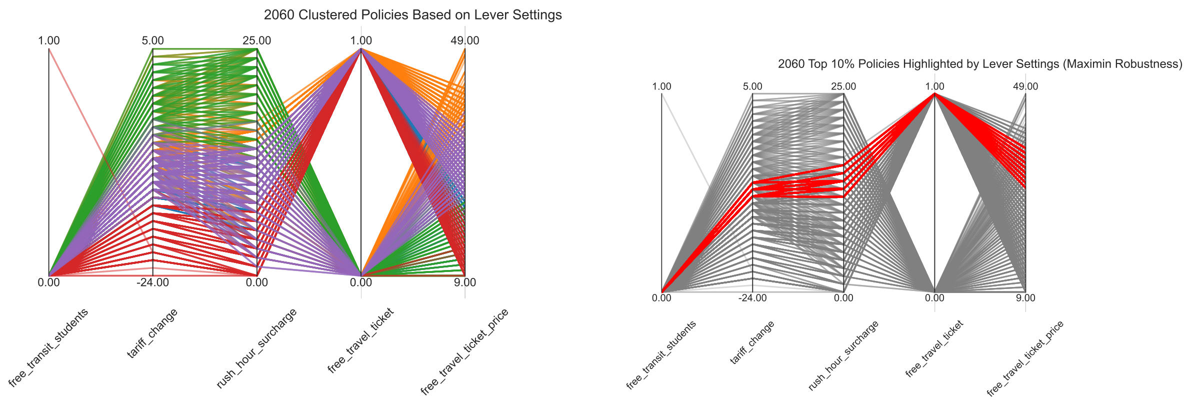


(a) Clustered outcomes for the 2060 Balanced Formulation.

(b) Outcomes associated with the top 10% performing policies in 2060 for the Balanced Formulation.

Figure F.14: The 2060 results for the Balanced Formulation based on outcomes.

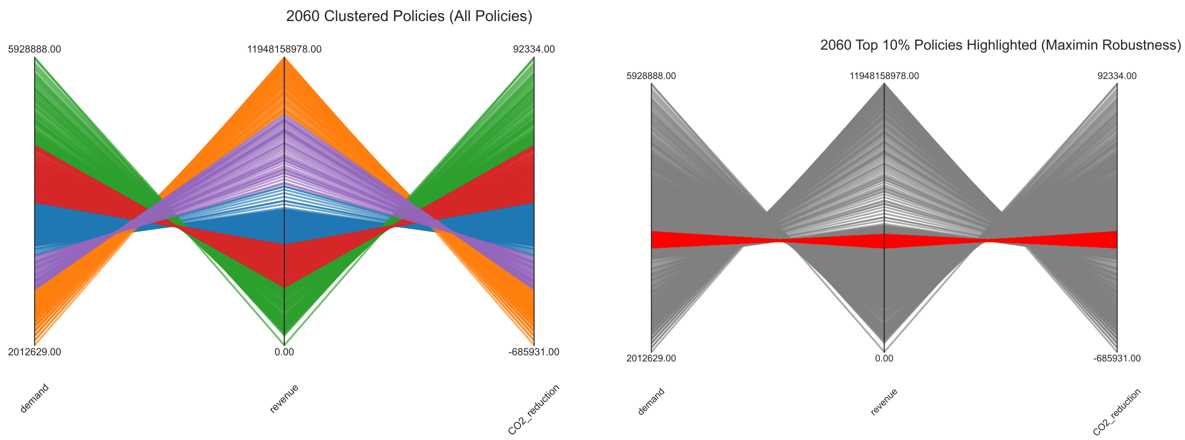
2060 Results Unrestrained Balanced Filter



(a) Clustered policies in 2060 (No Shortage)

(b) Top 10% policies in 2060 (No Shortage)

Figure F.15: Clustered policies and top-performing strategies in 2060 under the Unrestrained Balanced Filter.

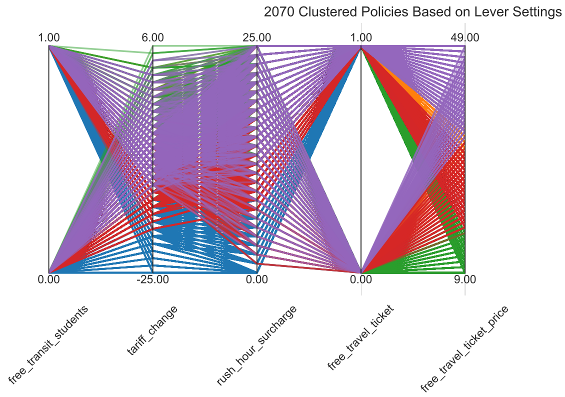


(a) Clustered outcomes for the 2060 Unrestrained Balanced Filter.

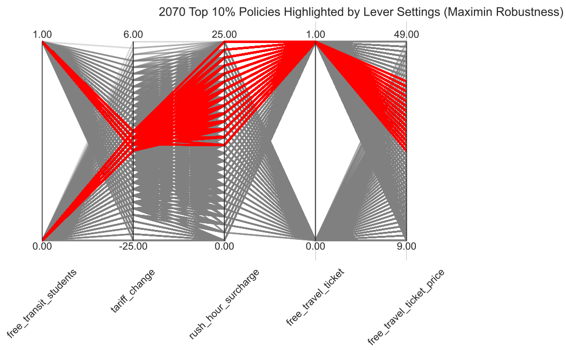
(b) Outcomes associated with the top 10% performing policies in 2060 for the Unrestrained Balanced Filter.

Figure F.16: The 2060 results for the Unrestrained Balanced Filter based on outcomes.

2070 Results Balanced Formulation

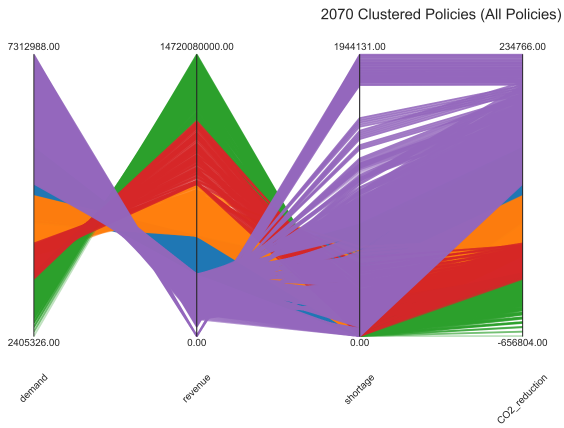


(a) Clustered policies in 2070 (With Shortage)

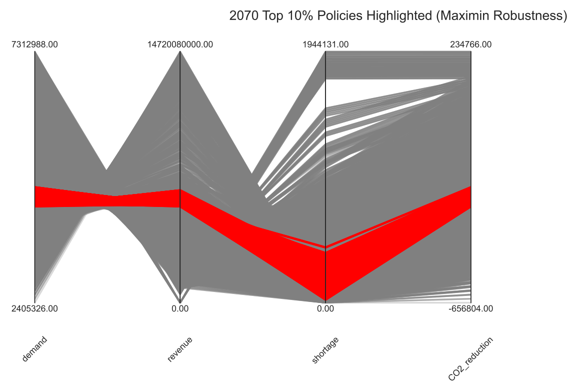


(b) Top 10% policies in 2070 (With Shortage)

Figure F.17: Clustered policies and top-performing strategies in 2070 under the Balanced Formulation.



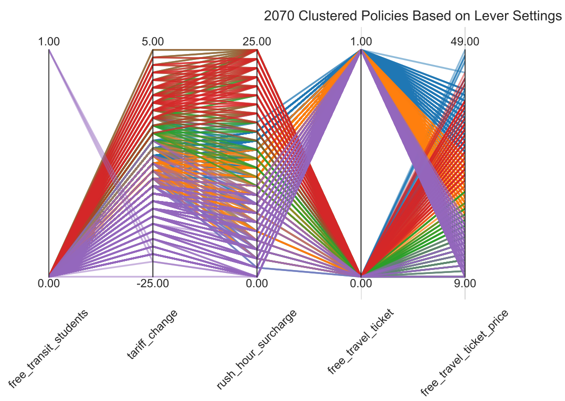
(a) Clustered outcomes for the 2070 Balanced Formulation.



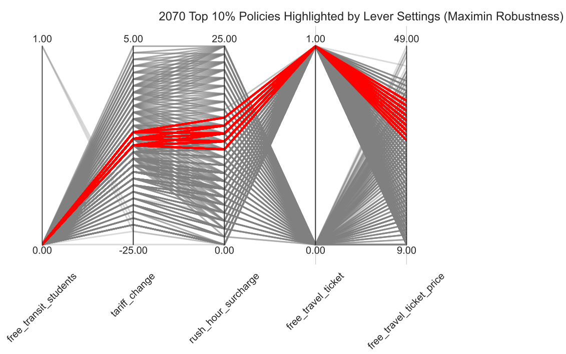
(b) Outcomes associated with the top 10% performing policies in 2070 for the Balanced Formulation.

Figure F.18: The 2070 results for the Balanced Formulation based on outcomes.

2070 Results Unrestrained Balanced Filter

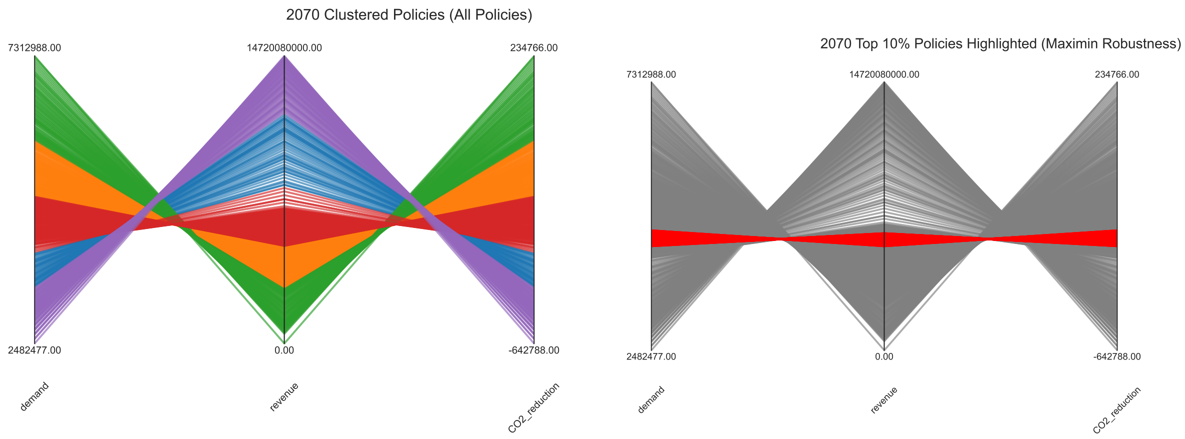


(a) Clustered policies in 2070 (No Shortage)



(b) Top 10% policies in 2070 (No Shortage)

Figure F.19: Clustered policies and top-performing strategies in 2070 under the Unrestrained Balanced Filter.



(a) Clustered outcomes for the 2070 Unrestrained Balanced Filter.

(b) Outcomes associated with the top 10% performing policies in 2070 for the Unrestrained Balanced Filter.

Figure F.20: The 2070 results for the Unrestrained Balanced Filter based on outcomes.

G

Model Validation and Baseline Results

To assess the plausibility of the simulation outputs, the model was first validated against real-world data from the year 2019. Observed figures for passenger demand and revenue were used as benchmarks to ensure that the baseline model could reasonably replicate system behavior under no-policy-change conditions. This validation step provided confidence that the model structure and parameterization were aligned with empirical realities. In addition, a sensitivity analysis was conducted to examine how variations in key model parameters and assumptions influenced the main outcomes in Appendix D.

Baseline 2019 Results

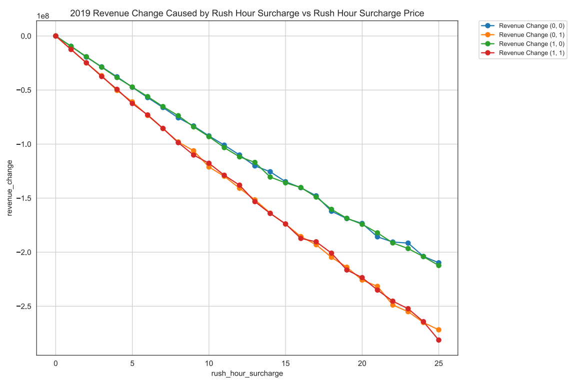


Figure G.1: 2019 revenue change vs rush hour surcharge

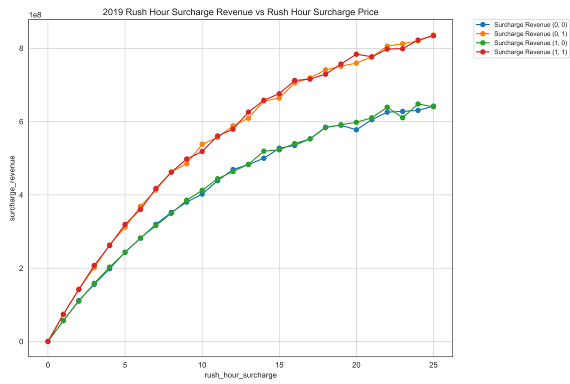


Figure G.2: 2019 surcharge revenue vs rush hour surcharge

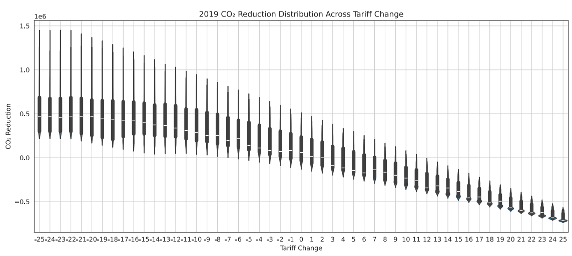


Figure G.3: 2019 violin CO_2 reduction distribution across tariff change

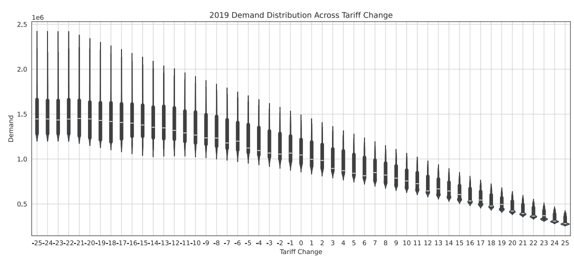


Figure G.4: 2019 violin demand distribution across tariff change

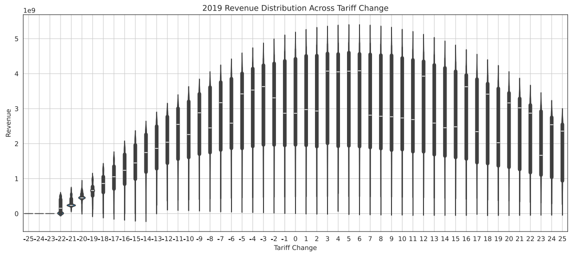


Figure G.5: 2019 violin revenue distribution across tariff change

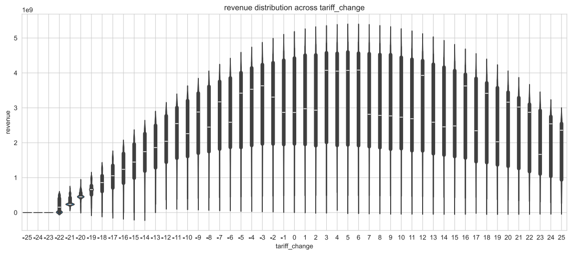


Figure G.6: 2019 violin

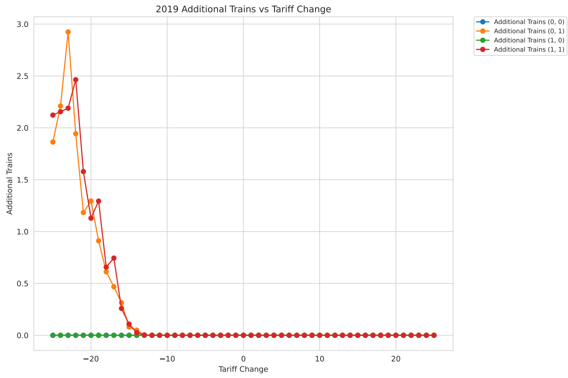


Figure G.7: 2019 additional trains vs tariff change

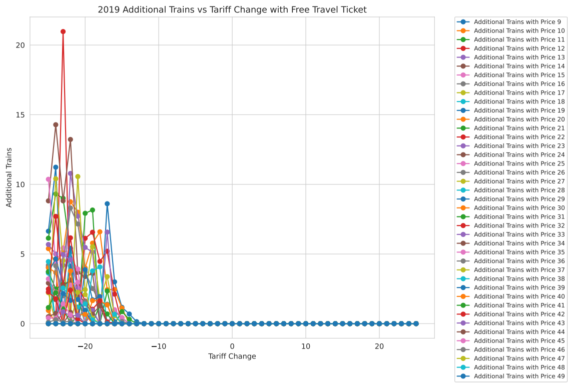


Figure G.8: 2019 additional trains vs tariff change (free travel ticket = 1)

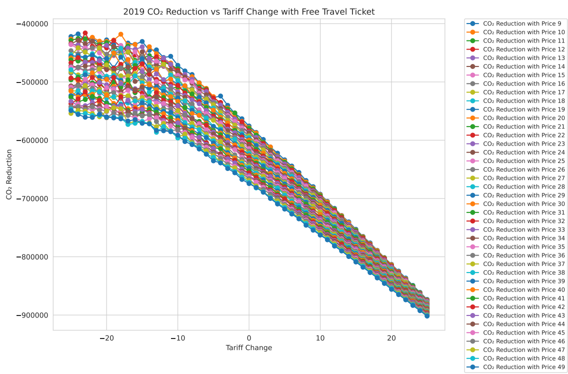


Figure G.9: 2019 CO_2 reduction vs tariff change (free travel ticket = 1)

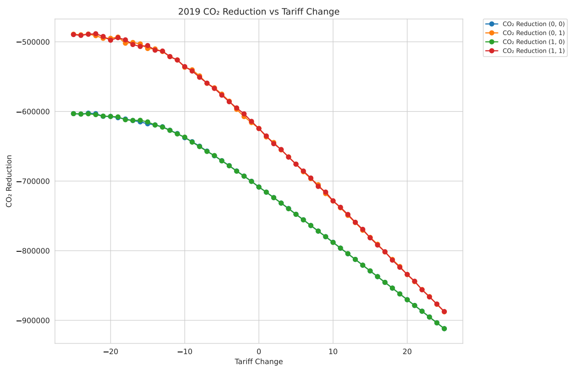


Figure G.10: 2019 CO_2 reduction vs tariff change

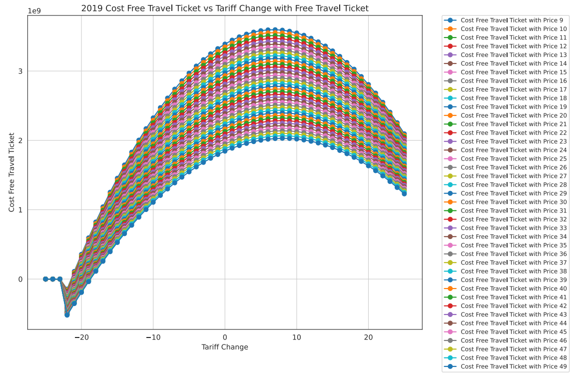


Figure G.11: 2019 cost for free travel ticket vs tariff change (free travel ticket = 1)

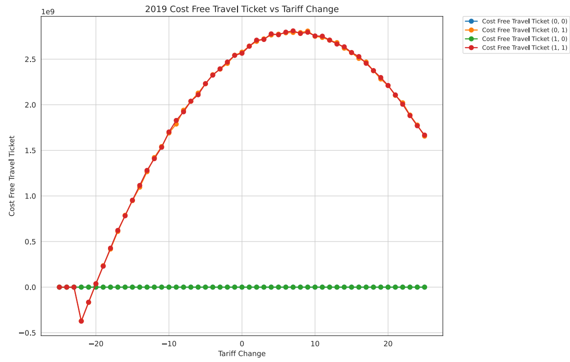


Figure G.12: 2019 cost for free travel ticket vs tariff change

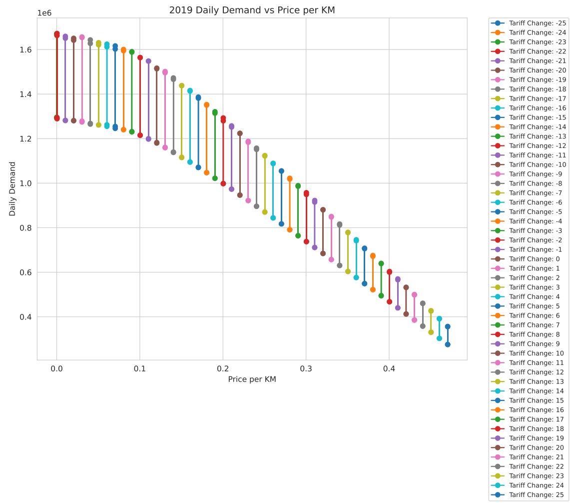


Figure G.13: 2019 daily demand vs price per km for tariff change = x

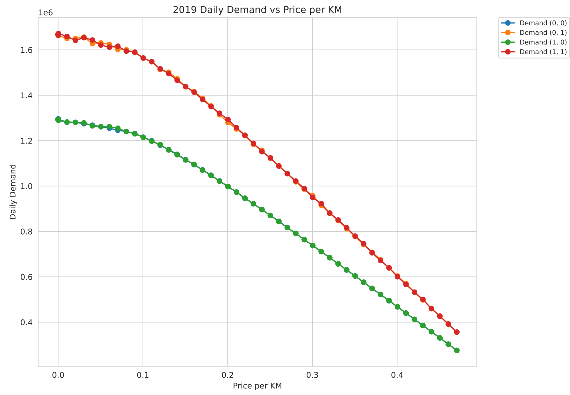


Figure G.14: 2019 daily demand vs price per km

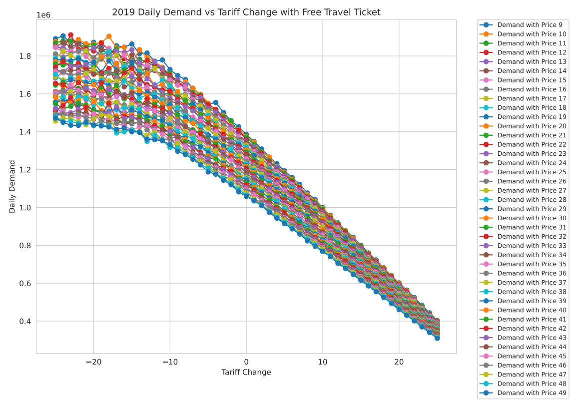


Figure G.15: 2019 daily demand vs tariff change (free travel ticket = 1)

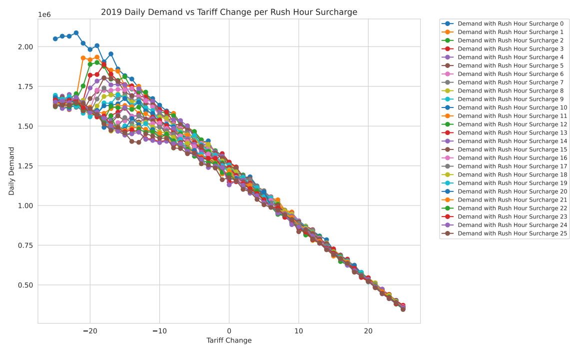


Figure G.16: 2019 daily demand vs tariff change (rush hour surcharge)

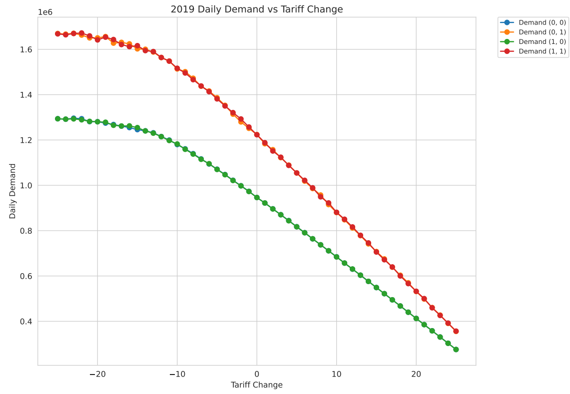


Figure G.17: 2019 daily demand vs tariff change

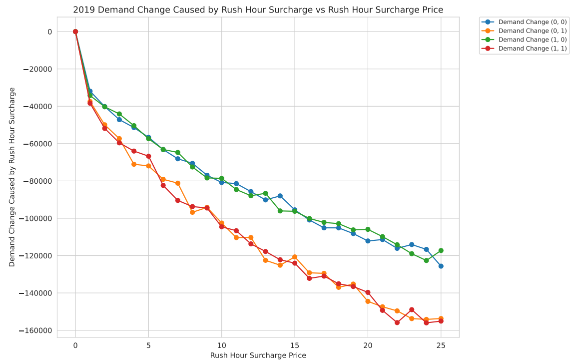


Figure G.18: 2019 demand change vs rush hour surcharge

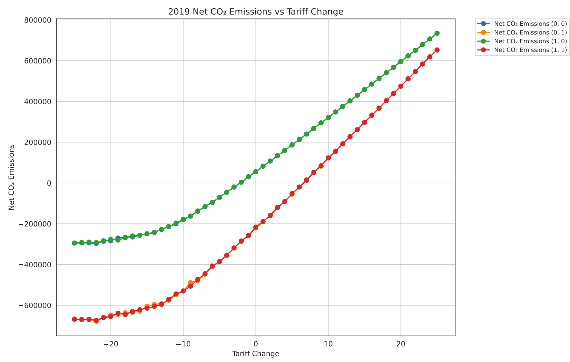


Figure G.19: 2019 net CO_2 emissions vs tariff change

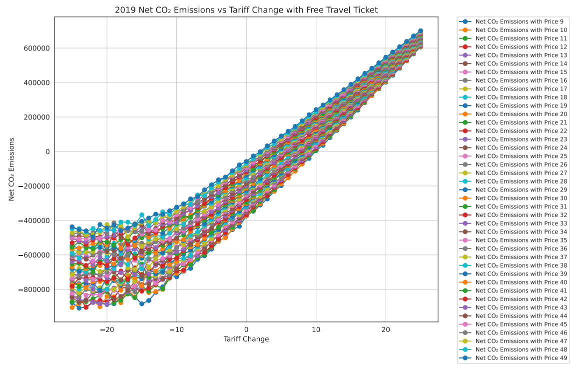


Figure G.20: 2019 net CO_2 emissions vs tariff change (free travel ticket = 1)

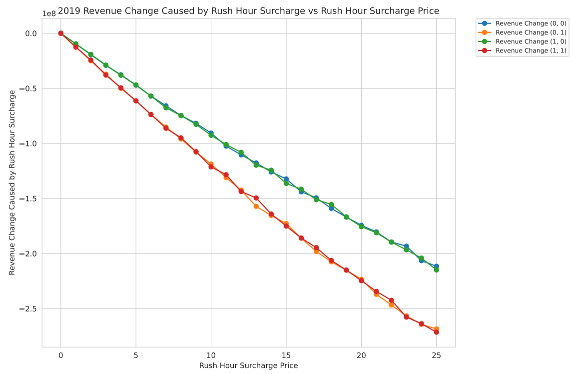


Figure G.21: 2019 revenue change vs rush hour surcharge

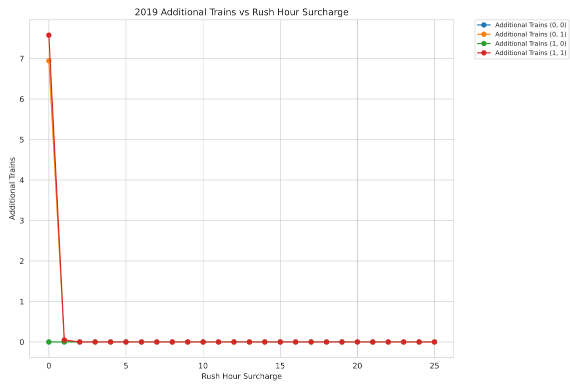


Figure G.22: 2019 revenue vs rush hour surcharge

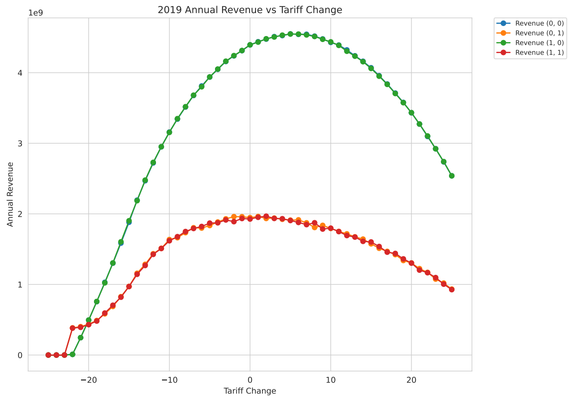


Figure G.23: 2019 revenue vs tariff change

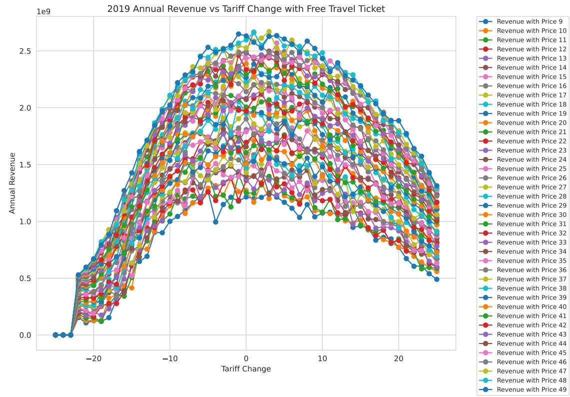


Figure G.24: 2019 revenue vs tariff change (free travel ticket = 1)

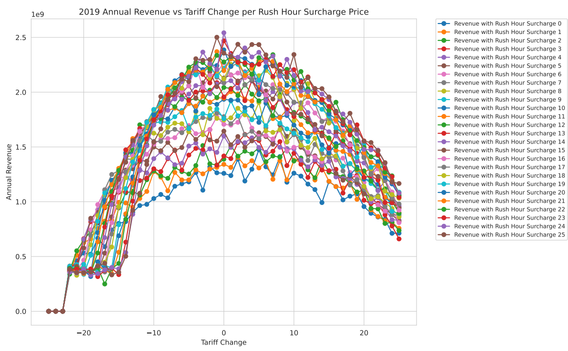


Figure G.25: 2019 revenue vs tariff change (rush hour surcharge)

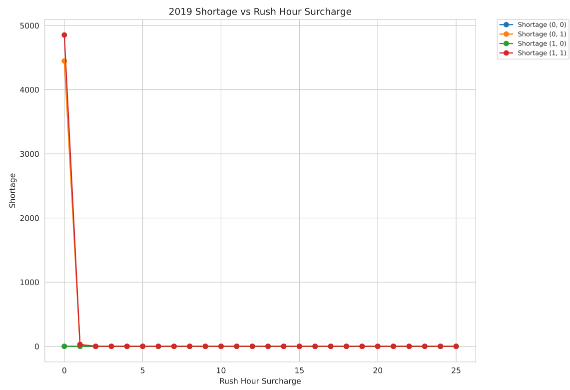


Figure G.26: 2019 shortage vs rush hour surcharge

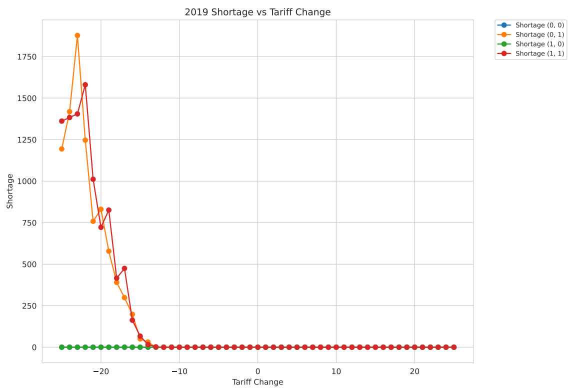


Figure G.27: 2019 shortage vs tariff change

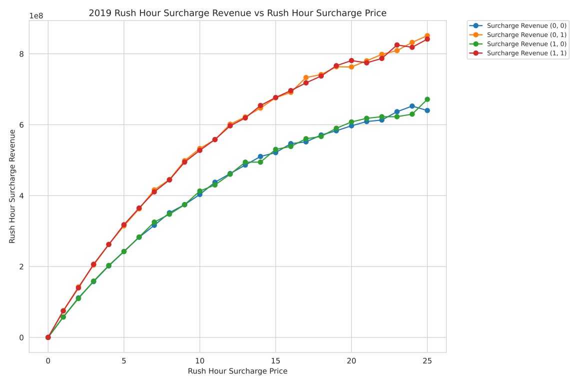


Figure G.28: 2019 surcharge revenue vs rush hour surcharge

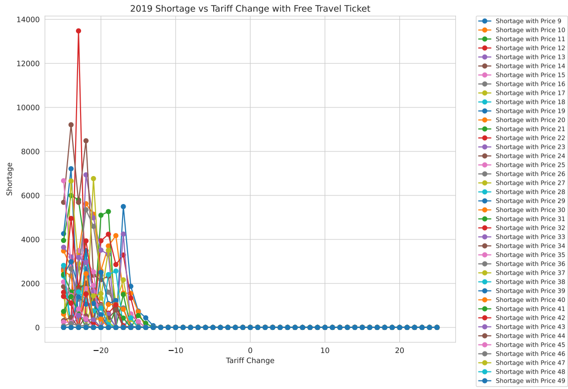


Figure G.29: 2019 shortage vs tariff change (free travel ticket = 1)

Baseline 2024 Results

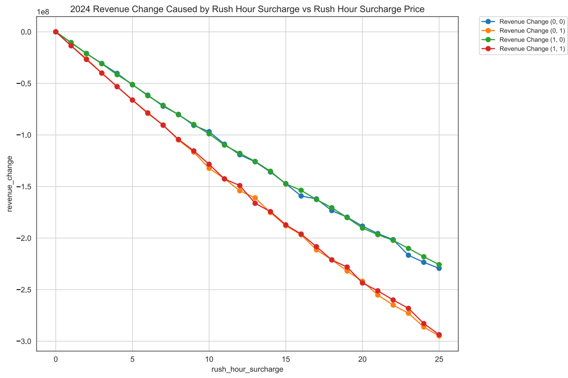


Figure G.30: 2024 revenue change vs rush hour surcharge

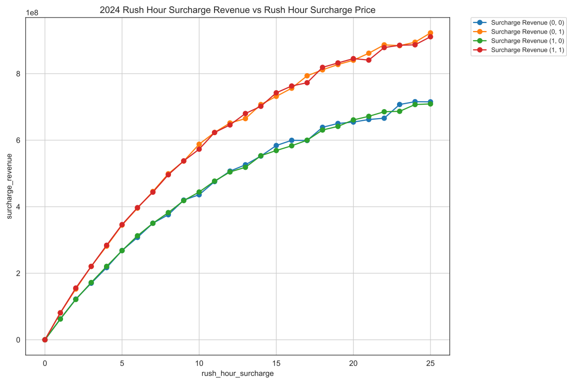


Figure G.31: 2024 surcharge revenue vs rush hour surcharge

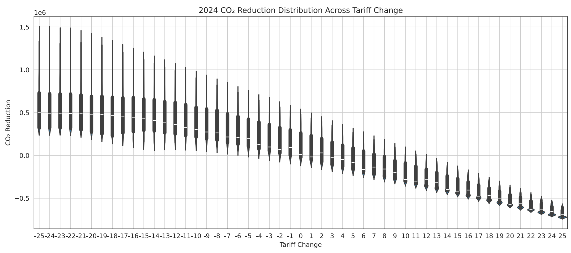


Figure G.32: 2024 violin CO_2 reduction distribution across tariff change

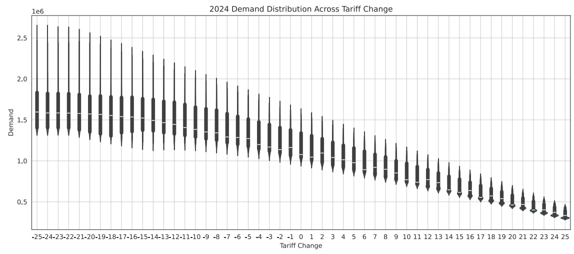


Figure G.33: 2024 violin demand distribution across tariff change

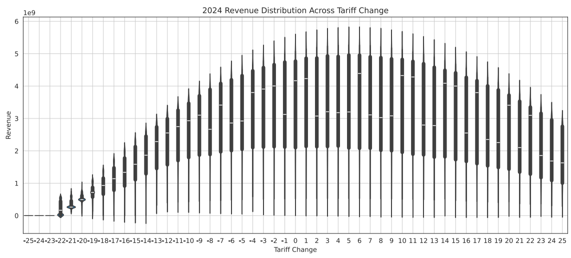


Figure G.34: 2024 violin revenue distribution across tariff change

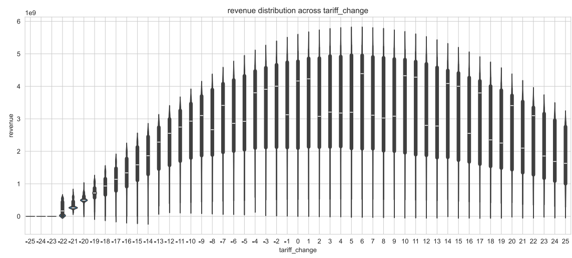


Figure G.35: 2024 violin

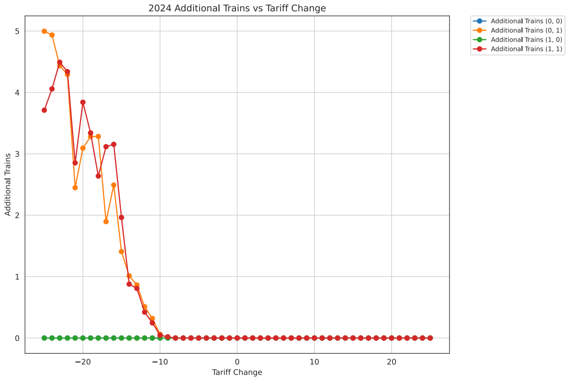


Figure G.36: 2024 additional trains vs tariff change

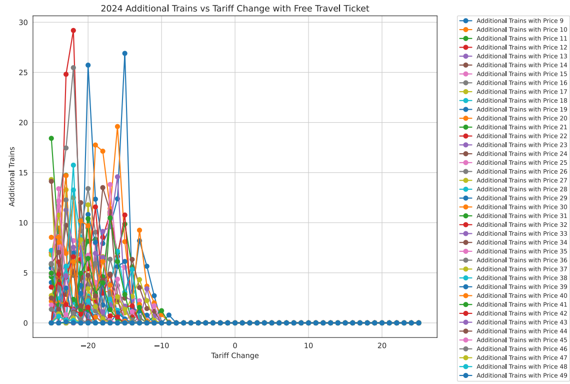


Figure G.37: 2024 additional trains vs tariff change (free travel ticket = 1)

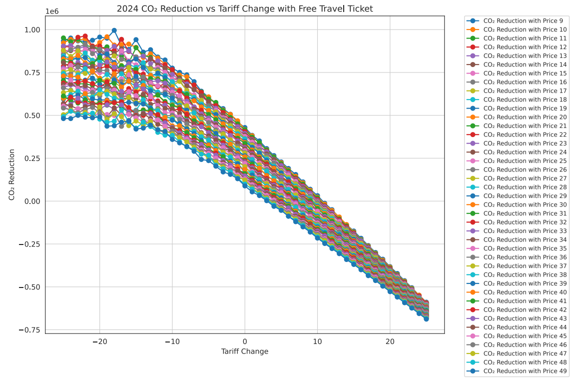


Figure G.38: 2024 CO_2 reduction vs tariff change (free travel ticket = 1)

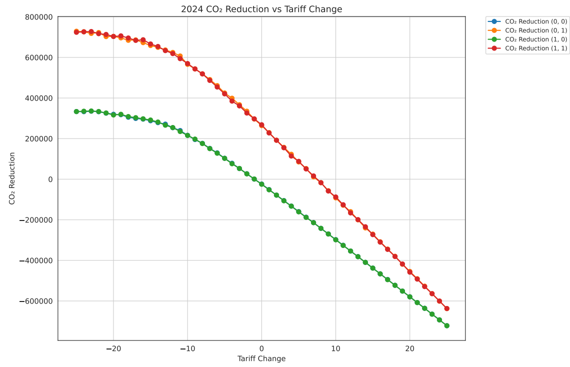


Figure G.39: 2024 CO_2 reduction vs tariff change

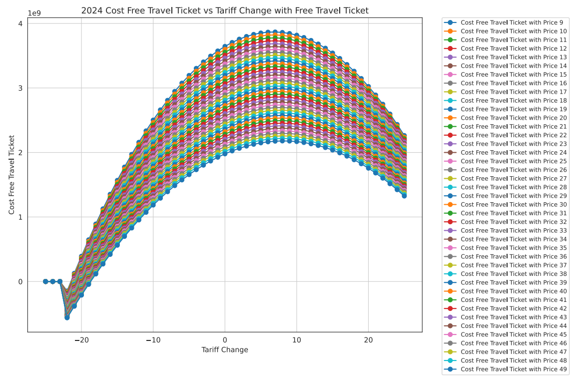


Figure G.40: 2024 cost for free travel ticket vs tariff change (free travel ticket = 1)

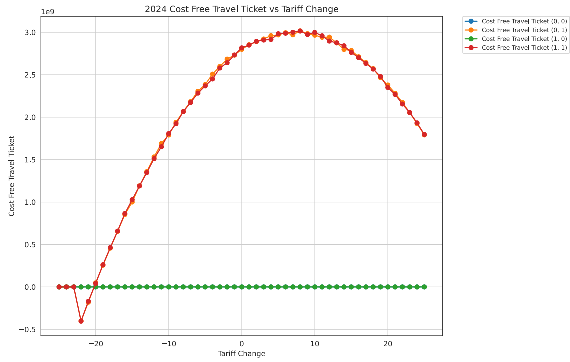


Figure G.41: 2024 cost for free travel ticket vs tariff change

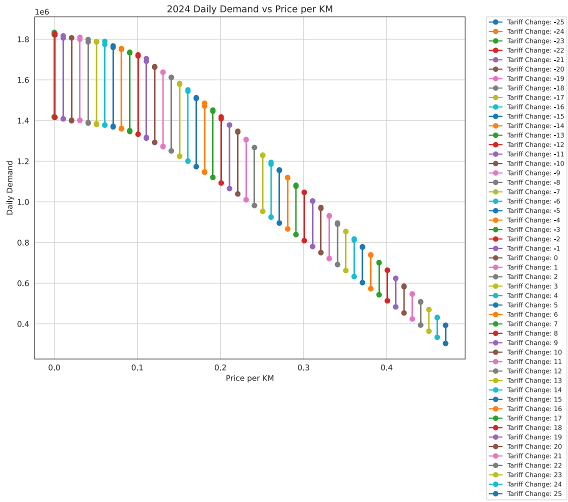


Figure G.42: 2024 daily demand vs price per km for tariff change = x

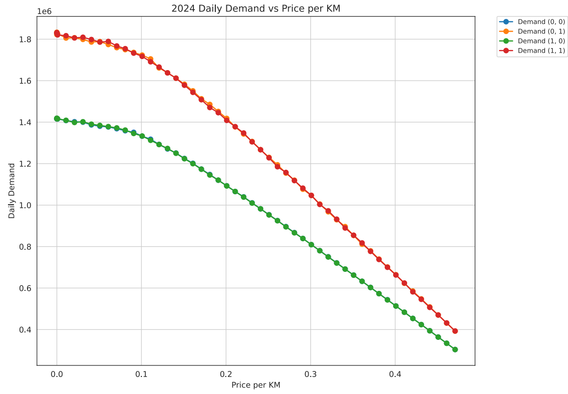


Figure G.43: 2024 daily demand vs price per km

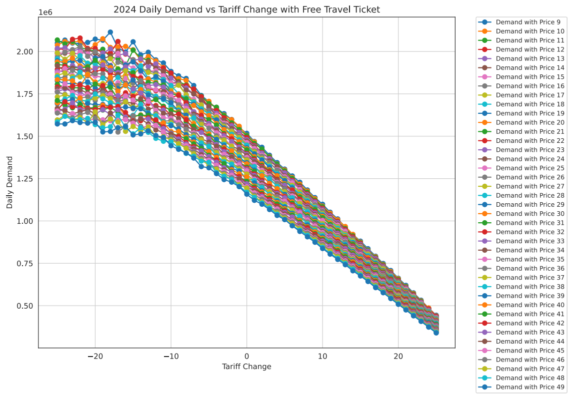


Figure G.44: 2024 daily demand vs tariff change (free travel ticket = 1)

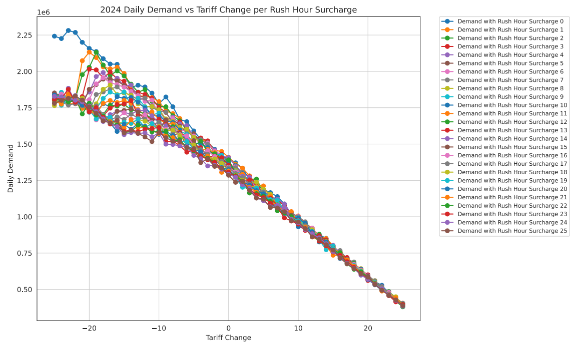


Figure G.45: 2024 daily demand vs tariff change (rush hour surcharge)

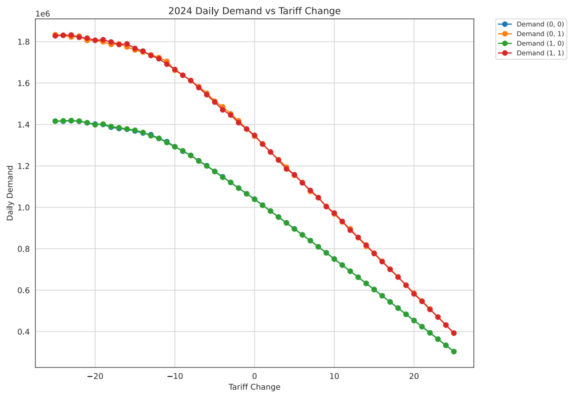


Figure G.46: 2024 daily demand vs tariff change

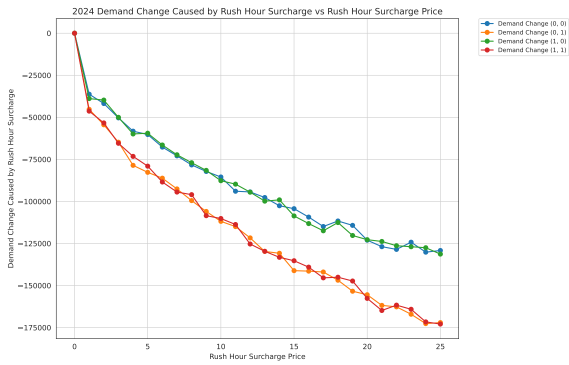


Figure G.47: 2024 demand change vs rush hour surcharge

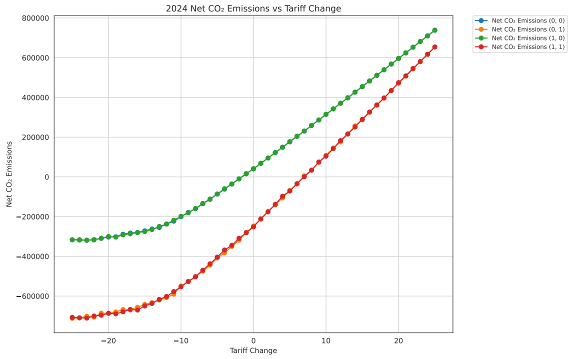


Figure G.48: 2024 net CO_2 emissions vs tariff change

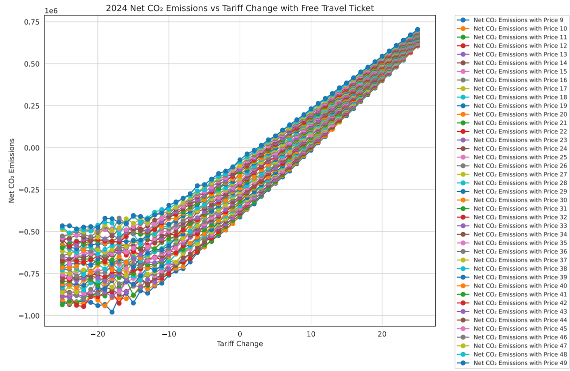


Figure G.49: 2024 net CO_2 emissions vs tariff change (free travel ticket = 1)

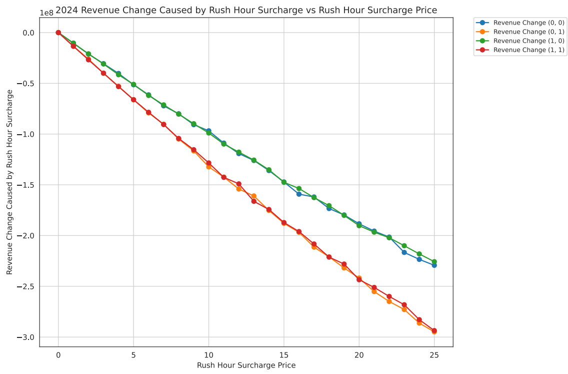


Figure G.50: 2024 revenue change vs rush hour surcharge

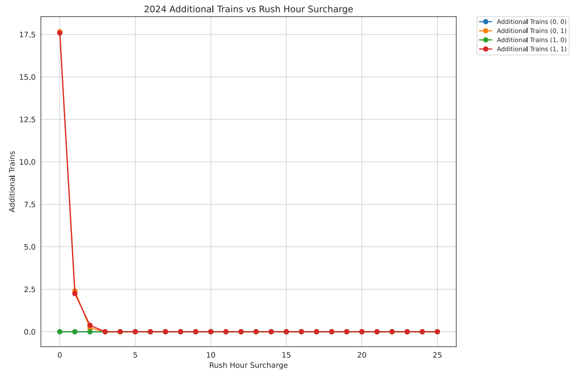


Figure G.51: 2024 revenue vs rush hour surcharge

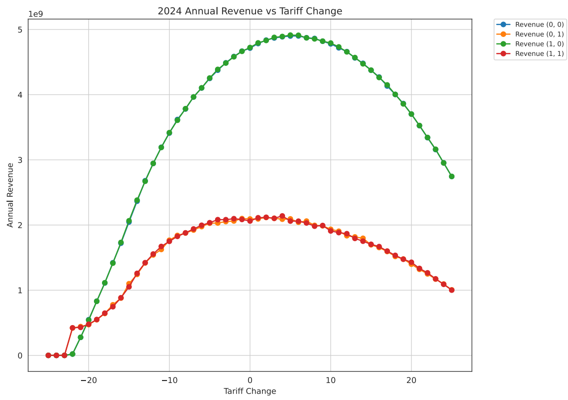


Figure G.52: 2024 revenue vs tariff change

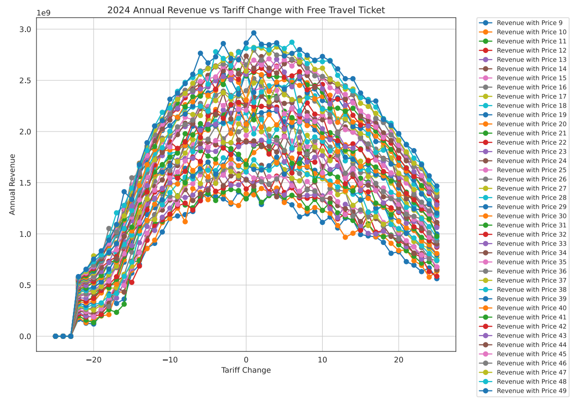


Figure G.53: 2024 revenue vs tariff change (free travel ticket = 1)

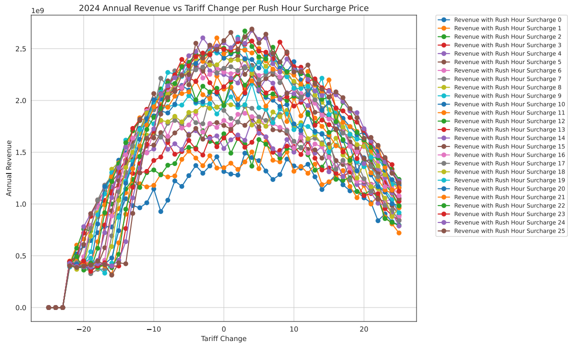


Figure G.54: 2024 revenue vs tariff change (rush hour surcharge)

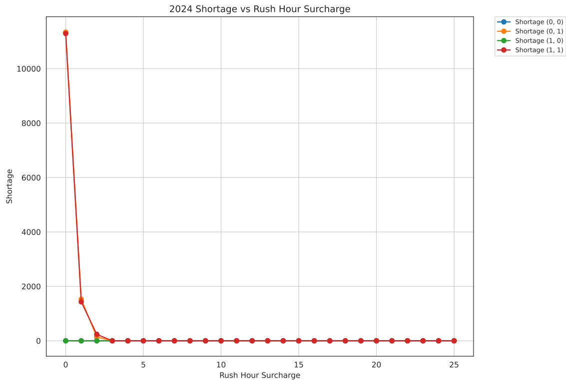


Figure G.55: 2024 shortage vs rush hour surcharge

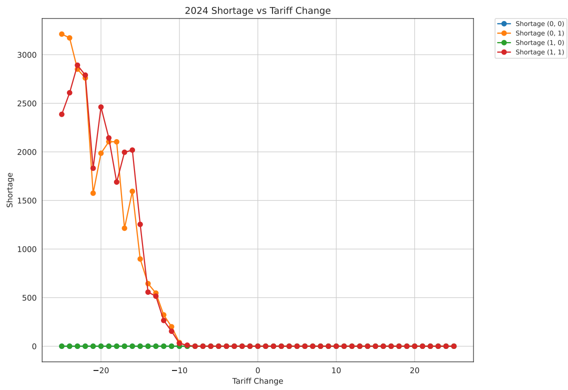


Figure G.56: 2024 shortage vs tariff change

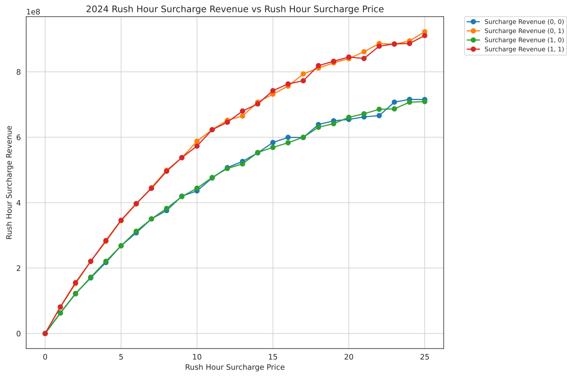


Figure G.57: 2024 surcharge revenue vs rush hour surcharge

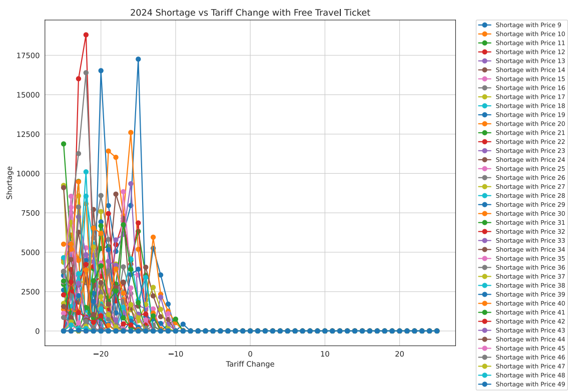


Figure G.58: 2024 shortage vs tariff change (free travel ticket = 1)

Baseline 2030 Results

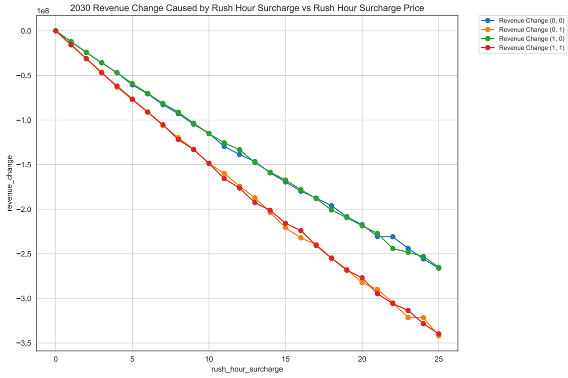


Figure G.59: 2030 revenue change vs rush hour surcharge

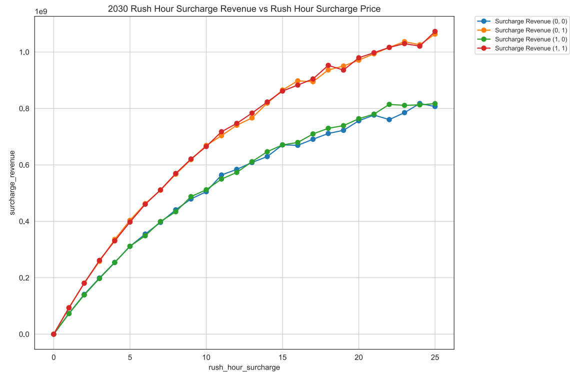


Figure G.60: 2030 surcharge revenue vs rush hour surcharge

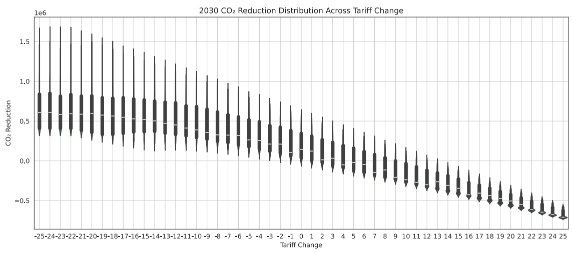


Figure G.61: 2030 violin CO_2 reduction distribution across tariff change

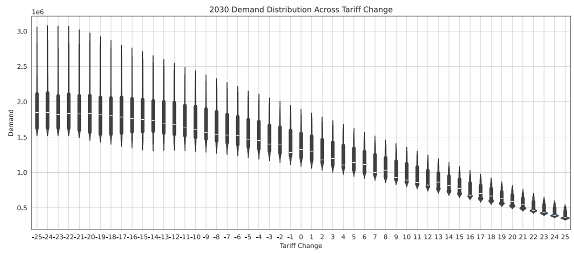


Figure G.62: 2030 violin demand distribution across tariff change

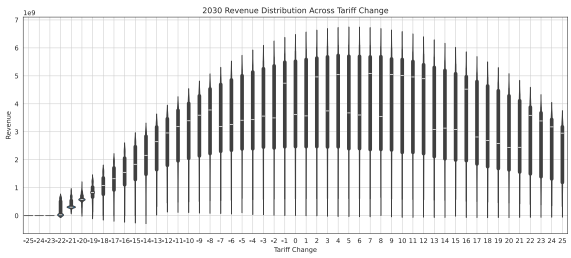


Figure G.63: 2030 violin revenue distribution across tariff change

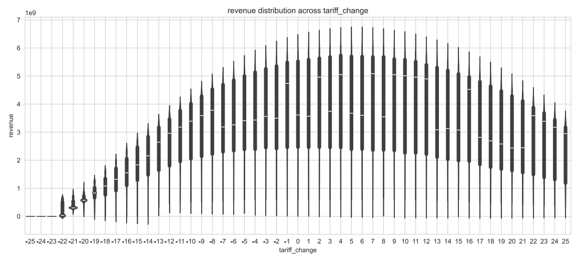


Figure G.64: 2030 violin

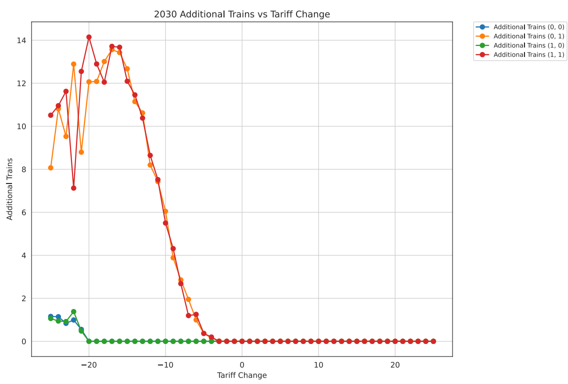


Figure G.65: 2030 additional trains vs tariff change

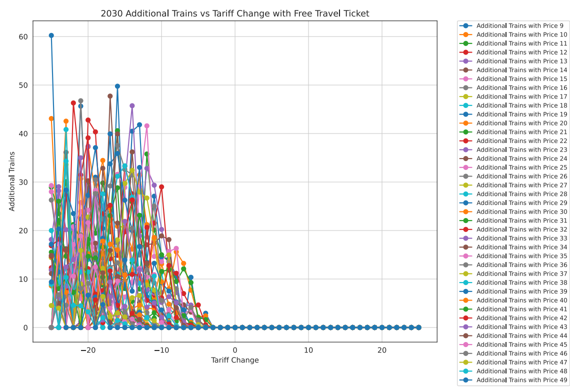


Figure G.66: 2030 additional trains vs tariff change (free travel ticket = 1)

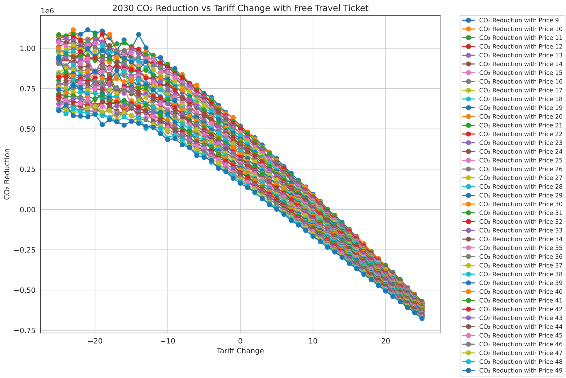


Figure G.67: 2030 CO_2 reduction vs tariff change (free travel ticket = 1)

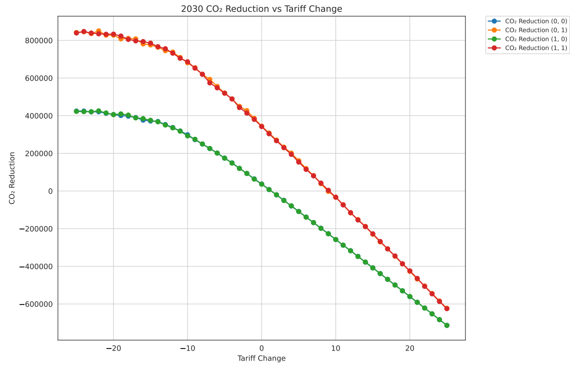


Figure G.68: 2030 CO_2 reduction vs tariff change

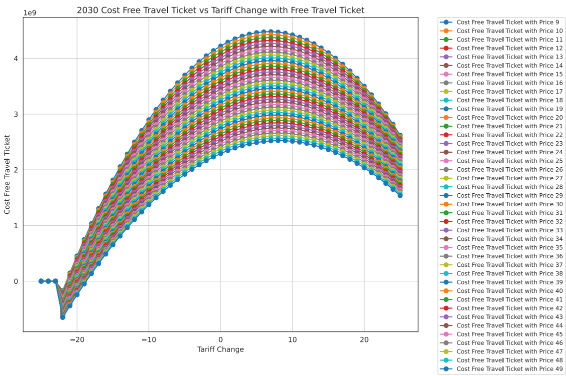


Figure G.69: 2030 cost for free travel ticket vs tariff change (free travel ticket = 1)

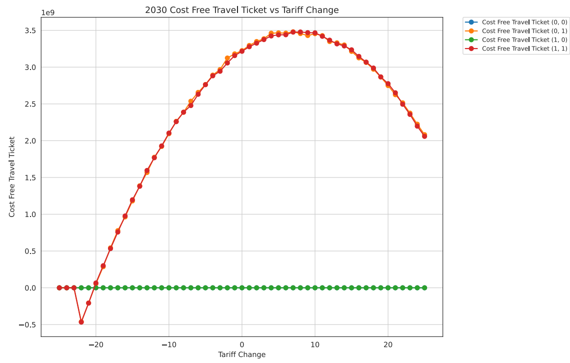


Figure G.70: 2030 cost for free travel ticket vs tariff change

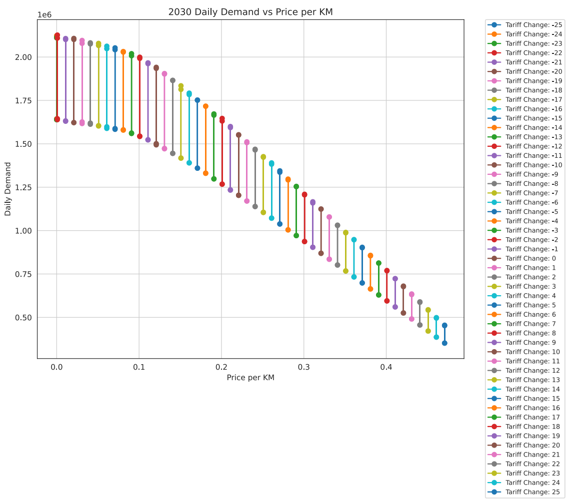


Figure G.71: 2030 daily demand vs price per km for tariff change = x

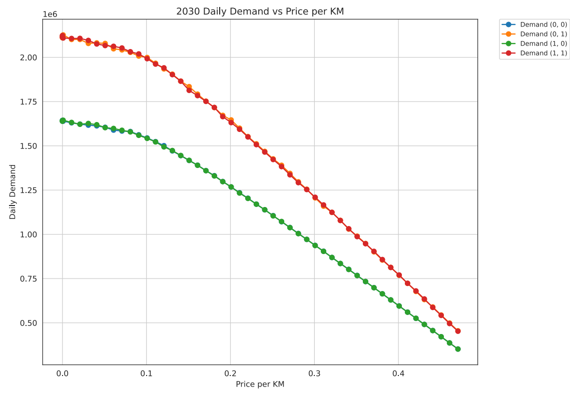


Figure G.72: 2030 daily demand vs price per km

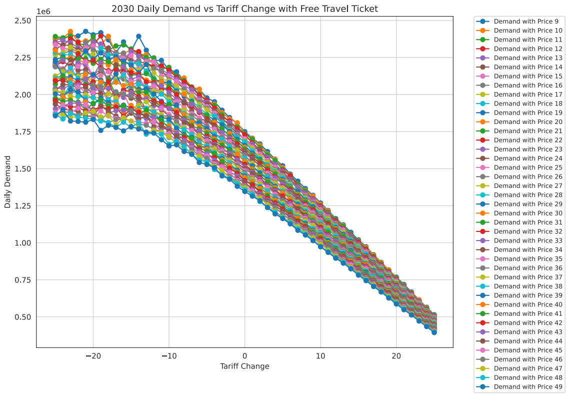


Figure G.73: 2030 daily demand vs tariff change (free travel ticket = 1)

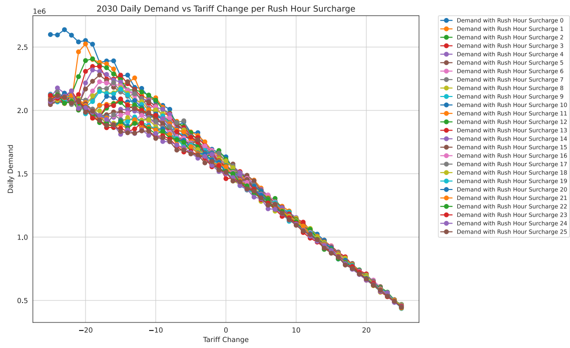


Figure G.74: 2030 daily demand vs tariff change (rush hour surcharge)

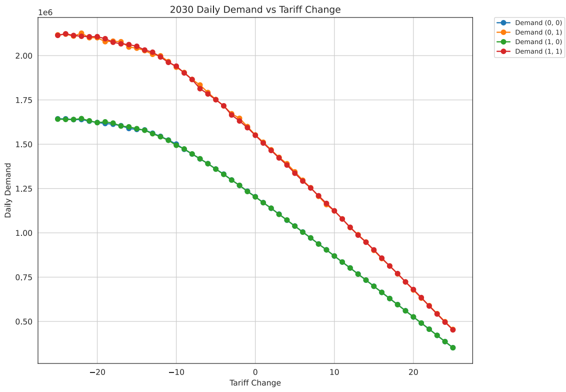


Figure G.75: 2030 daily demand vs tariff change

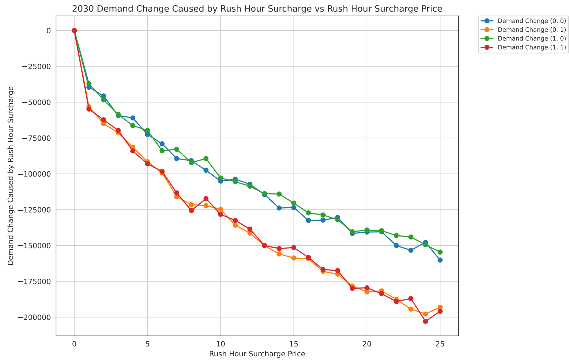


Figure G.76: 2030 demand change vs rush hour surcharge

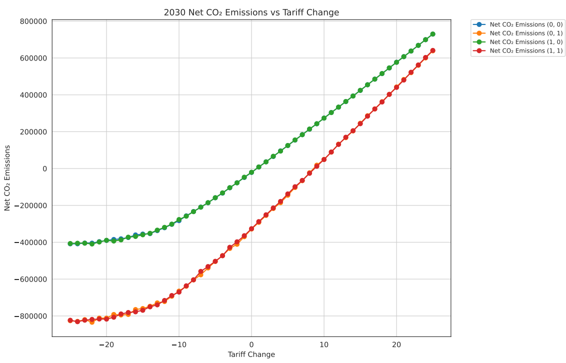


Figure G.77: 2030 net CO_2 emissions vs tariff change

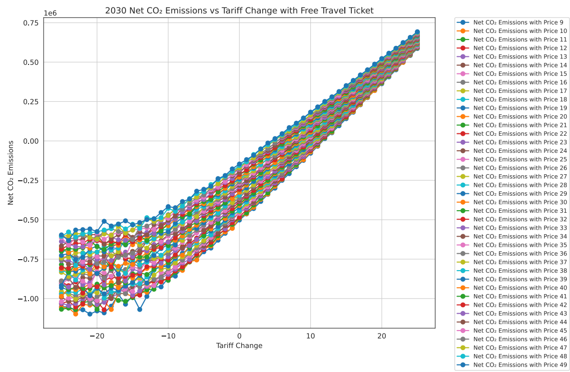


Figure G.78: 2030 net CO_2 emissions vs tariff change (free travel ticket = 1)

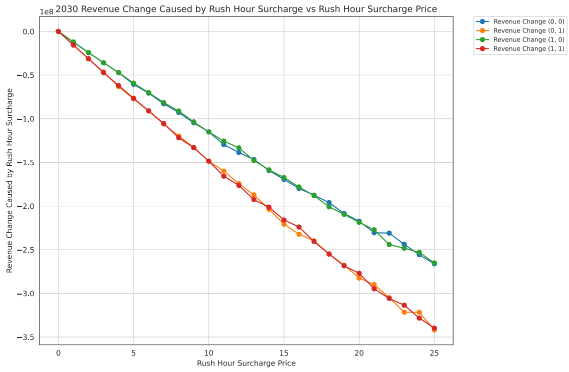


Figure G.79: 2030 revenue change vs rush hour surcharge

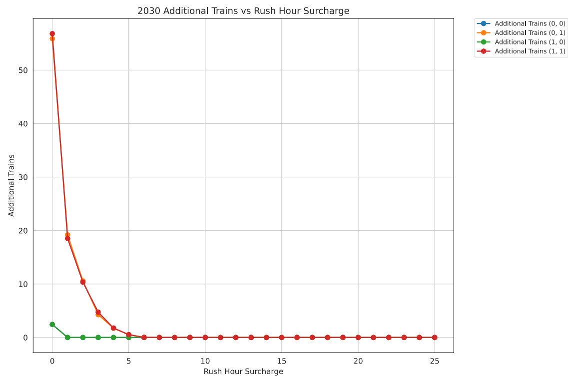


Figure G.80: 2030 revenue vs rush hour surcharge

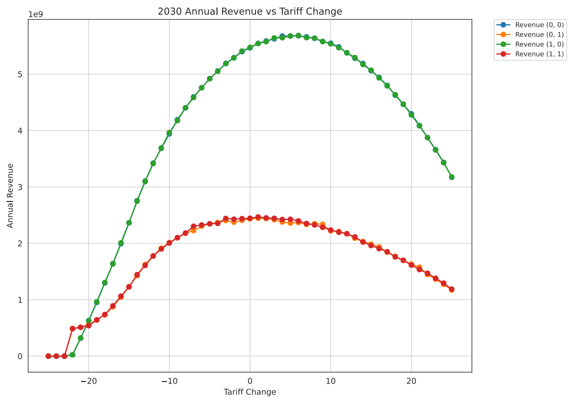


Figure G.81: 2030 revenue vs tariff change

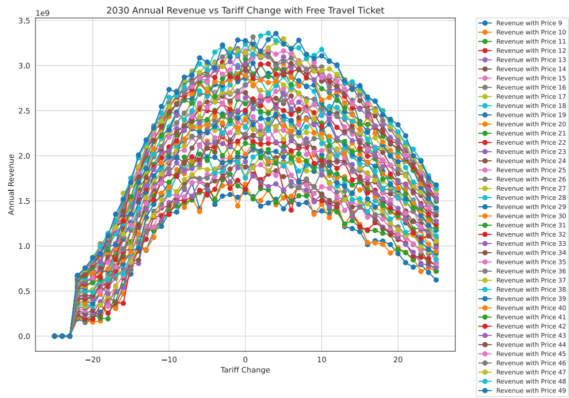


Figure G.82: 2030 revenue vs tariff change (free travel ticket = 1)

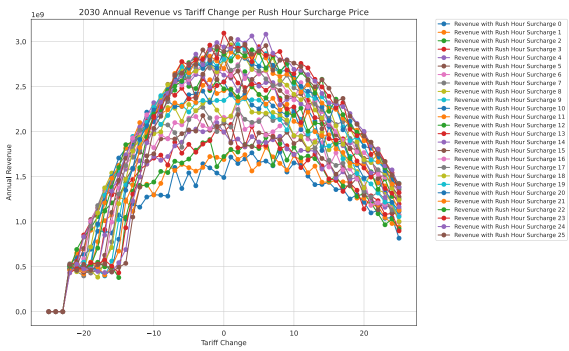


Figure G.83: 2030 revenue vs tariff change (rush hour surcharge)

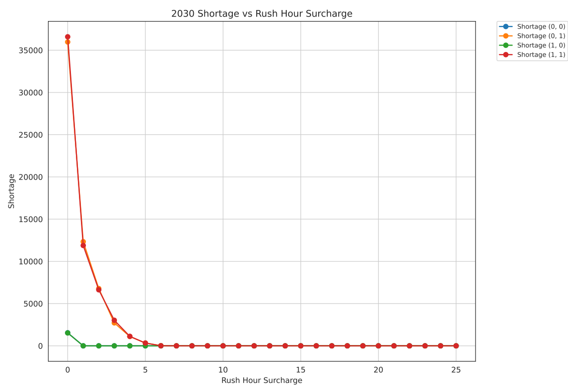


Figure G.84: 2030 shortage vs rush hour surcharge

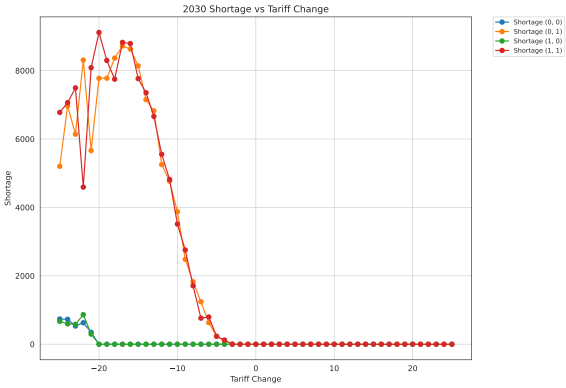


Figure G.85: 2030 shortage vs tariff change

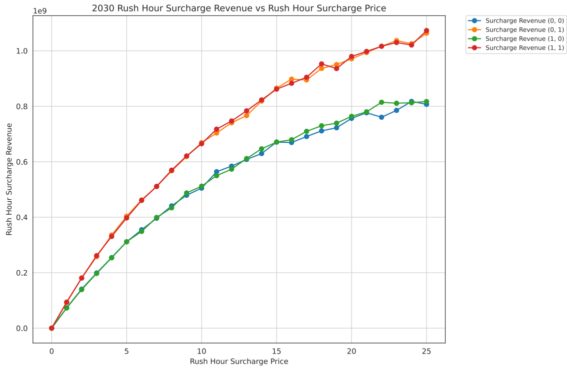


Figure G.86: 2030 surcharge revenue vs rush hour surcharge

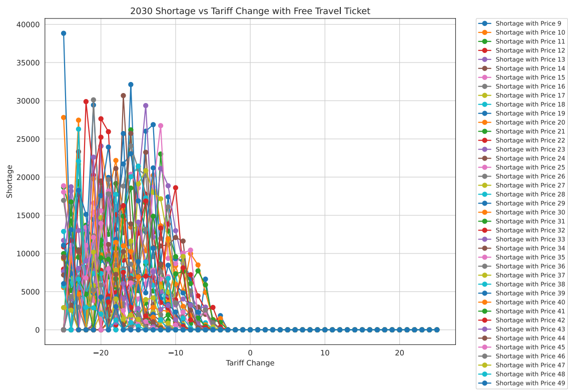


Figure G.87: 2030 shortage vs tariff change (free travel ticket = 1)

Baseline 2040 Results

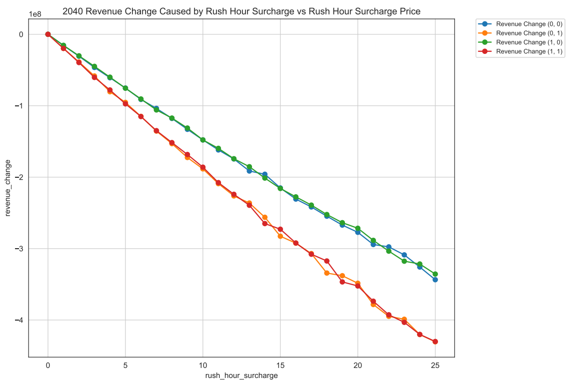


Figure G.88: 2040 revenue change vs rush hour surcharge

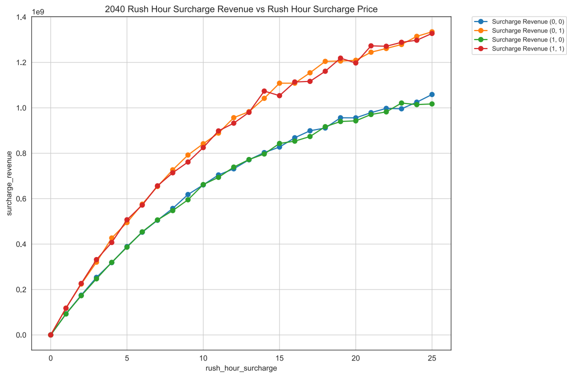


Figure G.89: 2040 surcharge revenue vs rush hour surcharge

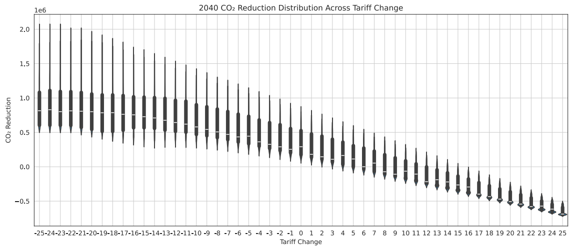


Figure G.90: 2040 violin CO_2 reduction distribution across tariff change

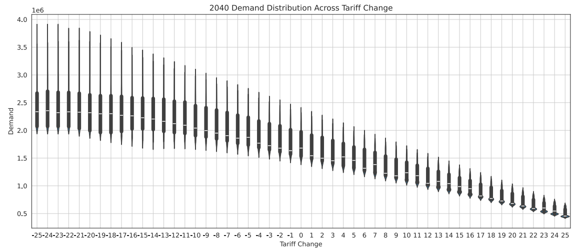


Figure G.91: 2040 violin demand distribution across tariff change

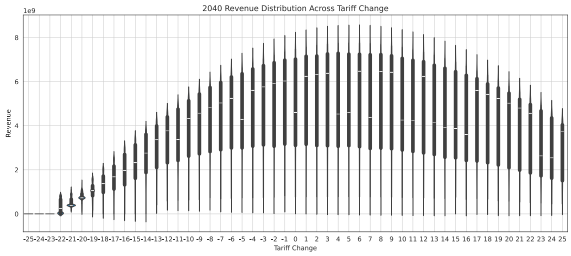


Figure G.92: 2040 violin revenue distribution across tariff change

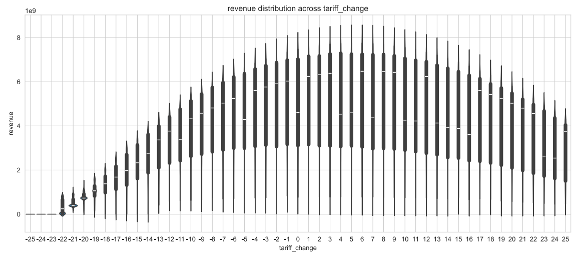


Figure G.93: 2040 violin

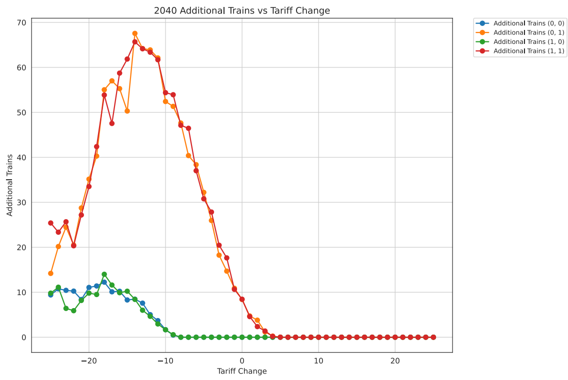


Figure G.94: 2040 additional trains vs tariff change

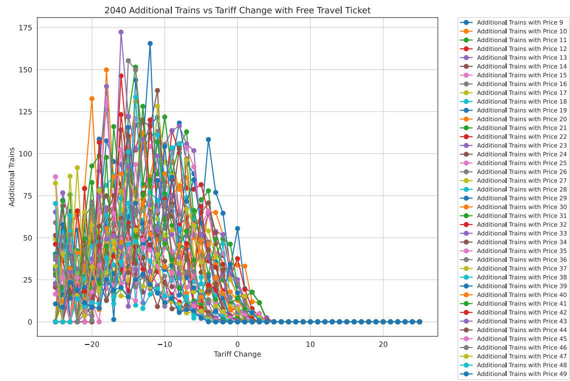


Figure G.95: 2040 additional trains vs tariff change (free travel ticket = 1)

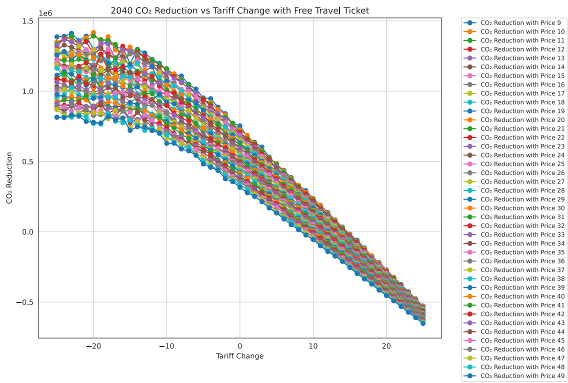


Figure G.96: 2040 CO_2 reduction vs tariff change (free travel ticket = 1)

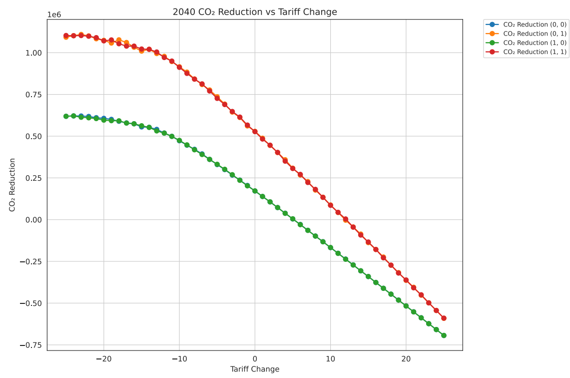


Figure G.97: 2040 CO_2 reduction vs tariff change

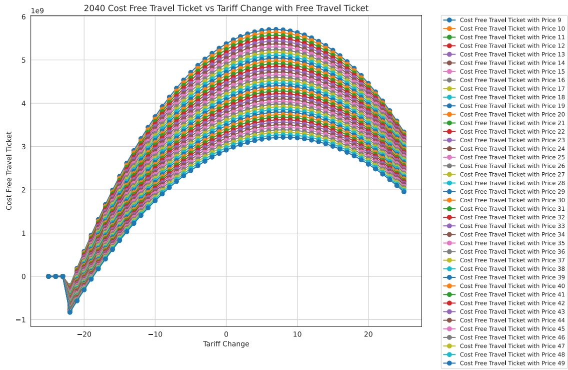


Figure G.98: 2040 cost for free travel ticket vs tariff change (free travel ticket = 1)

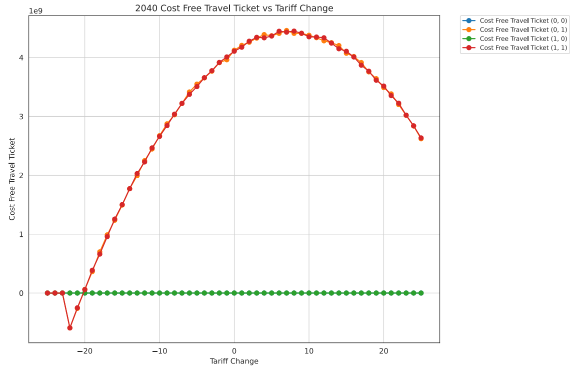


Figure G.99: 2040 cost for free travel ticket vs tariff change

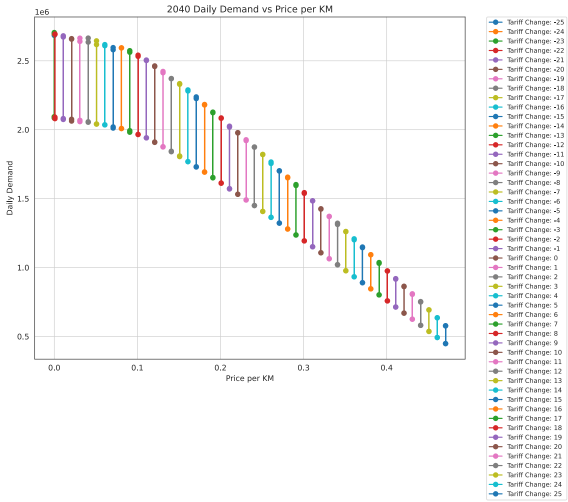


Figure G.100: 2040 daily demand vs price per km for tariff change = x

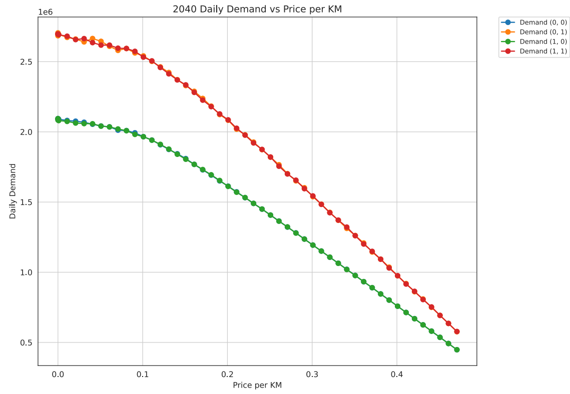


Figure G.101: 2040 daily demand vs price per km

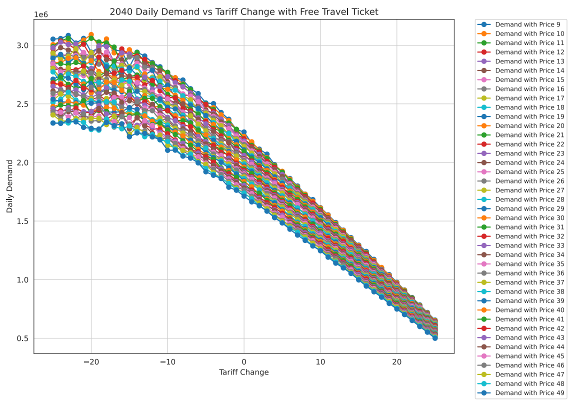


Figure G.102: 2040 daily demand vs tariff change (free travel ticket = 1)

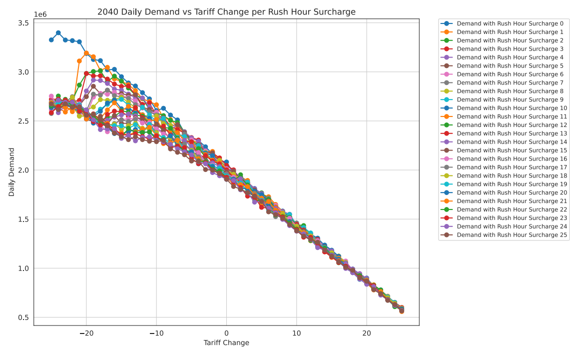


Figure G.103: 2040 daily demand vs tariff change (rush hour surcharge)

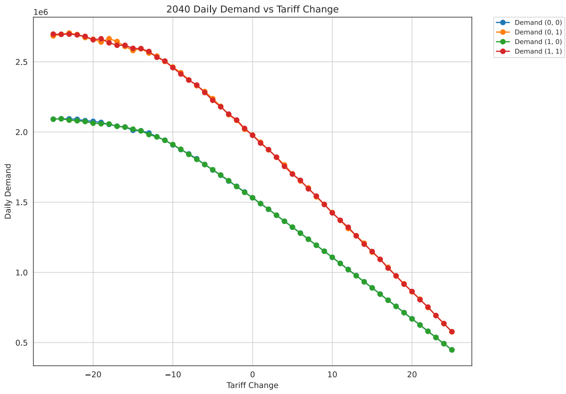


Figure G.104: 2040 daily demand vs tariff change

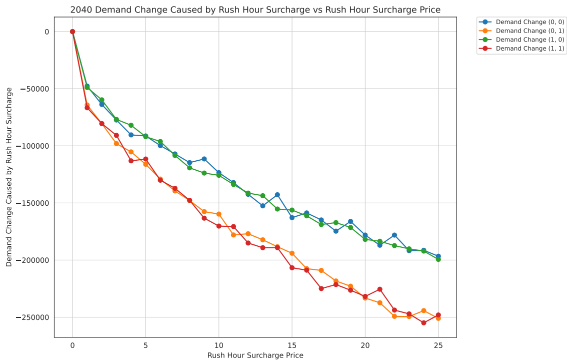


Figure G.105: 2040 demand change vs rush hour surcharge

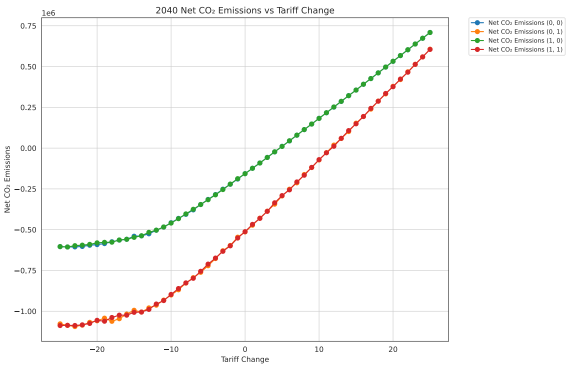


Figure G.106: 2040 net CO_2 emissions vs tariff change

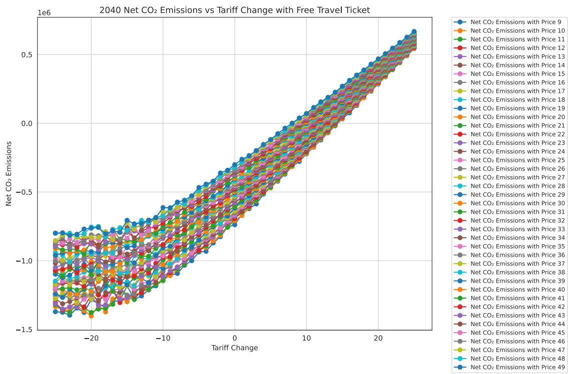


Figure G.107: 2040 net CO_2 emissions vs tariff change (free travel ticket = 1)

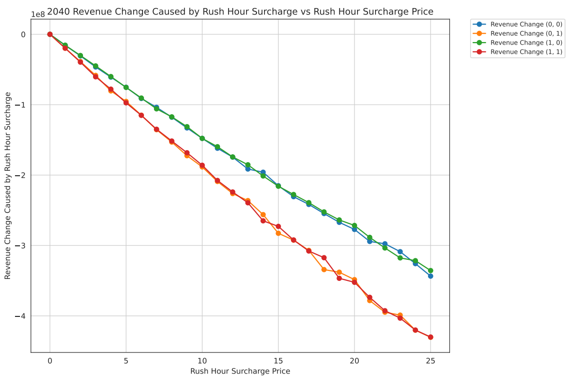


Figure G.108: 2040 revenue change vs rush hour surcharge

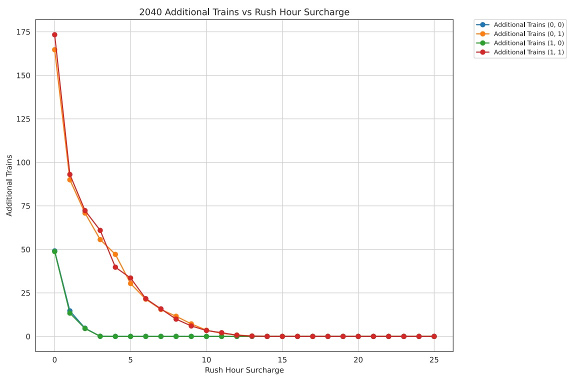


Figure G.109: 2040 revenue vs rush hour surcharge

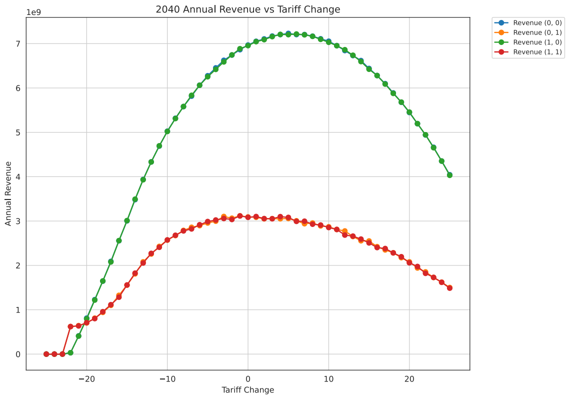


Figure G.110: 2040 revenue vs tariff change

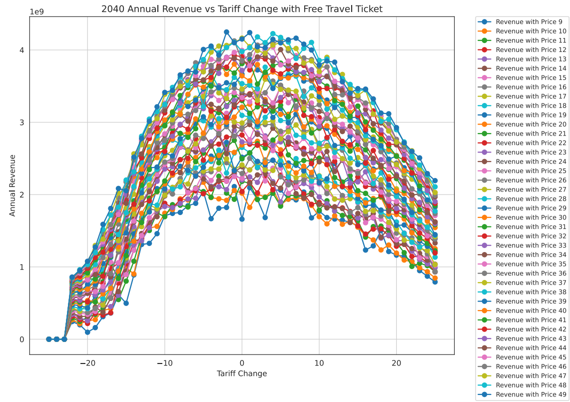


Figure G.111: 2040 revenue vs tariff change (free travel ticket = 1)

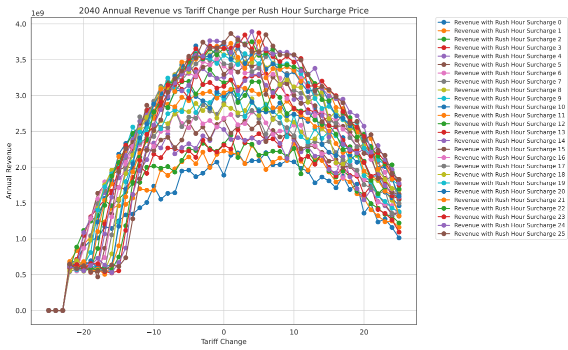


Figure G.112: 2040 revenue vs tariff change (rush hour surcharge)

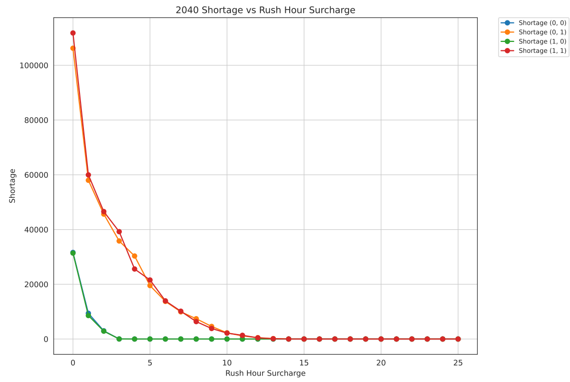


Figure G.113: 2040 shortage vs rush hour surcharge

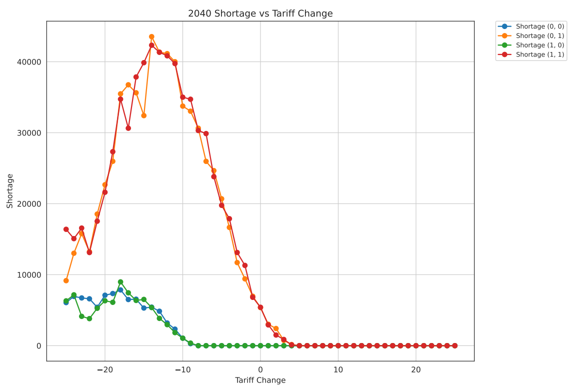


Figure G.114: 2040 shortage vs tariff change

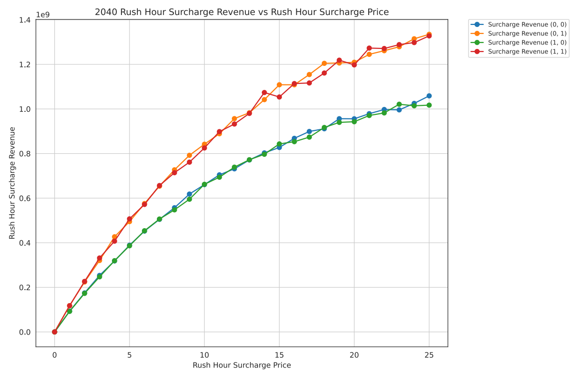


Figure G.115: 2040 surcharge revenue vs rush hour surcharge

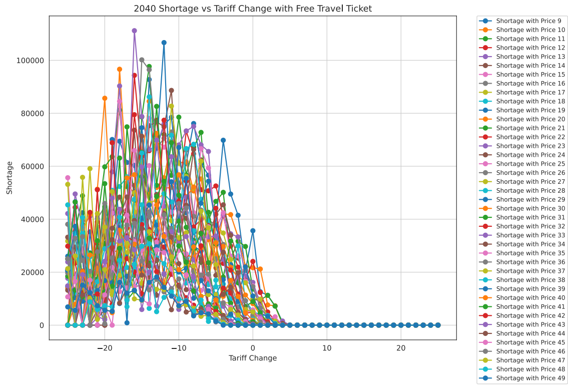


Figure G.116: 2040 shortage vs tariff change (free travel ticket = 1)

Baseline 2050 Results

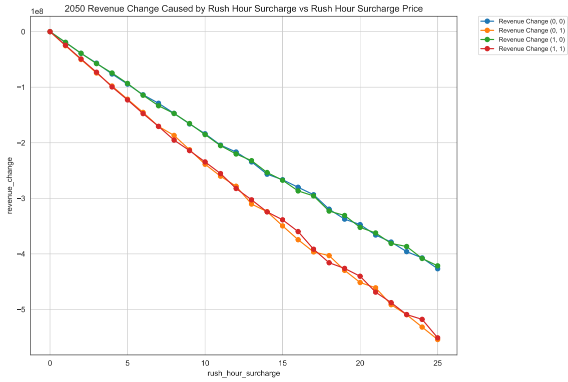


Figure G.117: 2050 revenue change vs rush hour surcharge

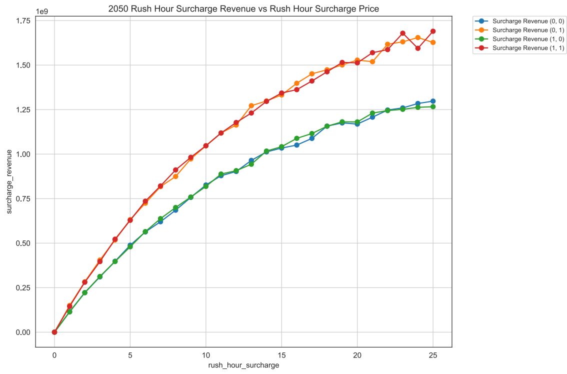


Figure G.118: 2050 surcharge revenue vs rush hour surcharge

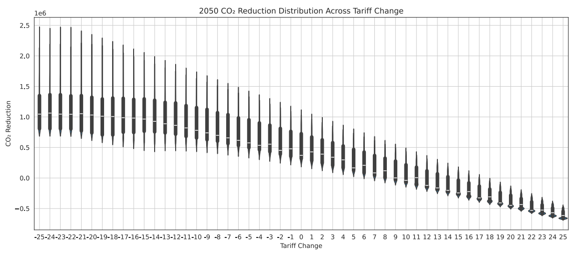


Figure G.119: 2050 violin CO_2 reduction distribution across tariff change

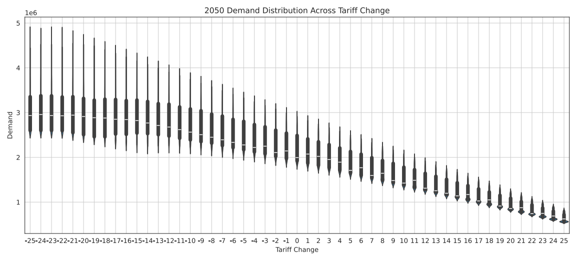


Figure G.120: 2050 violin demand distribution across tariff change

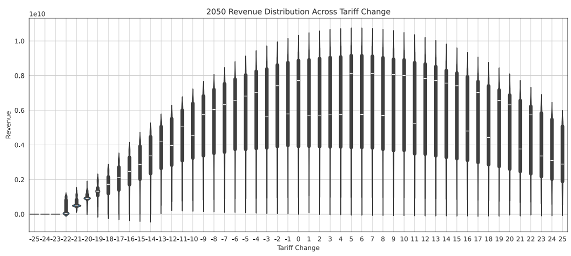


Figure G.121: 2050 violin revenue distribution across tariff change

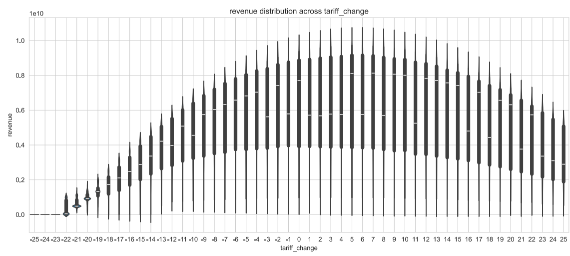


Figure G.122: 2050 violin

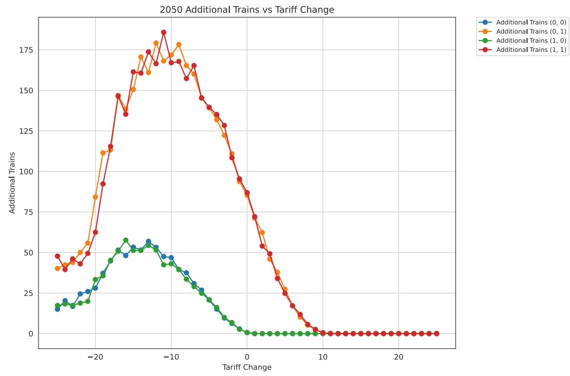


Figure G.123: 2050 additional trains vs tariff change

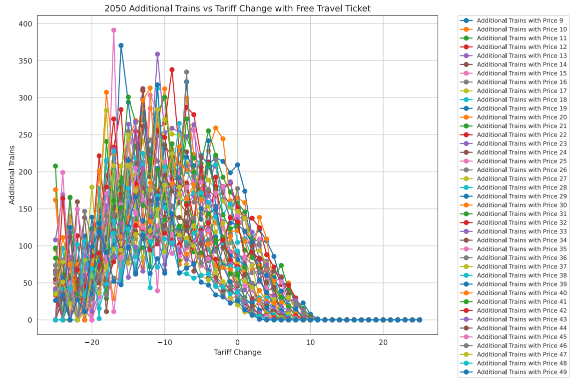


Figure G.124: 2050 additional trains vs tariff change (free travel ticket = 1)

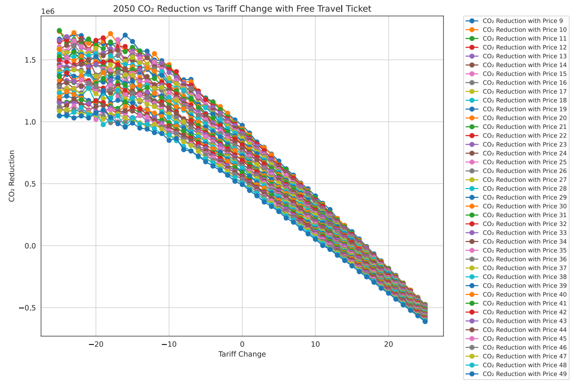


Figure G.125: 2050 CO_2 reduction vs tariff change (free travel ticket = 1)

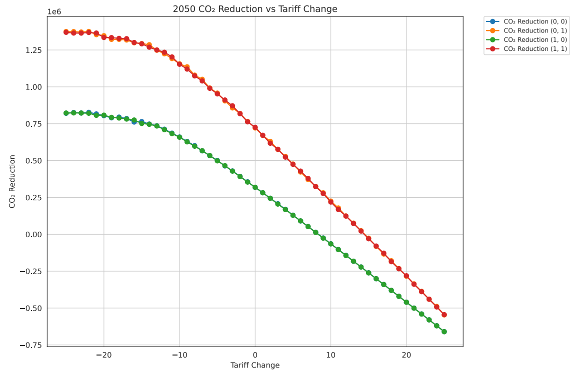


Figure G.126: 2050 CO_2 reduction vs tariff change

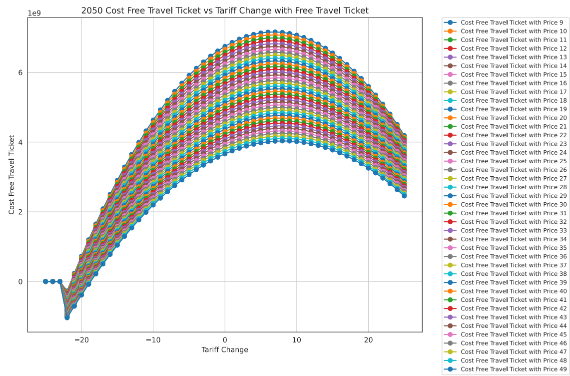


Figure G.127: 2050 cost for free travel ticket vs tariff change (free travel ticket = 1)

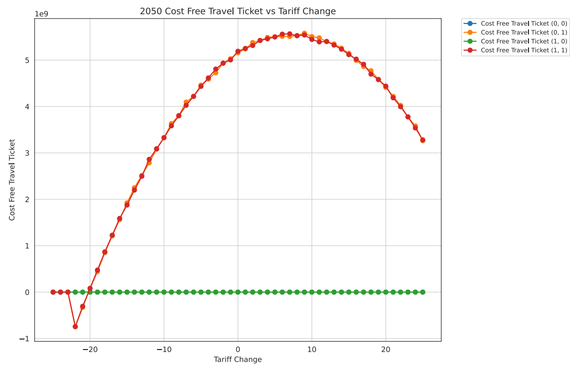


Figure G.128: 2050 cost for free travel ticket vs tariff change

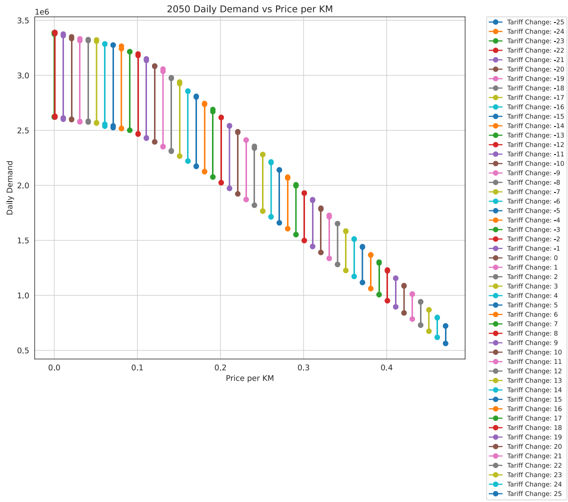


Figure G.129: 2050 daily demand vs price per km for tariff change = x

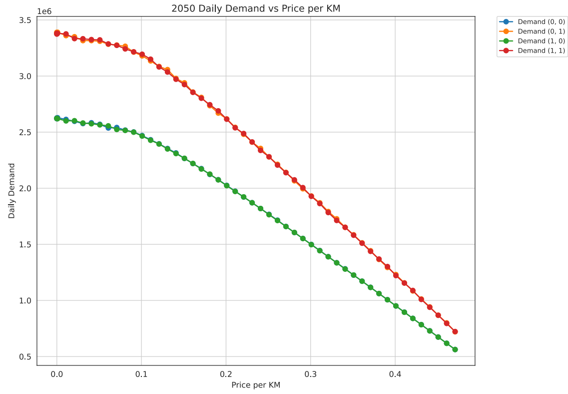


Figure G.130: 2050 daily demand vs price per km

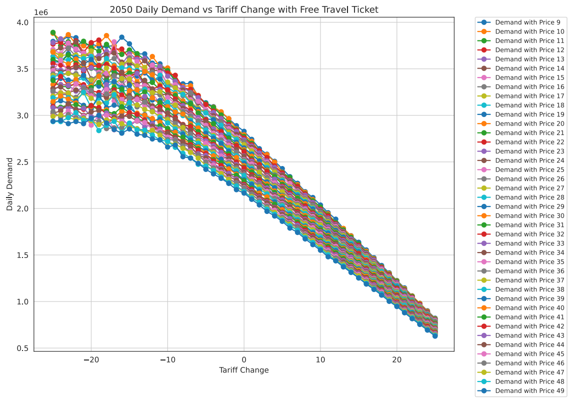


Figure G.131: 2050 daily demand vs tariff change (free travel ticket = 1)

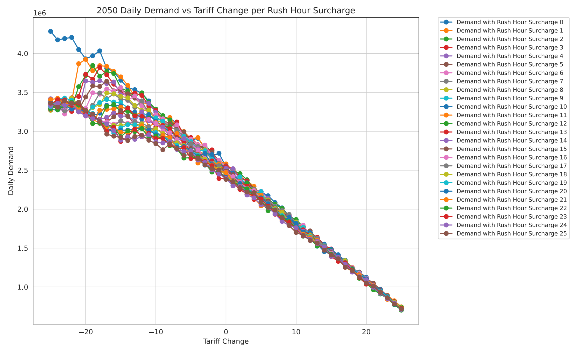


Figure G.132: 2050 daily demand vs tariff change (rush hour surcharge)

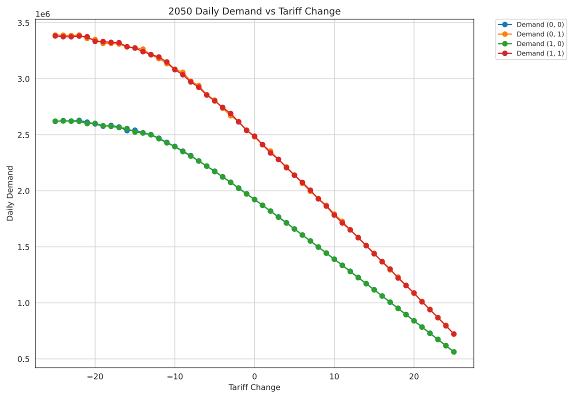


Figure G.133: 2050 daily demand vs tariff change

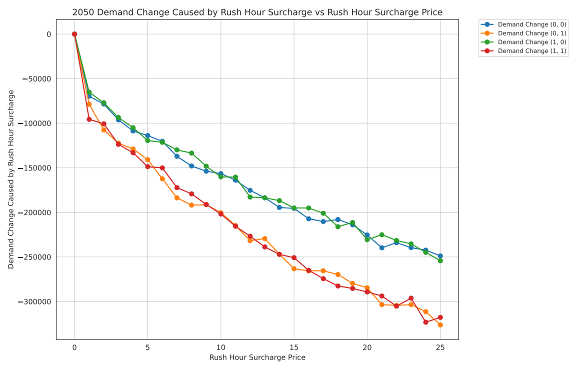


Figure G.134: 2050 demand change vs rush hour surcharge

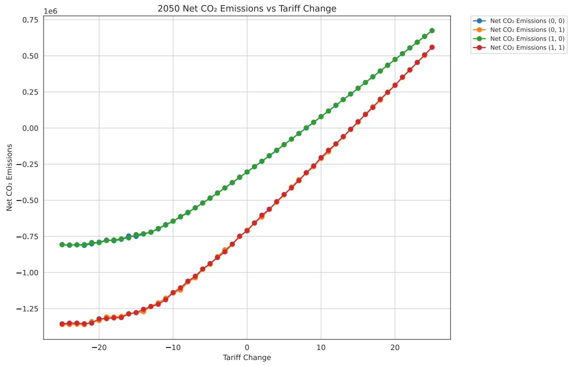


Figure G.135: 2050 net CO_2 emissions vs tariff change

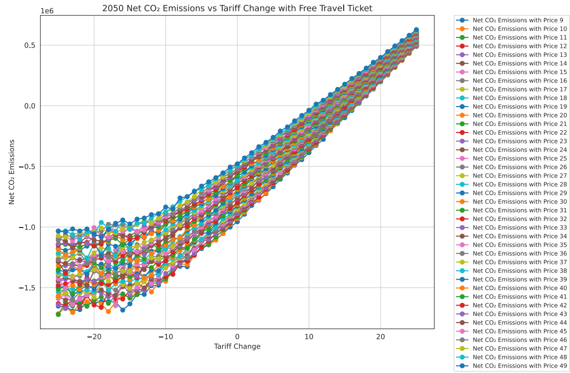


Figure G.136: 2050 net CO_2 emissions vs tariff change (free travel ticket = 1)

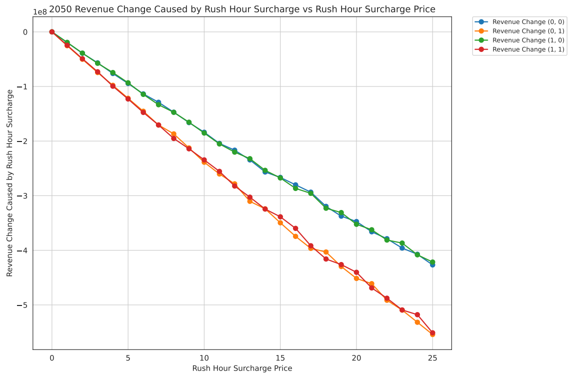


Figure G.137: 2050 revenue change vs rush hour surcharge

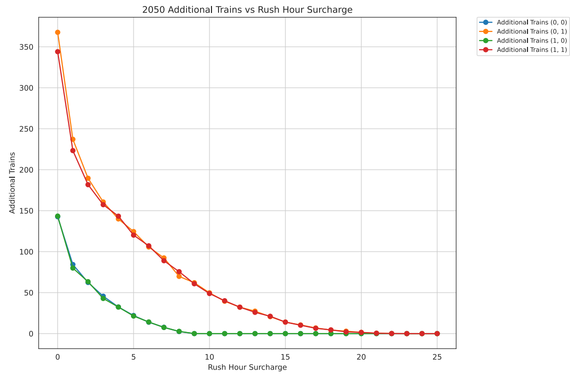


Figure G.138: 2050 revenue vs rush hour surcharge

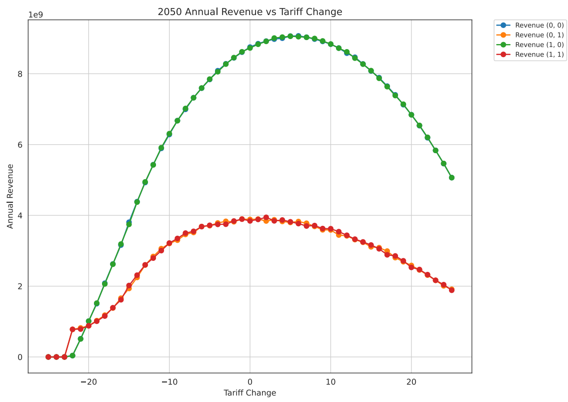


Figure G.139: 2050 revenue vs tariff change

Figure G.140: 2050 revenue vs tariff change (free travel ticket = 1)

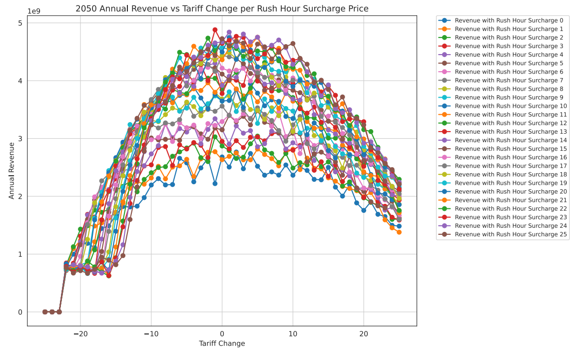


Figure G.141: 2050 revenue vs tariff change (rush hour surcharge)

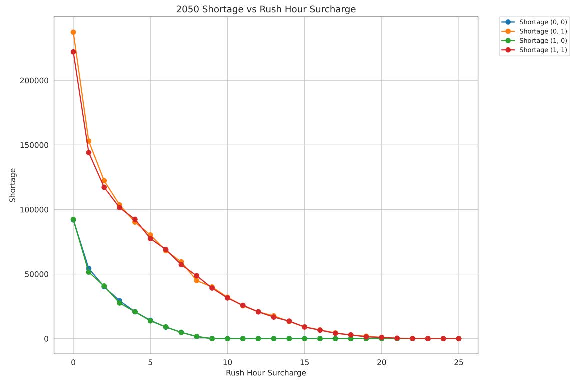


Figure G.142: 2050 shortage vs rush hour surcharge

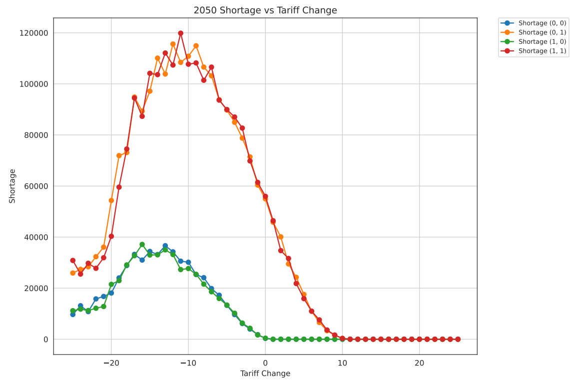


Figure G.143: 2050 shortage vs tariff change

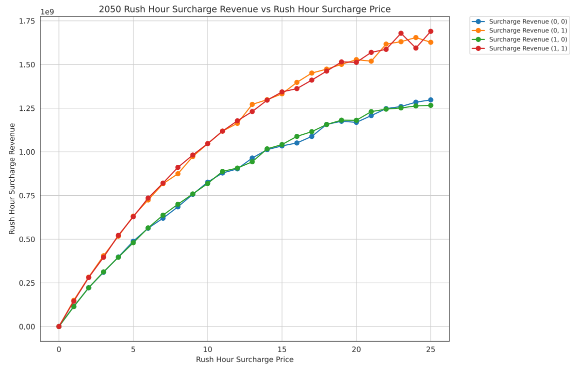


Figure G.144: 2050 surcharge revenue vs rush hour surcharge

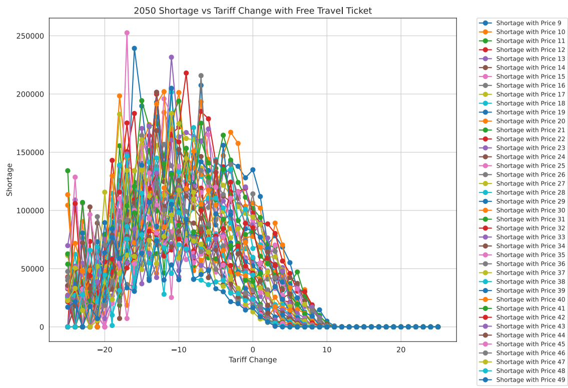


Figure G.145: 2050 shortage vs tariff change (free travel ticket = 1)

Baseline 2060 Results

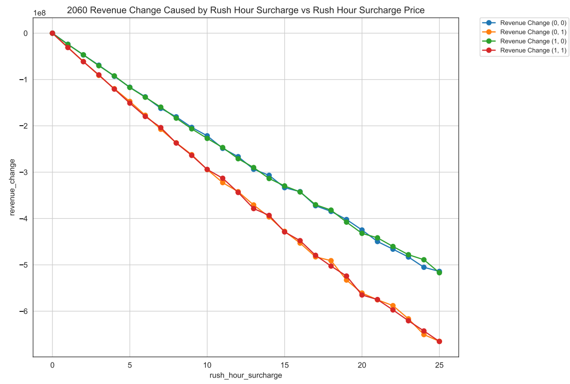


Figure G.146: 2060 revenue change vs rush hour surcharge

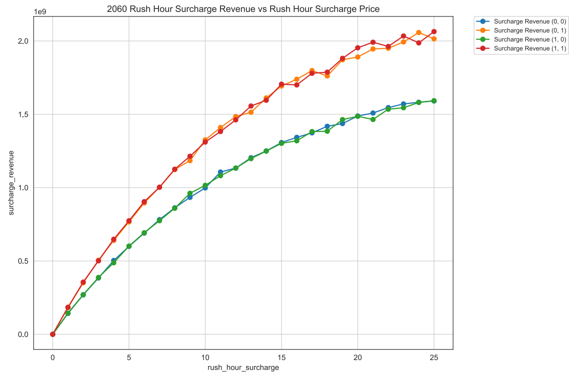


Figure G.147: 2060 surcharge revenue vs rush hour surcharge

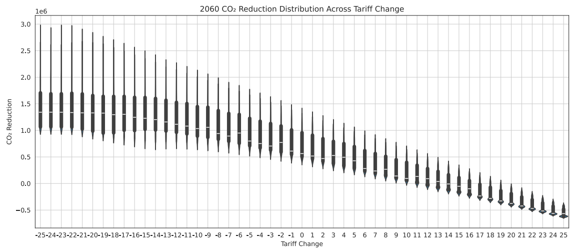


Figure G.148: 2060 violin CO_2 reduction distribution across tariff change

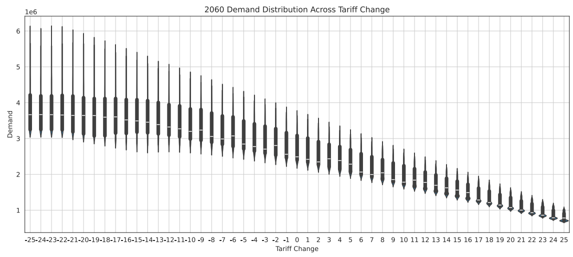


Figure G.149: 2060 violin demand distribution across tariff change

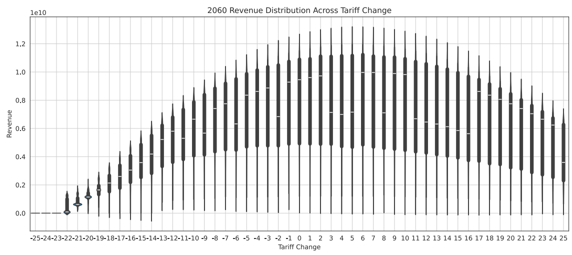


Figure G.150: 2060 violin revenue distribution across tariff change

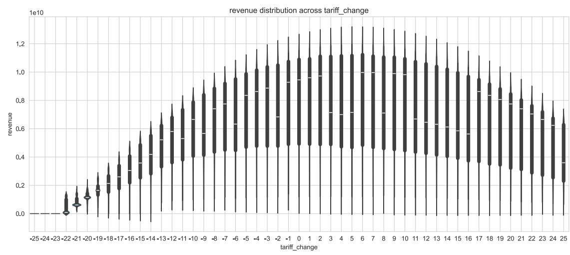


Figure G.151: 2060 violin

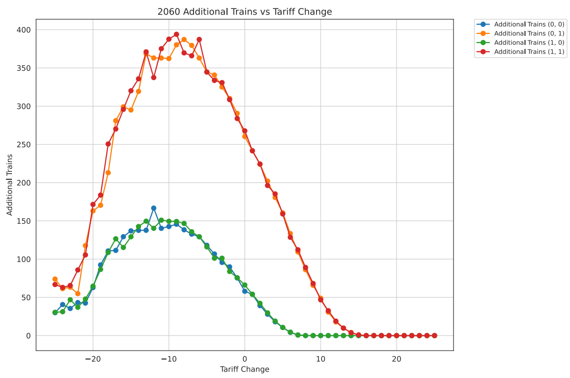


Figure G.152: 2060 additional trains vs tariff change

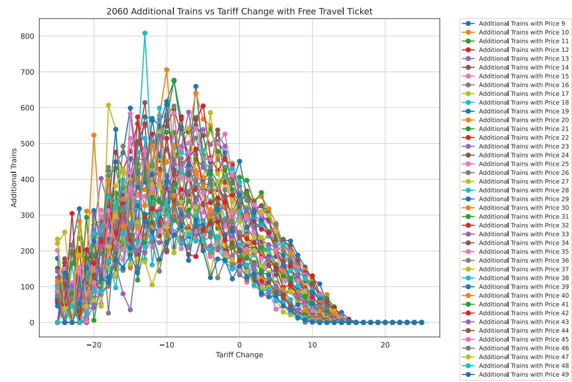


Figure G.153: 2060 additional trains vs tariff change (free travel ticket = 1)

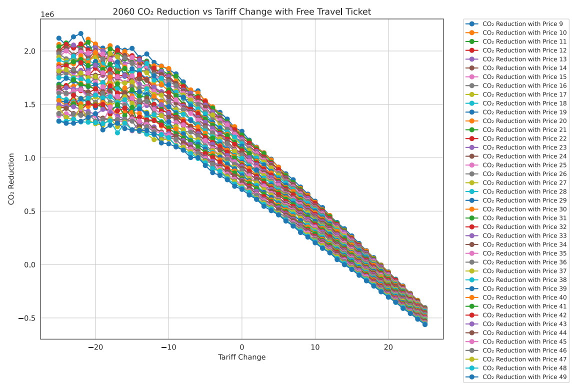


Figure G.154: 2060 CO_2 reduction vs tariff change (free travel ticket = 1)

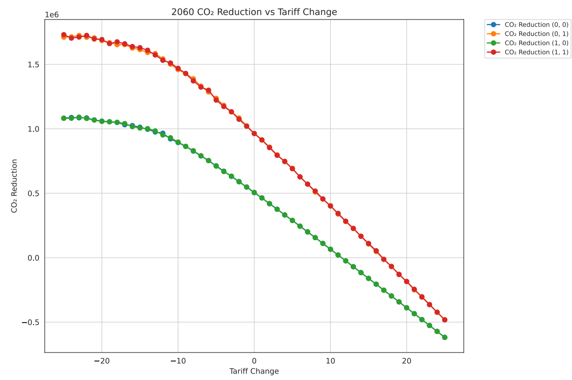


Figure G.155: 2060 CO_2 reduction vs tariff change

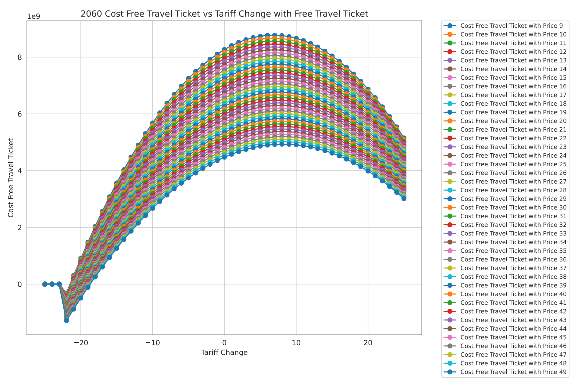


Figure G.156: 2060 cost for free travel ticket vs tariff change (free travel ticket = 1)

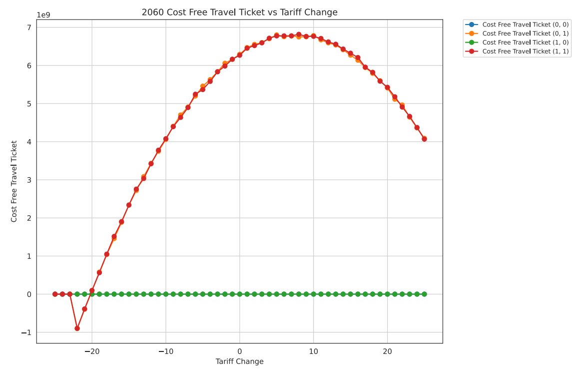


Figure G.157: 2060 cost for free travel ticket vs tariff change

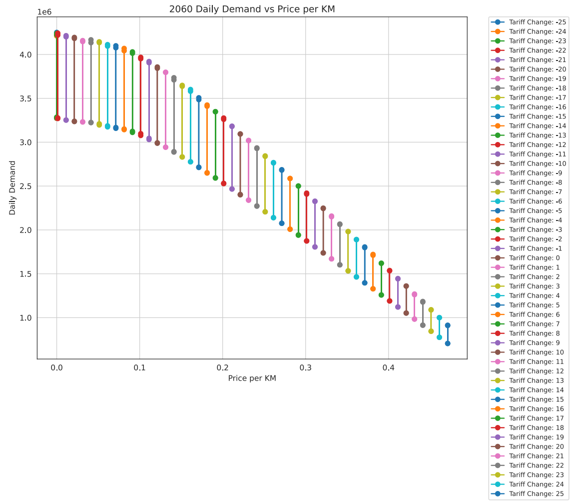


Figure G.158: 2060 daily demand vs price per km for tariff change = x

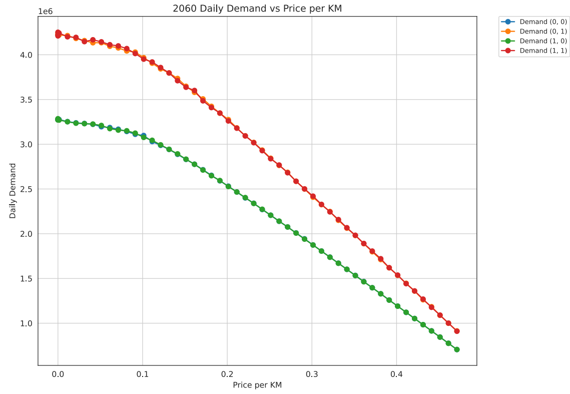


Figure G.159: 2060 daily demand vs price per km

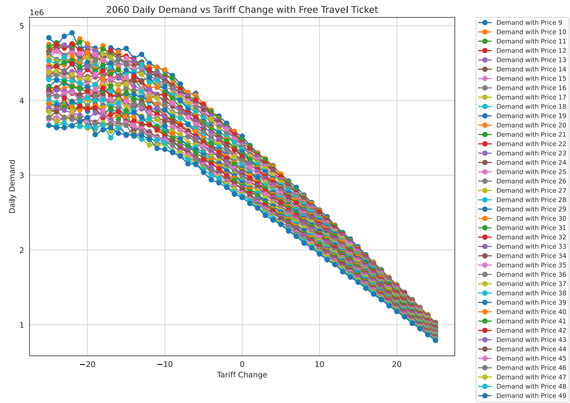


Figure G.160: 2060 daily demand vs tariff change (free travel ticket = 1)

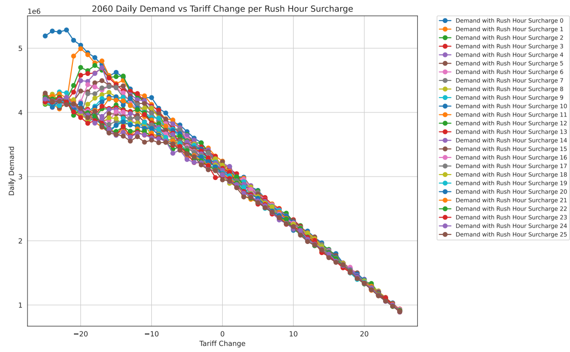


Figure G.161: 2060 daily demand vs tariff change (rush hour surcharge)

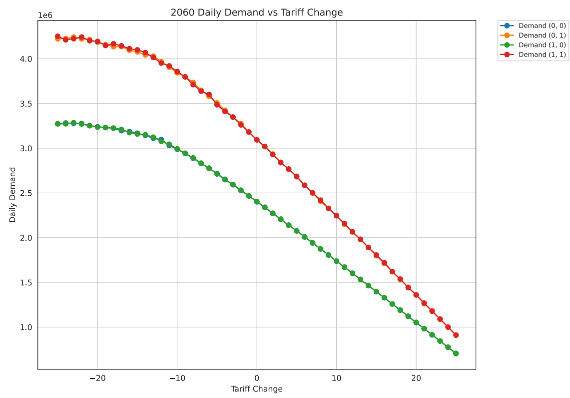


Figure G.162: 2060 daily demand vs tariff change

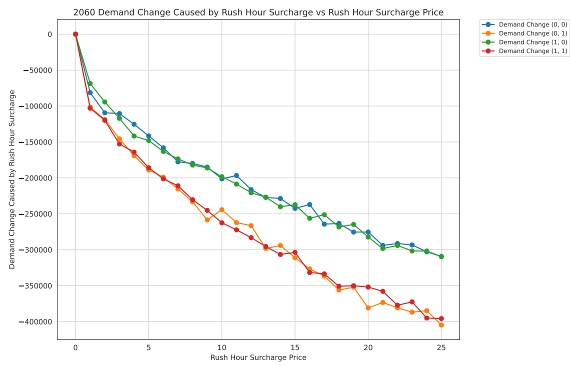


Figure G.163: 2060 demand change vs rush hour surcharge

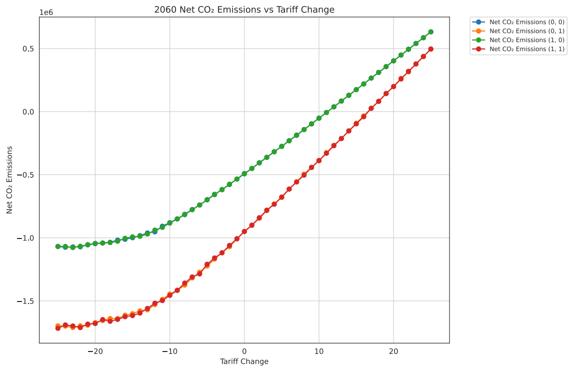


Figure G.164: 2060 net CO_2 emissions vs tariff change

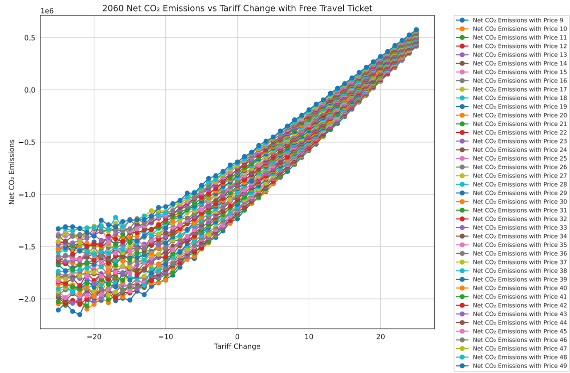


Figure G.165: 2060 net CO_2 emissions vs tariff change (free travel ticket = 1)

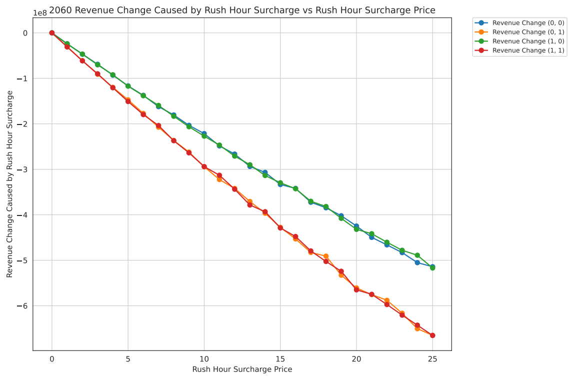


Figure G.166: 2060 revenue change vs rush hour surcharge

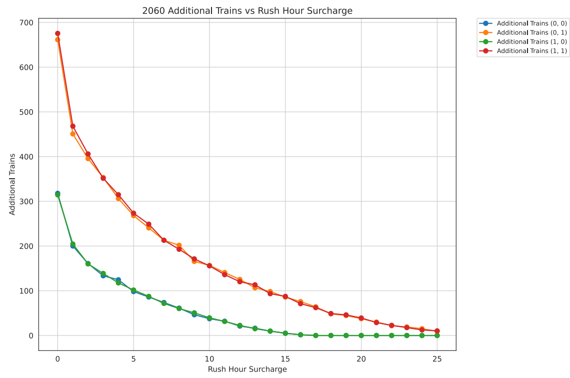


Figure G.167: 2060 revenue vs rush hour surcharge

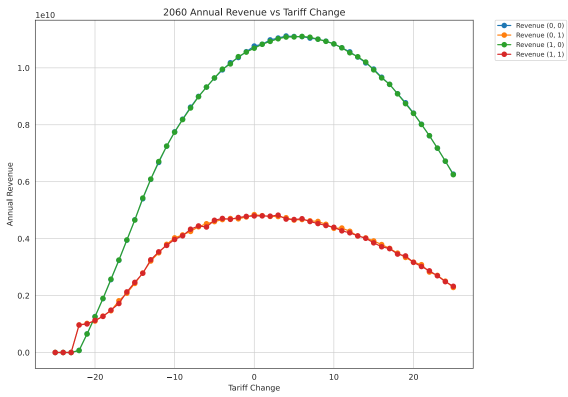


Figure G.168: 2060 revenue vs tariff change

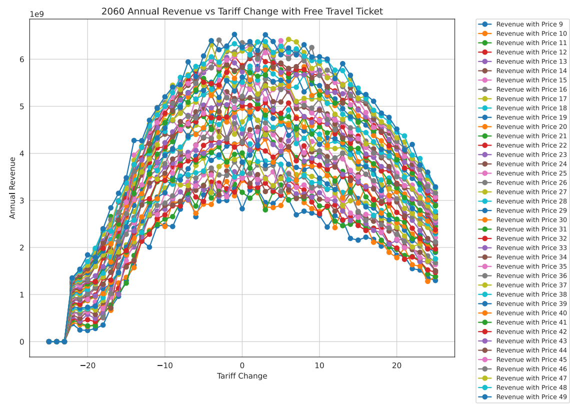


Figure G.169: 2060 revenue vs tariff change (free travel ticket = 1)

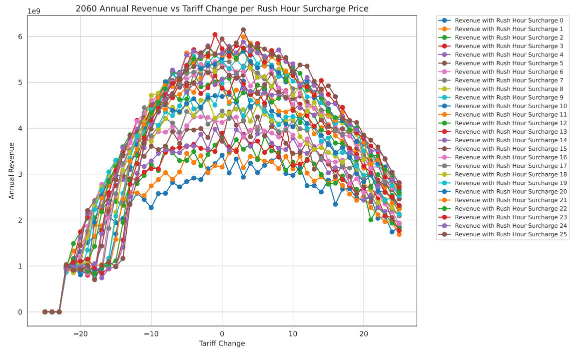


Figure G.170: 2060 revenue vs tariff change (rush hour surcharge)

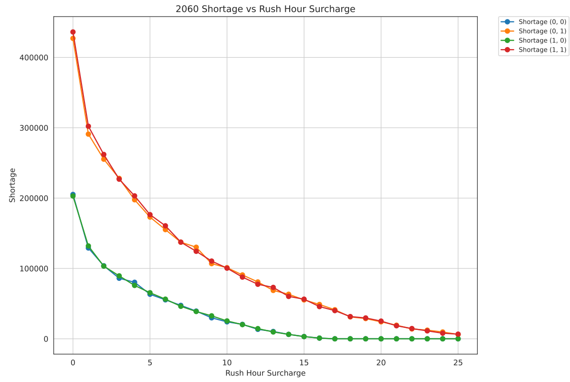


Figure G.171: 2060 shortage vs rush hour surcharge

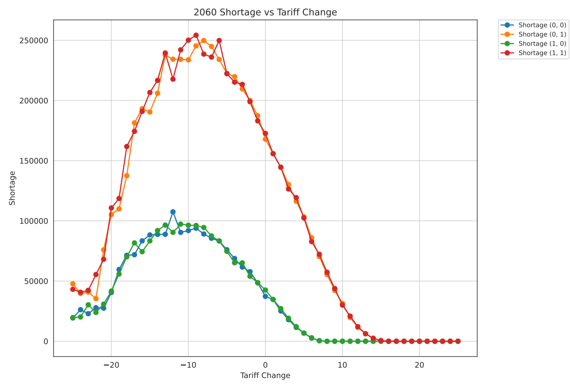


Figure G.172: 2060 shortage vs tariff change

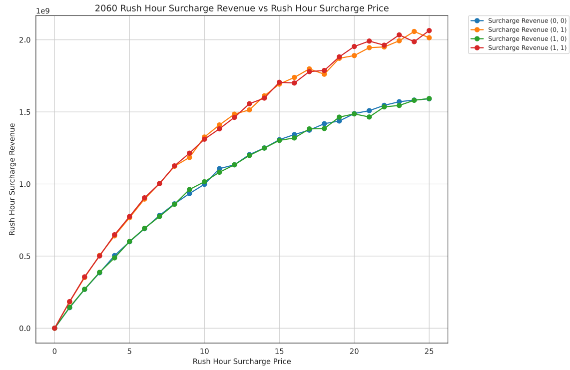


Figure G.173: 2060 surcharge revenue vs rush hour surcharge

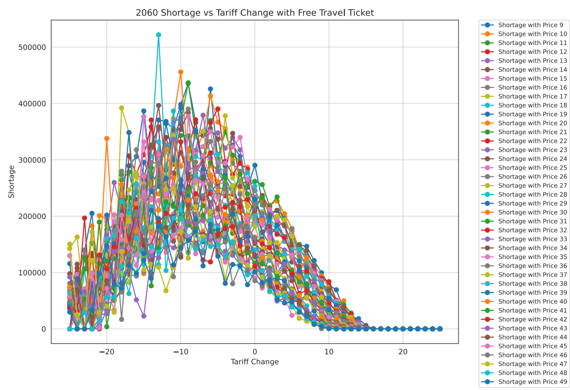


Figure G.174: 2060 shortage vs tariff change (free travel ticket = 1)

Baseline 2070 Results

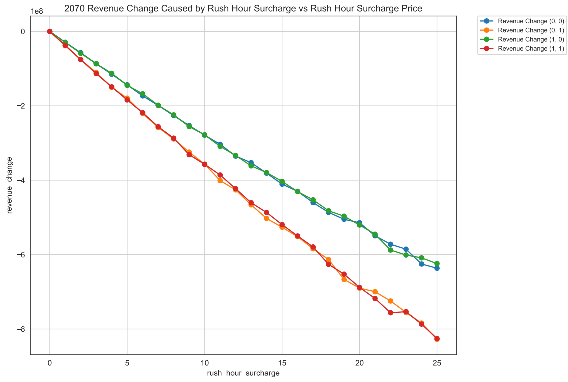


Figure G.175: 2070 revenue change vs rush hour surcharge

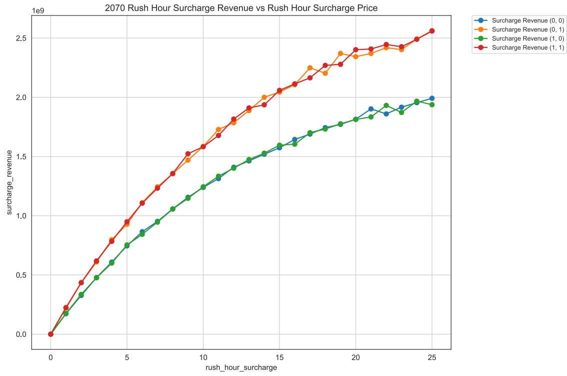


Figure G.176: 2070 surcharge revenue vs rush hour surcharge

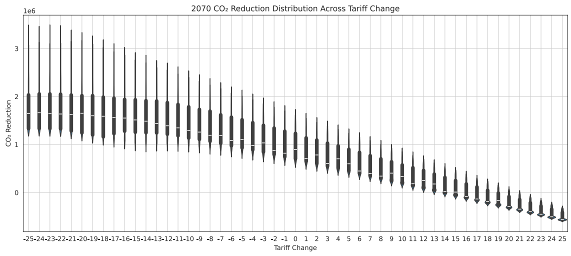


Figure G.177: 2070 violin CO_2 reduction distribution across tariff change

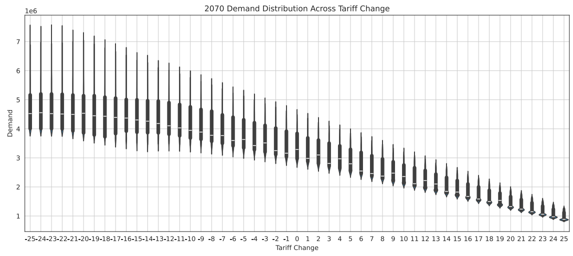


Figure G.178: 2070 violin demand distribution across tariff change

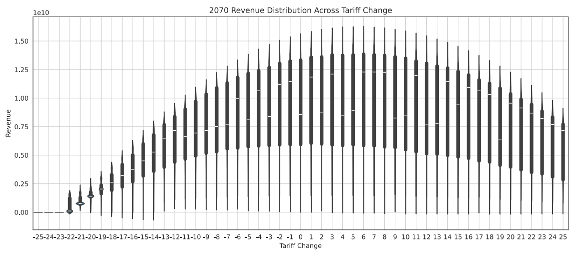


Figure G.179: 2070 violin revenue distribution across tariff change

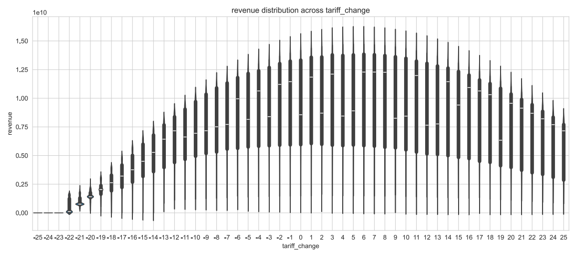


Figure G.180: 2070 violin

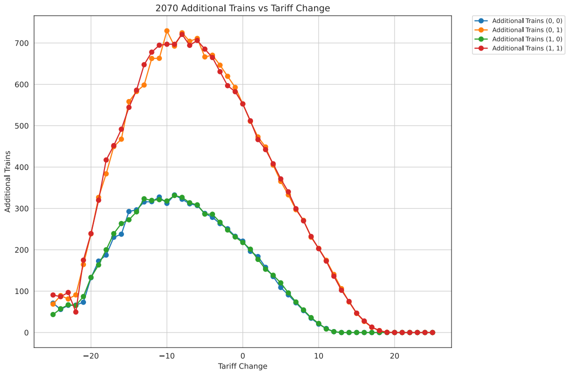


Figure G.181: 2070 additional trains vs tariff change

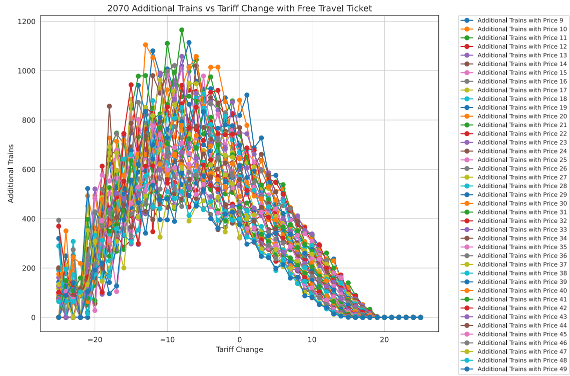


Figure G.182: 2070 additional trains vs tariff change (free travel ticket = 1)

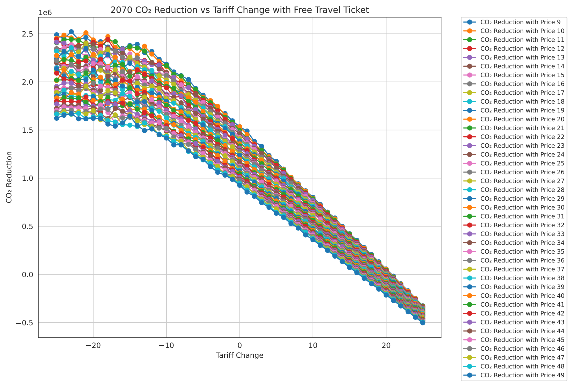


Figure G.183: 2070 CO_2 reduction vs tariff change (free travel ticket = 1)

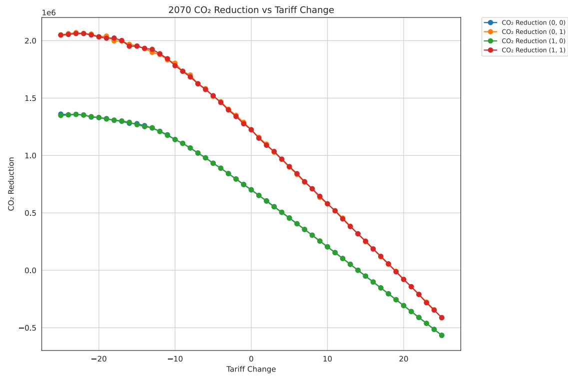


Figure G.184: 2070 CO_2 reduction vs tariff change

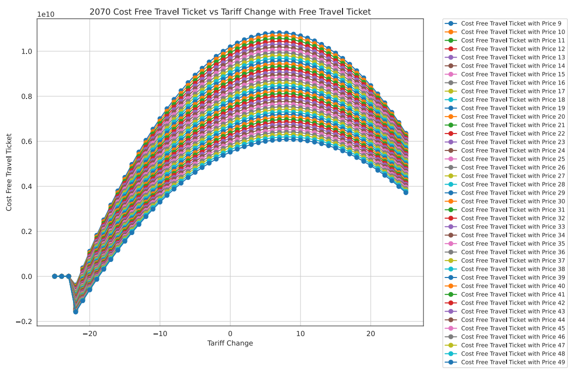


Figure G.185: 2070 cost for free travel ticket vs tariff change (free travel ticket = 1)

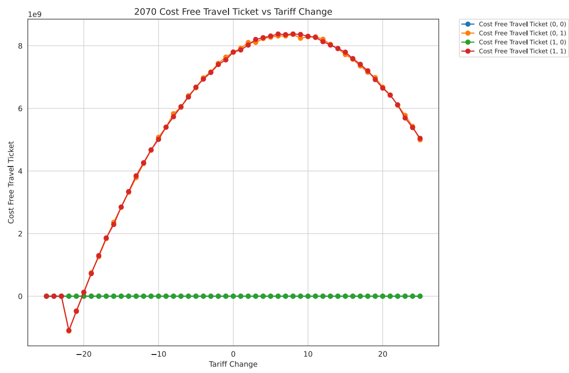


Figure G.186: 2070 cost for free travel ticket vs tariff change

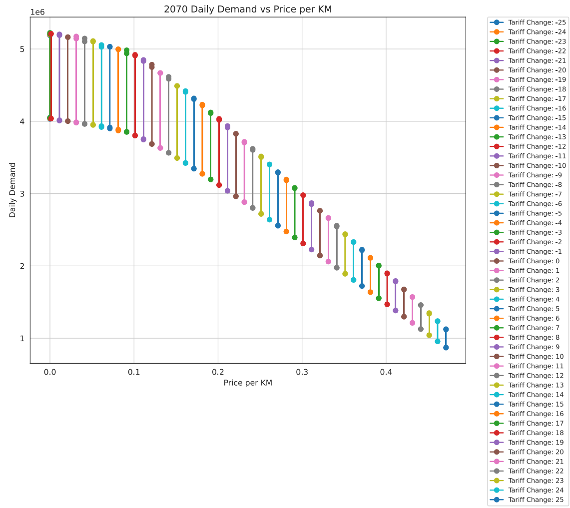


Figure G.187: 2070 daily demand vs price per km for tariff change = x

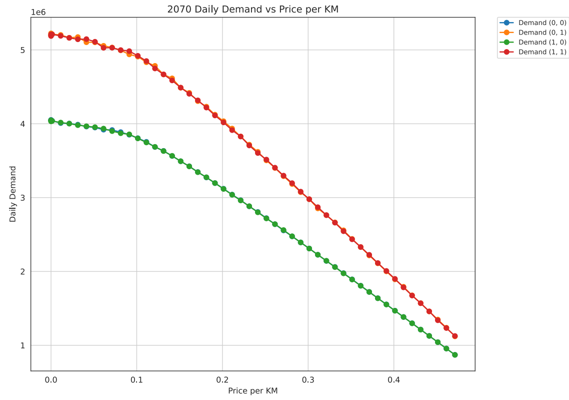


Figure G.188: 2070 daily demand vs price per km

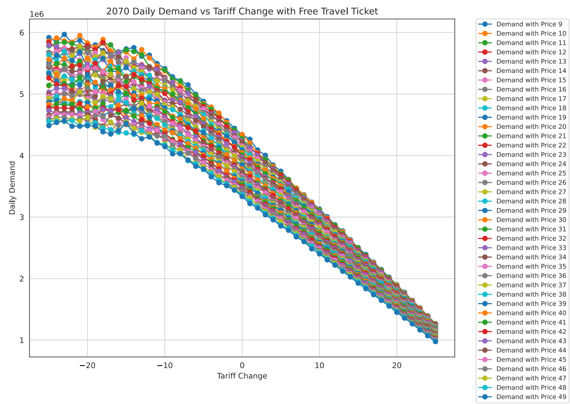


Figure G.189: 2070 daily demand vs tariff change (free travel ticket = 1)

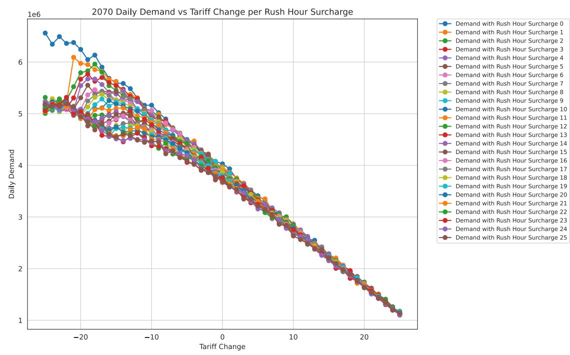


Figure G.190: 2070 daily demand vs tariff change (rush hour surcharge)

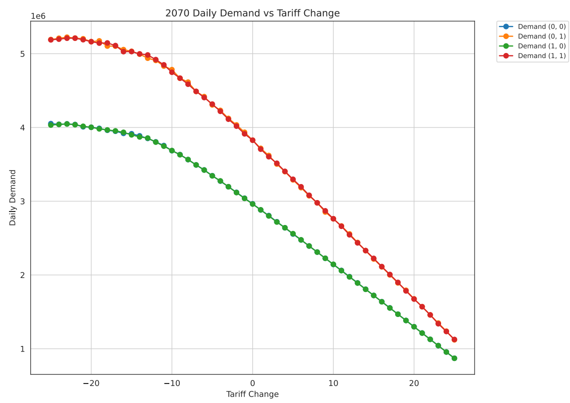


Figure G.191: 2070 daily demand vs tariff change

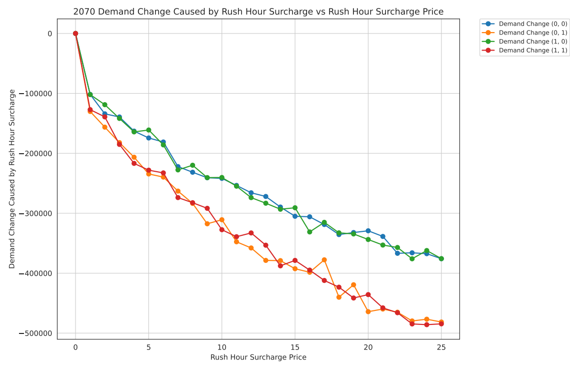


Figure G.192: 2070 demand change vs rush hour surcharge

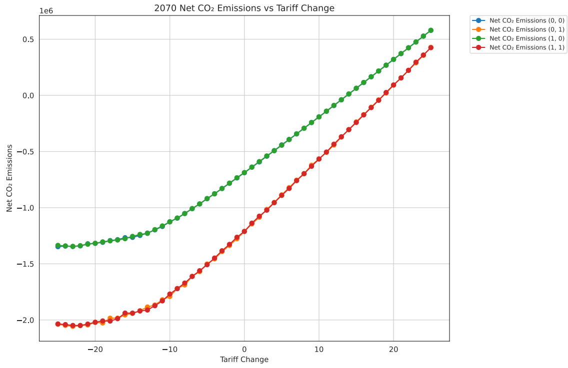


Figure G.193: 2070 net CO_2 emissions vs tariff change

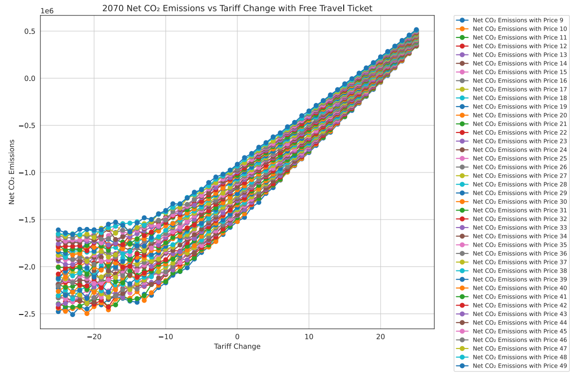


Figure G.194: 2070 net CO_2 emissions vs tariff change (free travel ticket = 1)

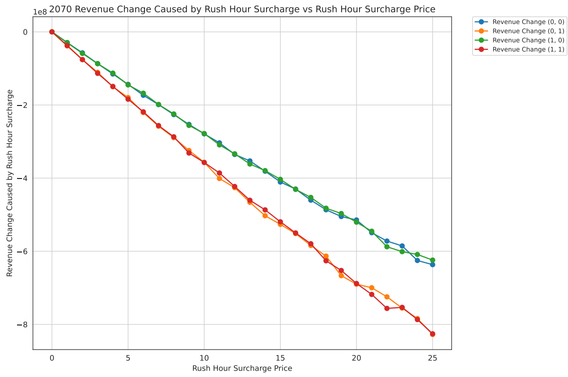


Figure G.195: 2070 revenue change vs rush hour surcharge

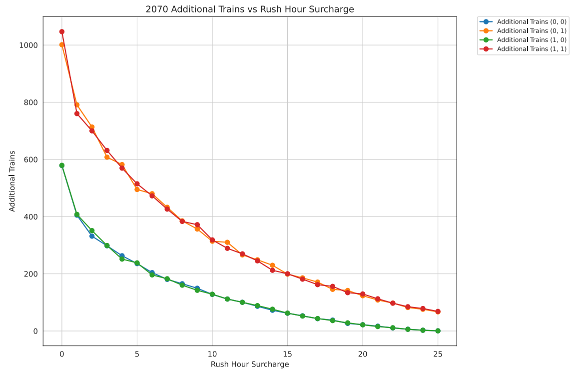


Figure G.196: 2070 revenue vs rush hour surcharge

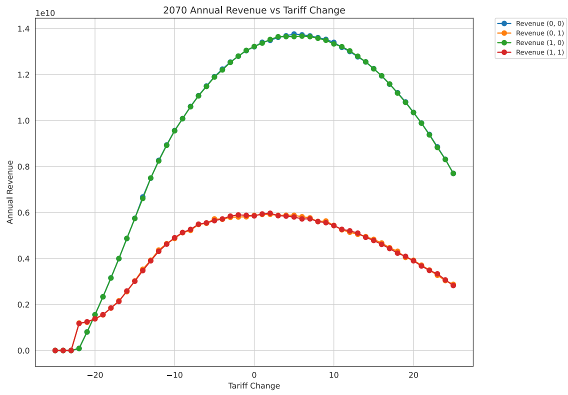


Figure G.197: 2070 revenue vs tariff change

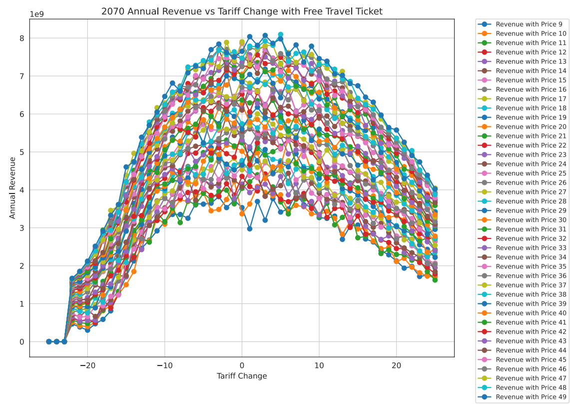


Figure G.198: 2070 revenue vs tariff change (free travel ticket = 1)

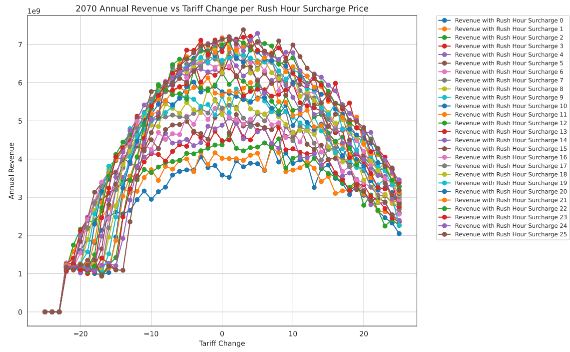


Figure G.199: 2070 revenue vs tariff change (rush hour surcharge)

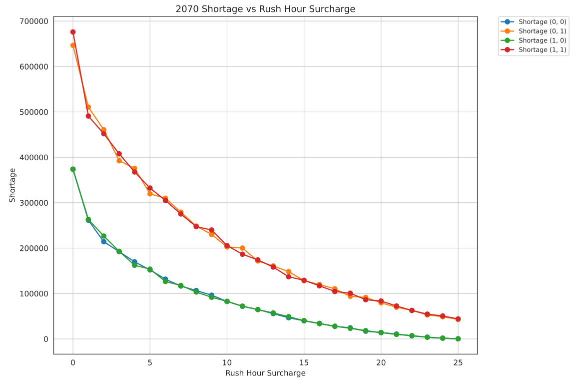


Figure G.200: 2070 shortage vs rush hour surcharge

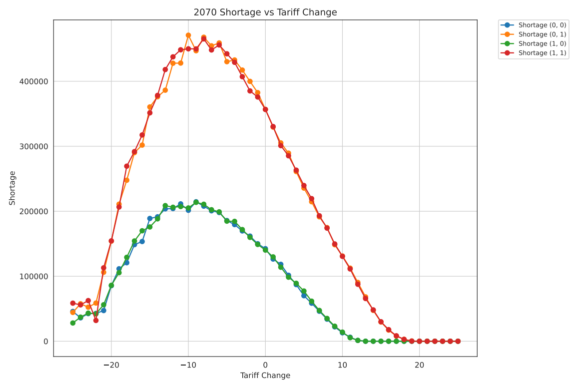


Figure G.201: 2070 shortage vs tariff change

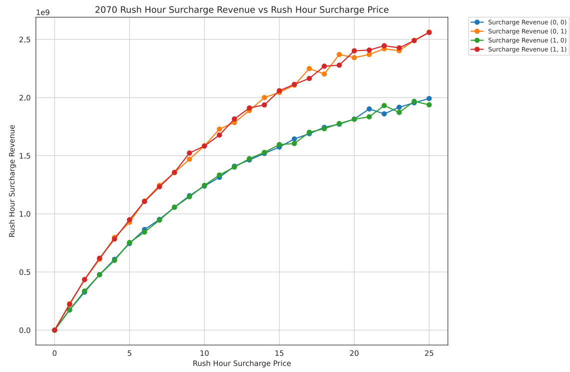


Figure G.202: 2070 surcharge revenue vs rush hour surcharge

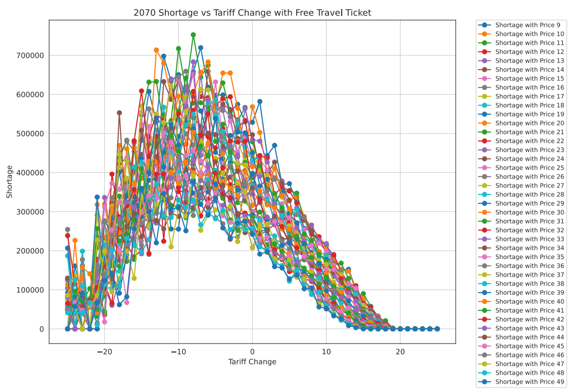


Figure G.203: 2070 shortage vs tariff change (free travel ticket = 1)

H
Model Input Data

The following sidewaystable presents the core dataset used in this research. It comprises a consolidated, multi-year panel of Dutch national-level variables relevant to rail transport demand, pricing, emissions, and demographic-economic indicators. The data spans from 2005 to 2022 and for 2024 and each decade from 2030 to 2070.

H.1. Data Sources and Compilation

Variables were compiled from a combination of open government statistics, institutional reports, academic publications, and transport industry datasets. Key sources include:

- **CBS StatLine and CBS publications** for population, education level, employment, income, car ownership, fuel prices, and international student mobility (Centraal Bureau voor de Statistiek, 2021, 2023a, 2023b, 2023c, 2023d, 2023e).
- **NS datasets** for revenue streams, fare pricing schemes, and national train usage patterns (Nederlandse Spoorwegen, 2023a, 2023b, 2023c).
- **KiM (Kennisinstituut voor Mobiliteitsbeleid)** annual mobility overviews for modal split data, behavioral metrics, and synthetic indicators for both pre- and post-COVID contexts (KiM, 2019, 2021, 2022, 2023a).
- **International datasets and literature** to inform pricing elasticities, international student flows, and macroeconomic contexts such as inflation and transport affordability (American Public Transportation Association, 2003; DutchNews.nl, 2023a, 2023b; Loder et al., 2022a, 2022b; Macrotrends LLC, 2024; Statista Research Department, 2023; Verband Deutscher Verkehrsunternehmen, 2022; World Bank, 2022).

H.2. Data Limitations

While care was taken to maintain internal consistency, sources vary in their methodology and reporting frequency. Notably, post-COVID travel behavior, pricing elasticity, and shifts in modal preference may introduce additional uncertainty(KiM, 2022; Loder et al., 2022a).

H.3. Raw Data

To improve readability, the data table has been split into two vertically stacked segments. Both tables are aligned by the shared `ds` (year) variable to enable direct comparison across indicators. Missing values were addressed using linear interpolation and future years were forecast using Prophet.

ds	km	reizigerskm	Population	PopAge0to5	Total_MBO	Total_HBO	Total_WO	Students_Total	Banen	Inkomen	Autobezit	Schipholpassagiers	Brandstofkosten	CarTripsDay	AvgKMCarTrip	CarKMYear	TrainTripsDay	AvgKMTrainTrip
2005	15200000000	15200	16305526	1213704	483.8	356.8	205.9	1046500	8769000	19600	7025000	44078000	1.39	1.00	16.79	99925970262	0.07	48.93
2006	15902000000	15902	16334210	1195352	496.2	366.7	208.6	1071500	8920000	19800	7148000	45989000	1.37	1.01	16.90	101765000000	0.07	48.54
2007	16284000000	16284	16357992	1169951	509.6	374.8	212.7	1097100	9150000	20200	7312000	47745000	1.42	1.01	16.97	102335000000	0.07	48.33
2008	16935000000	16935	16405399	1146623	513.9	383.7	220.5	1118100	9287000	20300	6557467	47392000	1.48	0.99	16.82	99710489420	0.07	48.33
2009	17082000000	17082	16485787	1131372	522.3	403.3	233.1	1158700	9222000	20400	6624256	43523000	1.35	1.00	17.06	102655000000	0.07	48.53
2010	17148000000	17148	16574989	1118226	528.0	416.6	242.3	1186900	9190000	20300	6422700	45137000	1.50	1.00	17.25	104360000000	0.07	48.19
2011	17633000000	17633	16655799	1110770	520.0	423.9	245.4	1189300	9259000	20300	6488900	49681000	1.64	0.97	17.76	104730000000	0.07	48.21
2012	17910000000	17910	16730348	1104544	510.9	421.7	241.4	1174000	9246000	20200	6563700	50976000	1.76	0.98	17.64	105566000000	0.07	48.18
2013	17997000000	17997	16779575	1094731	498.1	440.3	250.2	1188600	9756000	19900	6608800	52528000	1.74	0.98	17.77	106656000000	0.07	48.29
2014	18081000000	18081	16829289	1083549	481.4	446.4	255.7	1183500	9757000	20200	6617600	54941000	1.70	0.97	17.92	106775000000	0.08	48.41
2015	18485000000	18485	16900726	1074196	476.3	442.6	261.2	1180100	9881000	20400	6666800	58245000	1.56	0.95	18.06	105838000000	0.08	48.21
2016	18750062356	18750	16979120	1062649	483.4	446.6	268.0	1198000	10036000	20800	6311907	63526000	1.48	0.93	18.13	104493000000	0.08	48.39
2017	19025850587	19026	17081507	1054380	487.1	452.7	280.0	1219800	10282000	20900	6609796	68400000	1.55	0.93	18.31	106167000000	0.08	48.05
2018	19301638817	19302	17181084	1047360	497.1	455.7	294.7	1247500	10562000	21300	6669727	70957000	1.62	0.95	18.60	110810000000	0.08	48.07
2019	19577427048	19577	17282163	1041272	503.0	463.3	306.9	1273200	10788000	21500	6729658	71680000	1.65	0.94	18.63	110467000000	0.08	48.17
2020	19853215278	19853	17407585	1041053	508.8	489.3	331.4	1329500	10710000	21900	6633725	20885000	1.56	0.80	16.05	81582387861	0.04	46.28
2021	20129003509	20129	17475415	1033029	502.3	491.4	344.6	1338300	10941000	22152	6849521	25491000	1.82	0.81	16.80	86798988272	0.04	45.91
2022	20404791739	20405	17590672	1041394	484.2	476.9	344.2	1305300	11377000	22351	6849521	52471000	2.07	0.87	18.20	102040000000	0.05	46.68
2024	21181221565	21180	17621464	966767	488.8	508.4	325.7	1323001	11119040	21639	6256640	79086369	1.78	0.90	19.28	112046812123	0.09	47.85
2030	22641702755	22639	18113901	902204	476.6	556.7	370.4	1403102	11963526	22104	6158890	91480605	1.86	0.87	20.19	116937977970	0.09	47.73
2040	25629194314	25625	18882755	781073	468.0	629.7	433.0	1530587	13200766	23165	5768459	112105580	2.07	0.81	21.53	122620047354	0.10	47.32
2050	28201668692	28196	19690515	670087	450.7	708.3	504.6	1662585	14565683	24012	5548664	132754619	2.22	0.76	23.00	130154522007	0.11	47.06
2060	31189160251	31182	20459369	548956	442.1	781.3	567.2	1790070	15802922	25073	5158232	153379595	2.42	0.70	24.34	135836591392	0.12	46.65
2070	33761634628	33753	21267130	437970	424.8	859.8	638.8	1922067	17167840	25920	4938438	174028633	2.57	0.64	25.81	143371066045	0.13	46.39

ds	TrainKMperYear	RevenueNS_NL	RevenueNS_Total	PricePerKM	WeekOV	WeekendOV	NonOV	Intl_Tot	Intl_EU	Intl_NonEU	Students_Dutch	CO2_Cars	CO2_Trains	NOx_Cars	NOx_Trains	NOx_Cars.1	NOx_Trains.1
2005	14520494847	2046233824	4855633487	0.140	0.41	0.18	0.07	33140	20920	12220	1013360	18600	0.00	42.27	0.78	42.27	0.78
2006	14430098472	2036984340	4850351718	0.140	0.41	0.18	0.07	34600	23110	11490	1036900	18500	0.00	39.42	0.78	39.42	0.78
2007	14388587911	2032736921	4847926298	0.140	0.41	0.18	0.07	37650	26290	11360	1059450	18400	0.00	37.22	0.78	37.22	0.78
2008	14430287393	2037003671	4253000000	0.140	0.41	0.18	0.07	41580	30220	11360	1076520	18000	0.00	34.56	0.78	34.56	0.78
2009	14561005425	1822000000	3271000000	0.130	0.41	0.18	0.07	46350	34440	11910	1112350	17800	0.00	32.08	0.79	32.08	0.79
2010	14537226702	1851000000	3520000000	0.130	0.41	0.18	0.07	50570	38090	12480	1136330	17800	0.00	30.74	0.78	30.74	0.78
2011	14614164470	1915000000	3628000000	0.130	0.41	0.18	0.07	53720	41060	12660	1135580	17700	0.00	30.11	0.81	30.11	0.81
2012	14670440633	1942000000	4638000000	0.130	0.41	0.18	0.07	55610	43040	12570	1118390	17500	0.00	29.25	0.72	29.25	0.72
2013	14747199317	2012000000	3873000000	0.140	0.41	0.18	0.07	57580	44810	12770	1131020	17200	0.00	28.11	0.75	28.11	0.75
2014	16945882314	2081000000	4144000000	0.120	0.41	0.18	0.07	59130	46180	12950	1124370	17100	0.00	27.05	0.81	27.05	0.81
2015	16947507210	2305000000	4973000000	0.140	0.41	0.18	0.07	63130	48640	14490	1116970	17100	0.00	27.61	0.91	27.61	0.91
2016	17089688029	2358000000	5093000000	0.140	0.41	0.18	0.07	69080	52940	16140	1128920	17400	0.00	26.38	0.96	26.38	0.96
2017	17071941356	2441000000	5121000000	0.140	0.41	0.18	0.07	76920	58100	18820	1142880	17500	0.00	26.58	0.94	26.58	0.94
2018	17178609924	2527000000	5926000000	0.150	0.41	0.17	0.07	85930	64390	21540	1161570	17600	0.00	26.45	0.83	26.45	0.83
2019	17315621268	2661000000	6661000000	0.150	0.41	0.19	0.07	94310	70280	24030	1178890	17400	0.00	24.65	0.82	24.65	0.82
2020	8378479552	1539000000	6601000000	0.180	0.19	0.18	0.03	103820	78190	25630	1225680	14400	0.00	19.24	0.86	19.24	0.86
2021	8343881548	1519000000	6484000000	0.180	0.24	0.16	0.03	115190	87790	27400	1223110	14900	0.00	18.72	0.86	18.72	0.86
2022	10398982194	1624514851	6797219780	0.160	0.30	0.19	0.05	122290	93410	28880	1183010	16255	0.00	16.79	0.85	16.79	0.85
2024	18598978742	2680826872	6100497371	0.144	0.41	0.18	0.07	104160	81266	22967	1218863	16628	0.00	17.14	0.92	17.14	0.92
2030	20238820480	2941257140	6481320717	0.147	0.41	0.18	0.07	129403	101283	28186	1273576	16133	0.00	11.20	0.97	11.20	0.97
2040	22737539545	3396233980	7776206414	0.153	0.41	0.18	0.07	167947	133054	35039	1362617	15223	0.00	-0.44	1.06	-0.44	1.06
2050	25412021483	3835516024	8575957021	0.158	0.41	0.18	0.07	209136	166019	43276	1453268	14376	0.00	-10.77	1.15	-10.77	1.15
2060	27910740547	4290492864	9870842718	0.163	0.41	0.18	0.07	247679	197790	50129	1542308	13466	0.00	-22.41	1.24	-22.41	1.24
2070	30585222486	4729774909	10670593324	0.169	0.41	0.18	0.07	288869	230754	58366	1632959	12619	0.00	-32.74	1.32	-32.74	1.32

Table H.1: Model input data including prophet data for 2005-2070. Data for 2024 and each decade from 2030-2070 was calculated using Prophet.

Managing Uncertainties in Mobility Policy

Integrating Exploratory Modelling and Analysis for Informed Decision-Making in Dutch Passenger Rail Policy

Rhys Evans, MSc Engineering and Policy Analysis