Exploring the Rebound in Passenger Aviation

A System Dynamics Modeling Approach Exploring the Impact of Fuel Efficiency Rebound Effects on Passenger Aviation's Contribution to Global Decarbonization Goals

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A System Dynamics Modeling Approach Exploring the Impact of Fuel Efficiency Rebound Effects on Passenger Aviation's Contribution to Global Decarbonization Goals

by

S.E.G. Smit

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Acknowledgments

After an unforgettable period of study at Delft University of Technology, my academic journey has come to an end. This thesis, titled *Exploring the Rebound in Passenger Aviation*, was written to fulfill the requirements for the degree of Master of Science in Engineering and Policy Analysis. For this thesis, I was fortunate to combine fields I enjoyed the most throughout my studies. It brings together aviation and economics with sustainability, a field I believe is essential for our future. The research method involved System Dynamics modeling and programming in Python, which made the work even more rewarding. This interdisciplinary approach reflects what I appreciated most about my broad-based degree. My years in Delft have been a blend of hard work and moments of great joy, shaping me both academically and personally.

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Saskia E.G. Smit
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Executive Summary

Attention for the aviation industry's impact on climate change has increased significantly in recent years, as it is one of the fastest growing industries worldwide. Aviation contributes around 2.4% to the global emissions of CO_2 and an average of 3.5% to climate change because of fossil fuel consumption. If aviation continues its current trajectory of increasing traffic volumes, the sector will increasingly conflict with global decarbonization targets. Although aviation's emissions targets align with the overall goals of the Paris Agreement, it is unlikely that the sector will meet these goals. While efficiency measures are being implemented, concerns are growing over the short-term feasibility of current development scenarios. Given that radical engine innovations and large-scale deployment of Sustainable Aviation Fuels (SAF) are unlikely to become technically and commercially viable before 2040, improving fuel efficiency remains the most immediate and effective strategy for reducing emissions. The key short-term measures available to airlines under the four-pillar strategy proposed by the International Air Transport Association (IATA) can be summarized as follows:

- Invest in new generation, more **fuel-efficient aircraft** to increase average fuel efficiency;
- Implement strategies to increase **passenger load factors**;
- Optimize flight operations such as route planning to reduce **flight distances**.

As advancements in operational and aircraft fuel efficiency also enhance cost-effectiveness, airlines have the potential to significantly reduce fuel costs and pass these savings on to consumers, leading to lower ticket fares. This could further stimulate passenger demand, amplifying the existing upward trend in air travel. This feedback might result in a fuel efficiency rebound effect, partially or fully offsetting the intended emission reductions. Projections for future demand, fuel efficiency and the associated emission reduction in the literature often overlook the fuel efficiency rebound effect, leading to systematic overestimation of actual emission reductions.

The research addresses this critical knowledge gap by conceptualizing and quantifying how future fuel efficiency rebound effects may affect projected emission reductions in passenger aviation. Previous research identified rebound effects in aviation of 49%[1] between 1986 and 1999, and 18.8% between 2000 and 2013, based on retrospective analysis of empirical data. A forward-looking analysis of how fuel efficiency rebound effects may influence future emission projections is currently missing. The research estimates the fuel efficiency rebound effect over a 15-year time horizon, up to 2040. Indirect rebound effects[2] fall outside the scope of this analysis. With the aim of contributing to the integration of rebound dynamics into policy evaluation models and supporting robust policy design, the research adopts an exploratory approach by combining quantitative System Dynamics (SD) modeling with Scenario Analysis.

The research contributes to future predictive studies on rebound effects and broader emission reduction efforts in aviation. First, it conceptualizes the key drivers and feedback mechanisms of the rebound effect using a systems thinking approach. Second, it captures these dynamics in a compact System Dynamics model, that operates without relying on extensive empirical data. Third, it estimates the rebound effect and its implications within a reference scenario, and explores a range of plausible scenario outcomes. Fourth, it analyzes these outcomes to identify influential combinations of market-specific uncertain parameters. Finally, the research highlights critical market-specific empirical data

[1]The rebound effect is typically expressed as the ratio of the lost savings to the expected savings, representing the share of the emission reduction potential offset by the rebound of efficiency improvements.

[2]*Indirect rebound effects* occur when the intended reduction in activity, emission or resource usage from a specific measure was achieved, but the same actor increases consumption of other goods, services or related operations, leading to an overall increase in other activities, emissions, or resource usage.

gaps that must be addressed to narrow the plausible range of model results.

The model results indicate an emission reduction potential of 14% compared to a scenario without any efficiency improvements. Within a reference scenario, a rebound effect of 91.3% was estimated over the 2025-2040 period, offsetting the majority of this potential and resulting in an actual net reduction of only 1.3%. The magnitude of the rebound and its impact on emissions is influenced by market-specific uncertainties, including airline pricing strategies, fare elasticity of demand, and the market shares of different haul segments. To capture a range of plausible outcomes, 1000 rebound simulation runs were conducted, incorporating varying combinations of these uncertainties. Figure 1 summarizes the key simulation results of the reference scenario and the scenario analysis.

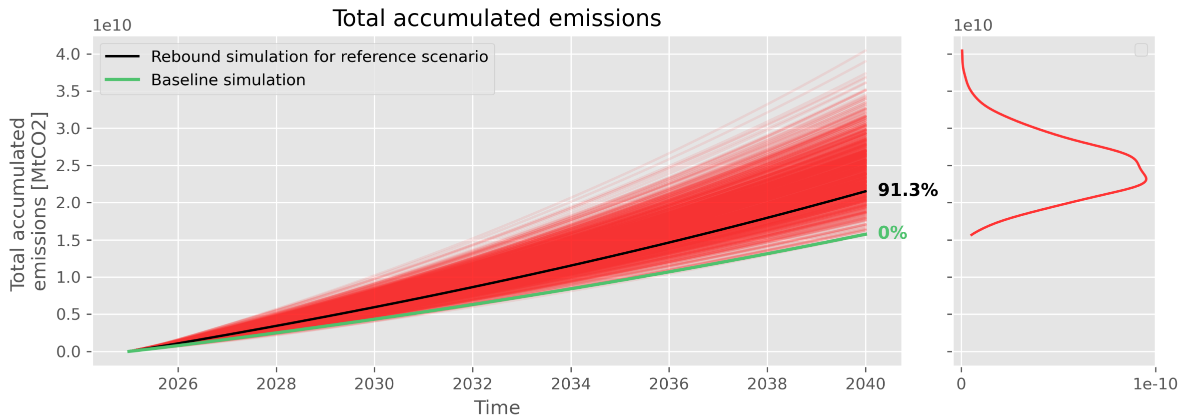

Figure 1: The red lines represent CO_2 emissions in an ensemble of 1000 rebound simulation runs, without a constraint on the cumulative growth in flight volume. The density plot in the right section of the figure visualizes the distribution of the final time outcomes. The black line represents emissions in the rebound simulation for the reference scenario and the corresponding offset of the emission reduction potential. The green line represents emissions in the baseline simulation, which implies a 0% offset and full realization of the emission reduction potential, as rebound feedback was excluded.

Using the Patient Rule Induction Method (PRIM) algorithm[3], outcomes of interest were evaluated based on a rebound effect threshold, defined as any scenario in which a larger share of the emission reduction potential is offset relative to the reference scenario. The extent to which fuel cost savings are passed on to consumers appeared to be less influential, as the analysis revealed that even at its minimum value, a substantial rebound effect can occur. However, a higher average pass-through rate remains undesirable, as it is associated with an even greater magnitude of the rebound effect. The main conclusions of this analysis are summarized below.

The magnitude of the rebound effect exceeds the 91.3% observed in the reference scenario, under the following conditions:

- Consumers exhibit a **high sensitivity to fare price reductions** per passenger-kilometer;
- Relatively **high market shares of longer haul segments** compared to that of short-haul segments;
- Airlines can fully capitalize on demand growth, i.e. the potential **amount of flights is unrestricted.**

The rebound effect estimated in the research is significantly higher than the rebound effects of 49% and 18.8% reported in previous research. This discrepancy can be attributed to key methodological differences, including the use of a *ceteris paribus* approach that isolates behavioral feedback effects, and the exclusive focus on passenger aviation, whereas previous research also included cargo operations. The results indicate that the rebound effect in passenger aviation can offset a substantial portion

[3]The PRIM algorithm identifies combinations of uncertain input parameters that are strongly associated with specific model outcomes, helping to explore key drivers of system behavior.

of the emission reduction potential in the reference scenario. In most other scenarios, the effect is even more pronounced, with projected outcomes showing a complete offset or even an additional increase in emissions. These findings highlight a significant risk that the sector's contribution to global emission reduction targets is being overestimated, as the effectiveness of the key short-term measures under the four-pillar strategy proposed by the IATA is substantially diminished by the rebound effect. The findings also inform key recommendations for policy makers and for future research.

Policy Recommendations

- **Integrate rebound feedback into policy evaluation models** to systematically consider rebound-implications that may offset anticipated efficiency gains when evaluating the effectiveness of proposed policy measures.
- **Stimulate the adoption of SAF** to decouple emissions from air traffic growth, limit the sector's reliance on fuel efficiency improvements, and constrain its capacity to meet growing passenger demand.
- **Strengthen carbon pricing mechanisms and implement fiscal measures** to impose constraints on the sector's economic expansion and counteract mechanisms that drive the rebound effect. Tax incomes can be used to commercialize Sustainable Aviation Fuels.

Recommendations for Future Research

- **Address knowledge gaps in data availability** to narrow the range of plausible outcomes. Empirical research should focus on collecting data on market share distributions, fare elasticities of demand, fuel cost pass-through rates by carrier type and the maximum potential of flight volumes.
- **Integrate rebound feedback into conventional emission projection models** to account for behavioral responses to efficiency gains and avoid overestimating their impact to global emission reduction targets.
- **Future modeling efforts** can improve the proposed System Dynamics model by capturing supply-demand dynamics, integrating multiple scale contexts, and embedding it in broader models.

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Nomenclature

Abbreviations

Below is a list of abbreviations and terms used in this thesis. They are listed alphabetically in separate categories for convenience.

Category	Abbreviation	Definition
Aviation Metrics	AKF	Aircraft-Kilometers Flown
	ASK	Available Seat-Kilometers
	PAX	Number of Passengers
	PLF	Passenger Load Factor
	RPK	Revenue Passenger-Kilometers
Environmental Policy & Concepts	CORSIA	Carbon Offsetting and Reduction Scheme for International Aviation
	EU ETS	EU Emission Trading Scheme
	GHG	Greenhouse Gas
	SAF	Sustainable Aviation Fuels
Modeling and Analysis Techniques	CLD	Causal Loop Diagram
	EMA	Exploratory Modeling and Analysis
	KPI	Key Performance Indicator
	LHS	Latin Hypercube Sampling
	PRIM	Patient Rule Induction Method
	SD	System Dynamics
	SFD	Stock Flow Diagram

Symbols

Below is a list of symbols used for variables in the formulas throughout this thesis, along with their corresponding units. They are listed alphabetically for convenience.

Symbol	Definition	Unit
d	Flight distance	[km]
D	Total annual passenger demand	[RPK/year]
e	CO_2 emissions per liter of jet fuel	[Mt/L]
E	Total CO_2 emissions	[Mt]
F	Fuel consumption	[L]
N	Annual number of flights	
p	Fare price	[eur/RPK]
α	Pricing strategy factor	
β	Baseline demand growth rate	

Symbol	Definition	Unit
γ	Change ratio fuel cost	
ε	Fare elasticity of demand	
η	Demand fulfillment rate	
λ	Fuel efficiency-induced demand growth rate	
ρ	Fuel efficiency induced fare price change ratio	

1 Introduction

Attention for the aviation industry's impact on climate change has increased significantly in recent years, as it is one of the fastest growing industries worldwide. The pre-pandemic traffic volumes recovered almost completely in 2023 and the demand for air travel is expected to double by 2040 (IATA, 2023). While this rapid growth presents significant opportunities for airlines, the aviation industry's environmental impact increasingly raises concerns for policymakers at both the European and global levels. Aviation contributes around 2.4% to the global emissions of CO_2 (Abrantes et al., 2021) and an average of 3.5% to climate change because of fossil fuel consumption (Lee et al., 2021). If aviation continues its current trajectory of increasing traffic volumes, the sector will increasingly conflict with global decarbonization targets.

Several international policies, including the Paris Agreement (UNFCCC, 2015), call for substantial reductions in CO_2 emissions from the aviation sector. To achieve these goals, the aviation sector follows a strategy proposed by the International Air Transport Association (IATA), which is built around four key pillars aimed at mitigating aviation's climate impact (Eurocontrol, 2021). As shown in figure 1.1, these pillars focus on aircraft technology, improvements in fuel efficiency, more efficient air traffic management and operational practices, and economic measures.

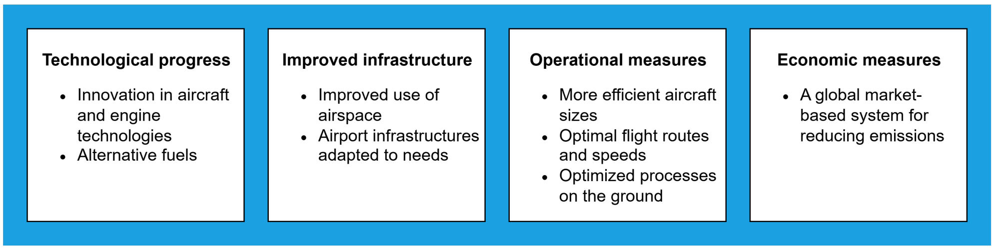

Figure 1.1: Overview Four-Pillar Strategy to mitigate aviation's climate impact. Adapted from: Kettler and Walls (2022)

Technological advancements play a crucial role in increasing efficiency, both by improving efficiency of kerosene-powered aircraft and by developing new engine technologies and alternative fuels (Kettler & Walls, 2022). Research suggests that emerging technologies, such as electric and hybrid-electric propulsion, hydrogen power, and sustainable aviation fuels (SAF), hold significant potential for making aviation more energy-efficient and sustainable (Avogadro & Redondi, 2024; ATAG, 2021; ICAO, 2022; IATA, 2021a). Operational measures complement these technological developments by optimizing flight routes, improving load factors, and enhancing ground operations, all of which contribute to continuous fuel efficiency improvements in daily operations (Kettler & Walls, 2022). Regulatory and economic measures like carbon caps and pricing, including the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) and the EU Emissions Trading Scheme (EU ETS), have helped slow aviation emissions growth. However, they have not led to an absolute reduction, as EU ETS does not fully cover global aviation and CORSIA lacks sufficient stringency (Proost, 2024).

Although aviation's emissions targets align with the overall goals of the Paris Agreement, it is unlikely that the sector will meet these goals (Grewe et al., 2021). While efficiency measures are being implemented, concerns are growing over the short-term feasibility of current development scenarios. Innovation in engine technology remains in an early stage and faces significant challenges, particularly for long-haul flights (Kettler & Walls, 2022). Hydrogen-powered aircraft may become commercially viable after 2040, but until then, liquid drop-in fuels will play a dominant role in aviation's decarbonization efforts (Davydenko & Hilbers, 2024). Among Sustainable Aviation Fuels (SAF), bio-fuels compete with food production, making synthetic fuels the most viable option in the coming years. These fuels can blend with conventional jet fuel and have the potential to fully replace petroleum-based fuels (IATA, 2021b; ICAO, 2016). However, their high cost - two to seven times that of kerosene - and limited availability present significant barriers to scaling production (Hong et al., 2019). With fuel expenses accounting for about a third of airline operating costs, widespread SAF adoption will require substantial investment from all stakeholders (Kettler & Walls, 2022).

Given that radical engine innovations and large-scale SAF deployment are unlikely to become technically and commercially viable before 2040, improving fuel efficiency remains the most immediate and effective strategy for reducing emissions. Indeed, advances in aircraft design and optimized operational practices are essential to minimizing aviation's carbon footprint while fossil fuels continue to dominate the sector (ATAG, 2021). According to (IATA, 2021b), replacing the existing global fleet with more advanced next-generation aircraft is estimated to reduce aviation energy demand and CO_2 emissions by approximately 10–15% by 2050 (IATA, 2021b). However, IATA also notes that without further mitigation measures, overall emissions are projected to exceed pre-pandemic levels, as aviation growth is expected to outpace these efficiency improvements. Conventional technological and operational efficiency improvements alone are unlikely to keep pace with demand growth, making them insufficient to prevent a continued rise in global CO_2 emissions (Peeters & Melkert, 2024).

As advancements in fuel efficiency also enhance cost-effectiveness, airlines have the potential to significantly reduce fuel costs as long as fossil fuels remain the dominant energy source. Profitability in the airline industry is relatively low. Given the fierce competition among airlines, even small cost differences can strongly influence pricing strategies (Grewe et al., 2021). For instance, U.S. airlines could lower fuel costs by nearly 19% between 2025 and 2050 (Kharina et al., 2016). If these savings are passed on to consumers, fare prices in the U.S. could decrease by up to $20 for short-haul flights and $105 for long-haul flights (Kharina et al., 2016). While these estimates are specific to the U.S., similar dynamics apply to global passenger aviation. As the global trend of increasing fuel efficiency reduces operating costs sector wide, airlines are likely to pass these savings on to consumers, leading to lower ticket fares (Koopmans & Lieshout, 2016). This cost reduction could further stimulate passenger demand, amplifying the existing upward trend in air travel. Due to the highly competitive nature of the airline industry, cost savings are typically reflected in lower fares, prompting increased passenger demand. This feedback might result in a fuel efficiency rebound effect (Evans & Schäfer, 2013), partially or fully offsetting the intended emission reductions, as illustrated in Figure 1.2. Understanding this effect is crucial for evaluating the true environmental benefits of fuel efficiency improvements in global passenger aviation.

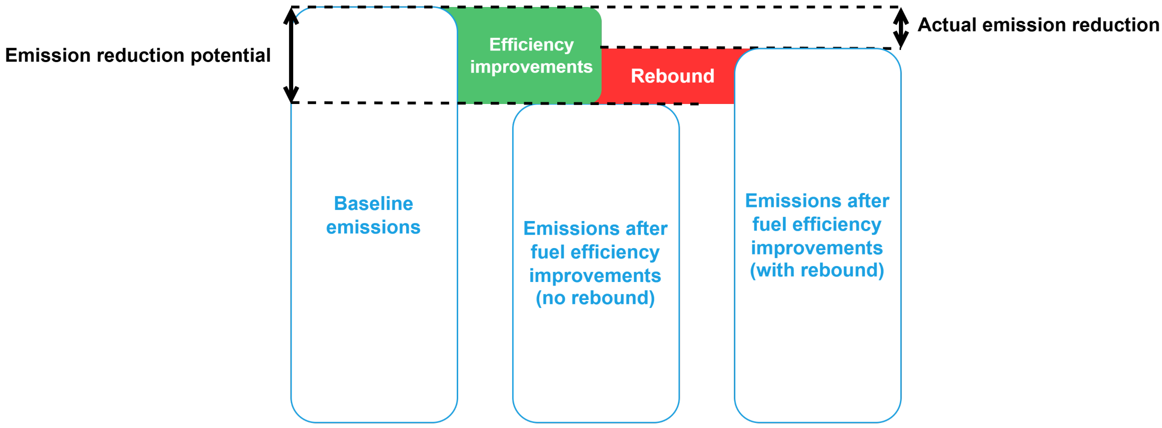

Figure 1.2: Visualization of fuel efficiency rebound effects

Projections for future demand, fuel efficiency, and the associated emission reductions in the literature often overlook the fuel efficiency rebound effect, leading to systematic overestimation of actual emission reductions. This limitation becomes evident when historical fuel efficiency improvements are compared with observed emission reductions, revealing significant discrepancies attributable to the rebound effect. Existing empirical and modeling studies have underscored the historical prevalence of rebound effects in aviation. Miyoshi and Fukui (2018) identified that between 1986 and 1999, the rebound effect in aviation reached approximately 49%, meaning that nearly half of the fuel efficiency improvements achieved were offset by an increase in total fuel consumption. This high rebound effect was largely driven by rapid traffic growth following industry liberalization and a decline in fuel prices. In the subsequent period, from 2000 to 2013, the rebound effect declined significantly to 18.8% (Miyoshi & Fukui, 2018). Previous work applying a systems thinking approach to rebound effects has enhanced understanding of their causal and dynamic characteristics (Hilty et al., 2006; Stasinopoulos et al., 2012; Guzzo et al., 2023). However, the aviation sector remains underexplored in this regard. The existing literature lacks a comprehensive conceptual and quantitative analysis of how fuel efficiency rebound effects may influence future emission projections. Moreover, to the best of current knowledge, such rebound mechanisms are not yet integrated in existing policy evaluation models.

Fuel efficiency rebound effects can occur in both passenger and cargo aviation. This research focuses specifically on global passenger aviation, as this sector is experiencing rapid growth and is particularly sensitive to fare prices (Koopmans & Lieshout, 2016), making it susceptible to unintended consequences of fuel efficiency improvements. While indirect rebound effects[1] may also contribute to offsetting fuel efficiency gains, they fall outside the scope of this research. Consequently, emissions from ground operations and efficiency improvements in this area are not considered. CO_2 is the primary GHG (greenhouse gas) emitted by aircraft due to fossil fuel consumption (Abrantes et al., 2021). Given its significant contribution to climate change, this research focuses on analyzing the impact of a fuel efficiency rebound effect in terms of CO_2 emissions[2]. The analysis is conducted over a 15-year time horizon (2025-2040), as beyond 2040, the increasing potential of a widespread adoption of radical engine technologies and SAF is expected to play a more substantial role in decarbonizing global passenger aviation. As these technologies are expected to reduce aviation's reliance on fossil fuels, the potential fuel efficiency rebound effect and its impact on decarbonization efforts is expected to become less significant in the long-term.

The objective of this research is to assess the relevance and implications of a potential fuel efficiency rebound effect and contribute to establishing a setup to integrate its dynamics into policy evaluation

[1] *Indirect rebound effects* occur when the intended reduction in activity, emission or resource usage from a specific measure was achieved, but the same actor increases consumption of other goods, services or related operations, leading to an overall increase in other activities, emissions, or resource usage (Malmaeus et al., 2023).

[2] Although significant uncertainty remains, the non-CO_2 impacts of aviation are estimated to be comparable in magnitude to those of CO_2 emissions alone (Lee et al., 2009)

models. Additionally, this research aims to support the development of stricter policies to achieve substantial global emission reductions in passenger aviation; a hard-to-abate sector. By analyzing the dynamics of the fuel efficiency rebound effect, it explores how this phenomenon could evolve unnoticed if left unaddressed. To achieve this, the research examines the structure and underlying dynamics of the passenger aviation system while estimating the potential magnitude of the rebound effect to effectively assess its impact. Given market-specific uncertainties and the lack of transparent data, this research combines a System Dynamics (SD) modeling approach with scenario analysis to examine how these uncertainties influence the magnitude and potential impact of the rebound effect. Exploring the rebound and its implications is essential for accurately evaluating the true environmental benefits of fuel efficiency improvements in global passenger aviation. This is of specific relevance as long as we continue to depend on fossil fuel consumption and conventional technologies for emission reduction. The results presented in this research are not intended to serve as precise forecasts of future emissions. Rather, the research aims to illustrate the fundamental challenges associated with translating efficiency improvements into meaningful reductions in absolute emissions.

This research utilizes Vensim DSS 10.2.2 to develop a quantitative SD model and simulate its behavior over a 15-year time horizon (2025-2040). This approach aims to capture the feedback dynamics of the rebound effect and to generate strategic insights, even with limited empirical data (Forrester, 1987; Sterman, 2000). Existing SD literature has made several contributions to estimating rebound effects in passenger transport. Achachlouei and Hilty (2016) demonstrate that feedback loops are a natural and effective concept for modeling rebound effects in transport systems using SD. Yim (2019) developed a system dynamics model to present and simulate rebound mechanisms within the context of the European automobile fuel efficiency sector. This research adopts an exploratory problem analysis approach, focusing on passenger aviation as the sector within the aviation industry due to its susceptibility to rebound effects and the unintended consequences arising from the industry's efforts to meet the targets of the Paris Agreement. Projected efficiency improvements, achieved through conventional aircraft technologies and operational practices, are used as baseline inputs for the model. Additionally, the model incorporates projected annual passenger demand growth as baseline input, which is linked closely to economic growth and GDP in the existing literature.

Research Questions

The research addresses two primary knowledge gaps: (1) the lack of comprehensive conceptualization and quantification of how potential future fuel efficiency rebound effects may affect projected emission reductions, and (2) the dearth of analysis of how the quantification of this effect depends on market-specific uncertainties. To address these knowledge gaps, the research answers the following main research question:

What is the potential impact of a future fuel efficiency rebound effect on the environmental benefits from efficiency improvements in passenger aviation?

The fuel efficiency rebound effect arises from efficiency improvements and the underlying systemic dynamics. To build an initial understanding of these feedback mechanisms, this research first identifies the key factors involved and conceptualizes their interactions, thereby addressing the first sub-question:

SQ1: What factors contribute to a fuel efficiency rebound effect and how do they interact?

To quantify the fuel efficiency rebound effect over time, the model's purpose and experimental design are first established to guide its structure and ensure it meets the research objectives. Subsequently, the conceptualized factors and interactions are translated into a quantitative model, addressing the second sub-question:

SQ2: How can a System Dynamics model effectively capture and integrate the key factors and interactions of a fuel efficiency rebound effect?

To evaluate the implications of the fuel efficiency rebound effect, this research proposes a reference scenario, applying the model to simulate system behavior over time. This addresses the third sub-question:

SQ3: What is an initial projection of the magnitude of the fuel efficiency rebound effect and the corresponding actual emission reduction through 2040 in the reference scenario?

Market-specific uncertainties affect both the magnitude and implications of the fuel efficiency rebound effect. To estimate the future rebound potential, it is essential to account for this uncertainty space. This analysis addresses the fourth and final sub-question:

SQ4: How do market-specific uncertainties impact the potential magnitude of a fuel efficiency rebound effect?

Addressing the research questions contributes to closing key knowledge gaps by conceptualizing the hypothesized behavior, quantifying it through a System Dynamics model, and generating strategic insights for policy design while explicitly accounting for uncertainty.

Thesis Structure

Chapter 2 outlines the methods used and specifies the model's purpose and experimental design for this research. Chapter 3 describes and conceptualizes key factors and interactions contributing to the rebound effect, and presents a dynamic hypothesis regarding the effects on model behavior of incorporating the rebound effect into the system. Chapter 4 provides an overview of the System Dynamics (SD) model, including its subsystems and interrelations, underlying assumptions, and the verification and validation processes. Chapter 5 presents an initial projection of the fuel efficiency rebound effect using a reference scenario and interprets its implications, assuming this scenario closely aligns with reality. Chapter 6 presents the results of a scenario analysis, interpreting the effects of various combinations of market-specific uncertainties. Chapter 7 reflects on the modeling choices, highlights limitations, and discusses the study's broader implications. Finally, Chapter 8 concludes by addressing the research question and offers policy recommendations, along with recommendations for future research.

2

Research Methodology

This chapter outlines the research methodology designed to answer the main research question. Section 2.1 provides an overview of the sub-questions and corresponding approaches, with a research flow diagram clarifying the coherence between the sub-questions and phases. Subsequently, Section 2.2 justifies the choice of System Dynamics (SD) as the modeling technique. Section 2.3 clearly defines the model's purpose, followed by a discussion of the experimental setup established to estimate the rebound effect in Section 2.4. Thereafter, Section 2.5 presents the approach for model verification and validation to ensure alignment with its intended purpose. Finally, Section 2.6 explains the role of scenario analysis within this research methodology.

2.1. Overview

This research aims to answer the following main research question:

What is the potential impact of a future fuel efficiency rebound effect on the environmental benefits from efficiency improvements in passenger aviation?

To address this question, this research combines System Dynamics modeling with Scenario Analysis. The following sections discuss the methods and approach applied per sub-question.

SQ1: What factors contribute to a fuel efficiency rebound effect and how do they interact?

The approach taken to address the first sub-question involves a review of relevant theory to conceptualize and build a dynamic hypothesis. A dynamic hypothesis represents an initial understanding of the underlying causes of the problematic behavior, identifying the key variables and feedback mechanisms believed to drive the hypothesized problematic behavior (Sterman, 2000). In this research, the reference mode for the problematic behavior is the potential occurrence of a fuel efficiency rebound effect. While not directly observable, this effect may explain why past efficiency improvements did not yield their full emission reduction potential and offers insight into how future reductions might remain limited if underlying dynamics are not addressed. The conceptualization and dynamic hypothesis are established through the following three steps:

1. **Identifying and describing the key factors contributing to a fuel efficiency rebound effect.** This step involves developing a system description based on a review of relevant literature and theoretical foundations.

2. **Conceptualizing the interactions between the key factors.** In this step, the key factors are synthesized into a Causal Loop Diagram (CLD) that illustrates the feedback mechanisms believed to drive the hypothesized problematic behavior.

3. **Formulating a dynamic hypothesis of the problematic behavior.** This step involves analyzing the CLD to identify archetypical feedback structures and to develop an initial hypothesis of how the system behaves over time.

The key factors and their interactions identified in this research phase provide the theoretical foundation for both the experimental design and the model. The formulation of the SD model is addressed in the subsequent sub-question.

SQ2: How can a System Dynamics model effectively capture and integrate the key factors and interactions of a fuel efficiency rebound effect?

The key factors and interactions are translated into equations forming a quantitative SD model that is, when simulated numerically, capable of establishing the occurrence and potential magnitude of a fuel efficiency rebound effect. The approach to addressing the second sub-question builds on the theoretical foundation established in response to SQ1, while ensuring compatibility with the model purpose and experimental design defined for this research in Sections 2.3 and 2.4. The SD model undergoes verification and validation to ensure its reliability and accuracy. Once validated, the model is applied to simulate the system behavior over time, in alignment with the experimental design established for this research.

SQ3: What is an initial projection of the magnitude of the fuel efficiency rebound effect and the corresponding actual emission reduction through 2040 in the reference scenario?

To address the third sub-question, initial results are simulated and interpreted to validate and quantify the fuel efficiency rebound effect. This is done using a single reference scenario approach, enabling a clear calculation of the implications. This reference scenario is built using parameter values positioned at the midpoint of the defined uncertainty range. The results from this reference scenario provide an early indication of the potential magnitude of the future fuel efficiency rebound effect and its associated impacts. These results provide a foundation for interpreting the outcomes in the scenario analysis.

While existing literature uses 2050 as the time horizon for aviation emission reduction projections, this research adopts 2040 as its time frame. The rationale for selecting this time frame is that, beyond 2040, radical shifts in technological innovation are expected to become commercially viable, potentially driving sharp decline in fossil fuel dependency. This transition may mitigate both the likelihood and the impact of a fuel efficiency rebound effect.

SQ4: How do market-specific uncertainties impact the potential magnitude of a fuel efficiency rebound effect?

To address the fourth sub-question, a Scenario Analysis approach is employed to examine how the magnitude and implications of the fuel efficiency rebound effect are influenced by market-specific uncertainties. The results addressing SQ3 provide a first indication of the potential magnitude of the future rebound effect and its associated impacts. Building on this, a comprehensive scenario analysis is conducted to explore how the rebound effect may evolve under a range of possible future conditions. The interpretation of these scenarios, along with their broader implications, is informed and contextualized by the reference scenario outcomes. Market-specific uncertainties are varied across experiments. The results are analyzed using the Patient Rule Induction Method (PRIM) algorithm to identify the most critical uncertainties in determining the magnitude and implications of the fuel efficiency rebound effect.

Answering the research sub-questions contributes to addressing the main research question by identifying key factors and mechanisms driving the rebound effect, and the critical uncertainties that influence its potential magnitude. These insights provide policy makers with a strategic understanding of the conditions under which a rebound effect may emerge, helping to inform policies aimed at preventing or mitigating its occurrence in passenger aviation.

Research Flow Diagram

The research process broadly follows the standard SD modeling cycle, a structured and widely recognized approach in SD research (Auping et al., 2024). The modeling cycle, as applied for this research, comprises the following steps: problem articulation, conceptualization, formulation, evaluation, initial results and scenario analysis. The modeling cycle is inherently iterative, meaning that its steps are not strictly sequential and may be revised multiple times throughout the research process. Figure 2.1 illustrates how the steps of the modeling cycle and the sub-questions are iteratively integrated in the phases of this research.

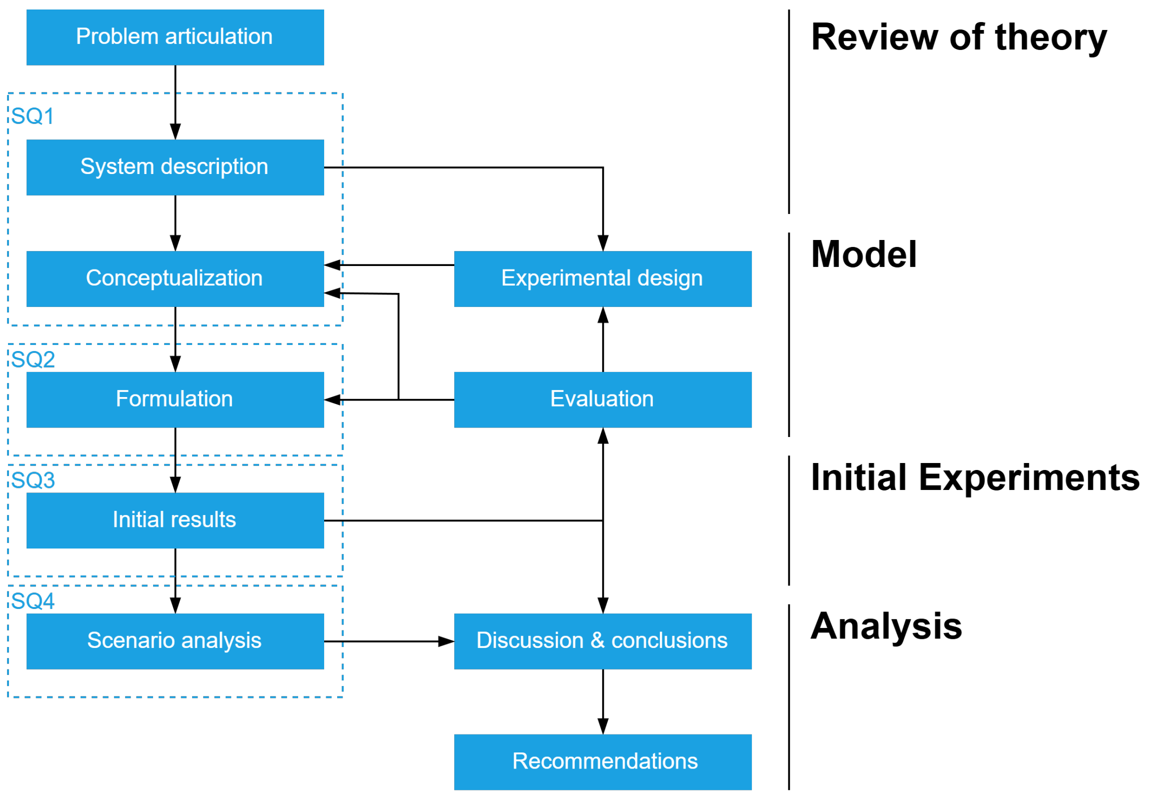

Figure 2.1: Research flow diagram

2.2. Modeling Technique: System Dynamics Modeling

Quantitative System Dynamics modeling serves as the primary modeling technique and the main research method in this research. SD modeling is particularly well-suited for examining the relationship between system behavior over time and its underlying structure (Forrester, 1987). Typical system structures modeled using SD include accumulations, delays and feedback loops. Feedback, in this context, refers to causal relationships that form closed loops, influencing system behavior over time (Auping et al., 2024). This feature is a fundamental characteristic of SD models, enabling a more dynamic and nonlinear approach beyond traditional linear thinking (Forrester, 1987). Quantitative SD is also valued for its ability to convey strategic insights without requiring extensive empirical data (Sterman, 2000). This is especially relevant to this research, where the fuel efficiency rebound effect in passenger aviation is the primary focus. Theory suggests that its occurrence is driven by the presence of a feedback loop within the system structure (Hilty et al., 2006; Stasinopoulos et al., 2012; Guzzo et al., 2023). Moreover, the aviation industry lacks comprehensive and easily accessible empirical data, underscoring the suitability of SD as a modeling technique for capturing underlying mechanisms of the fuel efficiency rebound effect. In addition, SD models almost always rely on aggregated variables to capture system-wide dynamics rather than individual variations (Rahn, 1985).

SD models are, in essence, sets of integral equations that define system behavior based on the specified model structure (Auping et al., 2024). The most essential elements in SD models are stock-variables, which accumulate over time and are influenced by inflows and outflows. Stocks can be interconnected through these flows, shaping the dynamics of the system. Additionally, the model structure includes constants and auxiliary variables that contribute to system behavior. The accumulation of a stock over time is mathematically defined by the following integral equation (Auping et al., 2024):

$$S_t = S_0 + \int_0^t (f_t - g_t)\, dt \tag{2.1}$$

Where:

S_t = value of stock S at time t

S_0 = initial value of stock S at time $t = 0$

f_t = inflow at time t

g_t = outflow at time t

Inflows and outflows can, in turn, be influenced by constants and auxiliary variables, as illustrated in Figure 2.2. This figure provides a visual representation of a simple stock-flow structure, corresponding to the integral equation. However, the constants and auxiliary variables influencing the flows in this figure, are not explicitly included in the integral equation.

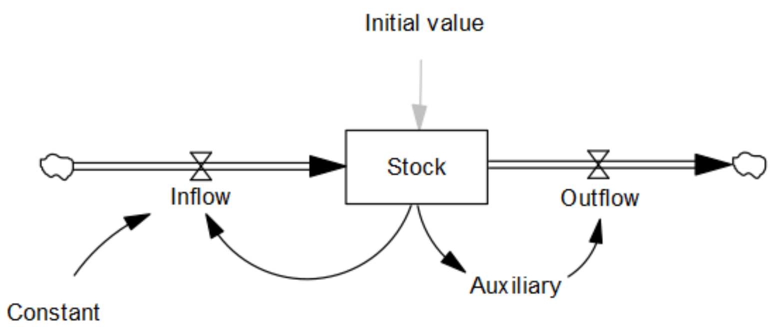

Figure 2.2: Stock-flow structure in diagrammatic conventions. Source: Auping et al. (2024)

Once initial values and constants are assigned, numerical integration techniques are used to simulate the behavior of the endogenous variables and visualize their changes over time. This involves solving the system of equations that define the dynamic interactions within the model at each time step, based on the specified initial conditions. In this research, the model is developed and simulated over the time horizon of 2025 to 2040 using Vensim DSS version 10.2.2. The model employs Euler integration with a time step of 0.0078125. Details of the initial parameter settings are provided in Chapter 4 and in the Excel file on Github[1].

[1] GitHub Repository

2.3. Model Purpose

The purpose of the model is to estimate the fuel efficiency rebound effect to assess its implications and generate strategic insights to inform policy development. This is achieved by integrating the dynamics of the fuel efficiency rebound effect to analyze the system's structure and behavior, and to estimate its magnitude and impact. To meet this objective, the model must capture the extent to which fuel cost savings stimulate increased demand, thereby partially or fully offsetting the expected emission reductions. This involves estimating the demand increase directly attributable to fuel efficiency and comparing resulting emissions. Additionally, the model estimates the emission reduction potential in the absence of rebound, enabling an estimation of actual emission reductions after accounting for the rebound effect.

The model operates under a *ceteris paribus* assumption. This approach allows for a clear analysis of the rebound effect - where lower fares stimulates higher demand. While, in reality, fluctuations in other variables may counteract some of the factors driving the rebound effect, this does not mean the rebound effect is absent. Rather, it may be covered by other dynamics.

2.4. Experimental Design

To ensure the results are valid and align with the purpose of this research, an experimental design is developed. This design for simulation experiments is derived from the model's purpose and the hypothesized behavior outlined in the dynamic hypothesis in Chapter 3. The experimental design is specifically developed to estimate the emission reduction potential and the fuel efficiency rebound effect, enabling an effective assessment of its impact ensuring alignment with the research objectives.

The hypothesis in Chapter 2 identified critical feedback mechanisms that were integrated into the experimental design to measure the rebound effect emerging from these interactions. The design determines which variables and interactions are included in each simulation experiment to generate the required information for meeting the research objectives. The experimental design primarily structures the execution of simulation experiments to ensure the accurate capture of the rebound's magnitude and implications, while also guiding the development of the model to align with this approach. The experimental design was refined iteratively based on insights from conceptualization and initial simulation results, enhancing its ability to capture and quantify the rebound effect with greater accuracy.

The experimental design consists of three simulations. The first is a null simulation, in which both efficiency improvements and associated feedback mechanisms are excluded. This simulation serves as a benchmark for estimating the theoretical emission reduction potential. The baseline simulation excludes the rebound feedback mechanisms but includes efficiency improvements, providing a reference point to isolate and quantify the rebound effect. Finally, the rebound simulation incorporates the feedback mechanisms associated with the rebound effect. It is first implemented as a single run to provide an initial estimation of the rebound effect and its implications. The rebound simulation is then conducted as a set of 1000 scenario runs, varying uncertain parameters to explore their impact on the magnitude of the rebound effect. Comparing the results of the baseline and rebound simulations provides an estimate of the potential scale of the fuel efficiency rebound effect. Input data, including baseline demand projections and anticipated efficiency improvements, are applied annually over the simulation time.

The model distinguishes between two components of demand growth: baseline demand growth and efficiency-induced demand growth. Baseline demand growth occurs independently of efficiency improvements, reflecting external factors such as population or economic growth. Efficiency-induced demand growth is driven by rebound feedback and reflects the additional demand as a response to hypothesized fuel savings resulting from operational and aircraft efficiency improvements. This distinction allows for a clear comparison between results of the baseline simulation and the rebound simulation. Figure 2.3 visually represents the experiment design, which serves as the foundation for both the initial results and the scenario analysis.

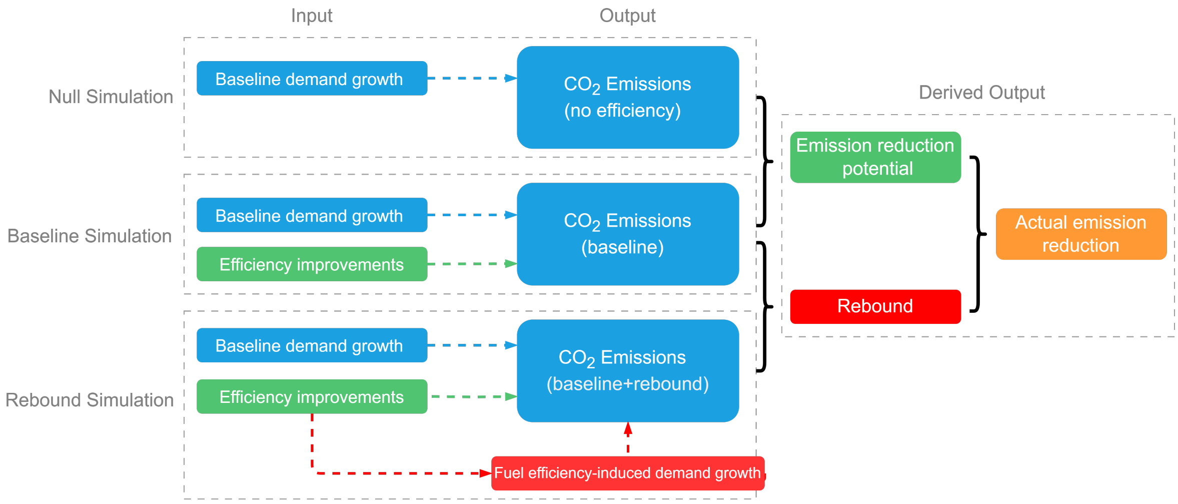

Figure 2.3: Experiment Design

2.5. Verification & Validation

In the *evaluation* step (Figure 2.1), the quality of the model is determined through various tests, focused on whether the model has been *constructed* and *simulated correctly* (verification), and whether it is *fit for purpose* (validation) (Barlas, 1996). Model validation refers to the process of building confidence in the model's usefulness (Forrester & Senge, 1980) rather than as a strict measure of its predictive accuracy. A model that is fit for purpose offers valuable insights into the system's structure and behavior, supporting policymaking processes (Forrester, 1961). Consequently, a model's validity is evaluated in relation to the specific purpose for which is was developed (Forrester & Senge, 1980).

Model verification in this research involves evaluating the suitability of the chosen numerical integration method and step size, verifying all equations and inputs for errors, testing individual subsystems and ensuring dimensional consistency (Pruyt, 2013). These tests are applied iteratively throughout the modeling process.

Validation tests were applied to establish confidence in a model's usefulness (Sterman, 2000; Pruyt, 2013). These tests fall into three main categories: (i) *direct structure tests*, which assess whether the model's relations and assumptions align with accepted theories and include all relevant variables; (ii) *structure-oriented behavior tests*, which examine whether the model's behavior and underlying mechanisms align with expectations, to identify key influences and further refine the model; and (iii) *behavior reproduction tests*, which evaluate how well the model's output matches known or historical data. To evaluate the model's validity, a selection of tests proposed by Forrester and Senge (1980) was conducted in this research. This selection of validation tests is presented in Table 2.1. The methodology and results are documented in the model chapter (Chapter 4) and Appendix B.

Table 2.1: Selection of validation tests per category

Category	Selected Validation Tests
Direct structure tests	Boundary adequacy test
Structure-oriented behavior tests	Sensitivity analysis Extreme conditions test
Behavior reproduction tests	Historical and future emissions data check

Boundary adequacy testing was conducted during the modeling process as a direct structure test to ensure that the model includes all essential feedback mechanisms and variables required to reproduce the fuel efficiency rebound effect, while excluding unnecessary complexity. This approach supports model validity by confirming that the model boundaries are appropriately defined in relation to the research objective. To complement this, a sensitivity analysis and extreme conditions tests were applied as structure-oriented behavior tests on the final model. Sensitivity analysis was selected to examine whether the model's conclusions are robust to uncertainties in parameter values, while the extreme conditions test was used to verify that the model generates plausible and consistent behavior under hypothetical extreme inputs. Together, these tests strengthen confidence in the behavioral reliability of the model. In addition, a historical and future emissions data check was performed to assess whether the model behavior aligns not only with observed historical patterns but also with established future emission projections reported in the literature. This test was selected to increase confidence in the model's ability to reflect real-world dynamics.

2.6. Scenario Analysis

The research combines SD modeling with Scenario Analysis to explore the future scenarios of the fuel efficiency rebound effect, which is essential due to its inherent uncertainty. This uncertainty arises from the complex and volatile dynamics of the aviation sector, influenced in part by the behavior of various stakeholders (Samunderu, 2024). To better understand the uncertainties surrounding the rebound effect, it is critical to explore plausible future developments through a comprehensive scenario analysis (Enserink et al., 2022). In this research, parametric uncertainties stem from two main sources: the limited availability of accessible data in the aviation sector and the lack of agreement about the behavioral responses of actors within the system. Scenario Analysis maps system behavior under uncertainty, when there is no knowledge or agreement on the plausible scenarios (Lempert et al., 2006). The experimental outcomes are analyzed to generate policy-relevant insights by evaluating the extent to which they align with the hypothesized rebound effect.

The research utilizes the EMA-workbench in Python for scenario analysis. Exploratory Modeling and Analysis (EMA) is particularly useful when sufficient information exists to build a model, but this information is inadequate to specify a single model that fully captures system behavior (Kwakkel & Pruyt, 2013). In traditional predictive modeling, a model is constructed by synthesizing known facts into a single representation to forecast system behavior (Bankes, 1993). This approach is employed during the initial results phase of this research (Figure 2.1), under the assumption of a reference scenario to validate and quantify the hypothesized rebound and interpret its implications. This reference scenario is selected from the set of plausible models, based on specific parameter values, assuming their correctness. However, as acknowledged in SD literature, for many complex systems, constructing a model that can serve as a valid surrogate for the real-world system is often infeasible due to the inherent difficulties of obtaining accurate measurements under uncertainty (Sterman, 2000). EMA addresses this uncertainty by generating a set of plausible models through numerous computational experiments (Bankes, 1993), enabling the systematic analysis of insights derived from an otherwise infinite range of plausible models.

A set of plausible scenarios is generated by selecting key parameters and defining their corresponding uncertainty ranges, within which their values can vary. These parameters are chosen for their expected significant impact on the magnitude of the rebound effect. The uncertainty range for each parameter is determined based on the minimum and maximum values it could realistically assume according to the literature. Each scenario represents a unique combination of values for these uncertain parameters. These values, along with their assignment for each scenario, are determined using Latin Hypercube Sampling (LHS). LHS divides the uncertainty space into a specified number of scenarios and randomly combines the values within each, ensuring both uniqueness and a uniform distribution (Huntington & Lyrintzis, 1998), as illustrated in Figure 2.4. Moreover, provided that the input and the number of scenarios remain constant, LHS will consistently generate the same set of scenarios, enhancing the reproducibility and reliability of this research.

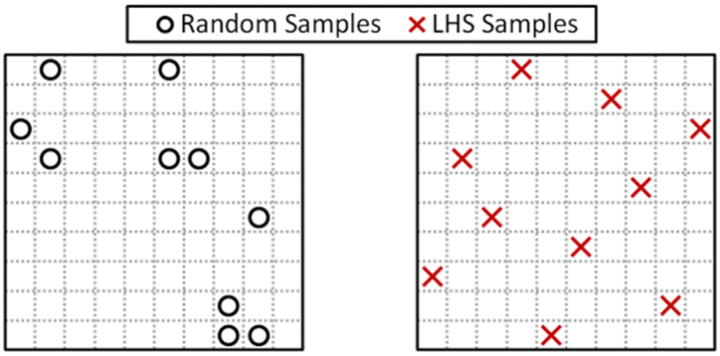

Figure 2.4: Random sampling versus Latin Hypercube Sampling for two dimensions. From: Preece and Milanović (2016)

In this analysis, the baseline scenario will remain constant, while 1000 runs will be performed for the rebound simulation to allow for a valid comparison of the potential rebound effects emerging from the same baseline. The resulting outputs are documented systematically and subjected to analysis. Figure 2.5 presents the conceptual framework for scenario analysis (Enserink et al., 2022), adapted to align with the objectives of this research.

Once a set of plausible scenario outcomes is generated, the PRIM algorithm is applied to identify the most influential combinations of market-specific uncertainties. PRIM is used to detect regions within the model input space that are strongly associated with outcomes of interest (Bryant & Lempert, 2010; Kwakkel et al., 2013). In this research, the outcomes of interest are twofold: (1) a rebound threshold at which a larger share of the emission reduction potential is offset relative to the reference scenario, and (2) the corresponding level of accumulated emissions resulting from such a rebound. To explore and identify the critical model input regions for the outcomes of interest, the model employs a lenient hill-climbing optimization procedure (Kwakkel & Jaxa-Rozen, 2016). This procedure iteratively refines the selection of input space by incrementally increasing the density of cases exhibiting the outcome of interest, while allowing trade-offs between coverage and precision (Bryant & Lempert, 2010). The research uses a Python implementation of PRIM as part of the EMA-workbench.

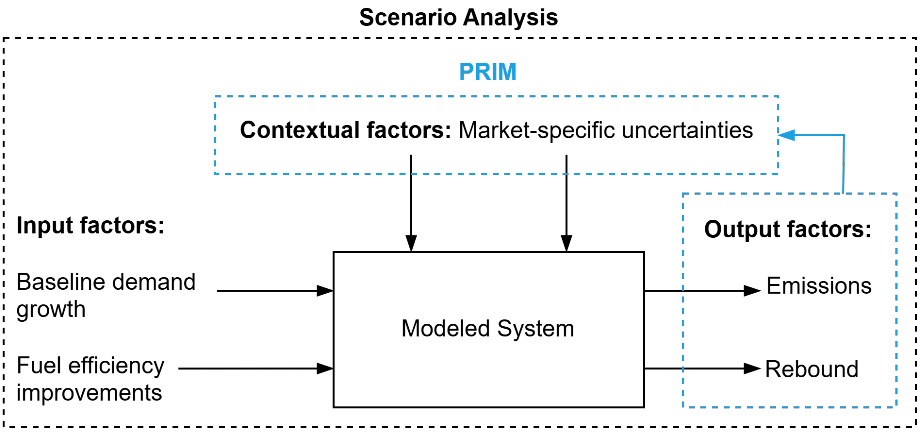

Figure 2.5: Framework for Scenario Analysis. Adapted from: Enserink et al. (2022)

Within the framework, the term *Modeled System* refers to the entity that exhibits the problematic behavior to be analyzed (Balci, 1994). This entity corresponds to the model configuration used for the full rebound simulation, as it captures the problematic dynamics relevant to the fuel efficiency rebound effect. This focus is appropriate given that only rebound simulation runs are conducted in the scenario analysis, while the parameter values of the baseline simulation are held constant to allow for a meaningful comparison. The rebound simulation incorporates all modeled variables, whereas the null and baseline simulations exclude certain variables, as discussed in Section 2.4.

3

Conceptualization & Hypothesis

This research applies quantitative System Dynamics (SD) modeling to examine the effects of the fuel efficiency rebound on potential emission reductions in passenger aviation. Prior to the formulation of the quantitative SD model, it is essential to conceptualize the underlying theory of the fuel efficiency rebound effect. This involves formulating a dynamic hypothesis that explains how key factors influence the problem behavior over time, addressing the following sub-question:

What factors contribute to a fuel efficiency rebound effect and how do they interact?

This chapter establishes the dynamic hypothesis through three steps. First, Section 3.1 identifies and describes the key factors of a fuel efficiency rebound in the passenger aviation system, based on existing literature. Second, Section 3.2 synthesizes these components and their interrelations into a Causal Loop Diagram (CLD) to conceptualize the underlying behavioral feedback mechanisms. Third, Section 3.3 identifies a corresponding system archetype and formulates a dynamic hypothesis based on this structure. The dynamic hypothesis serves as a foundation for the formulation of the quantitative SD model, which is presented in Chapter 4. Furthermore, it informs the interpretation of initial experiment results in Chapter 5 and the evaluation of scenario outcomes in 6

3.1. System Description

Several studies have investigated short-term strategies to reduce fuel consumption in global passenger aviation. These approaches show considerable alignment with the four-pillar strategy proposed by the International Air Transport Association (IATA). The key short-term measures available to airlines for lowering fuel consumption per passenger-kilometer can be summarized as follows:

- Invest in new generation, more **fuel-efficient aircraft** to increase average fuel efficiency;
- Implement strategies to increase **passenger load factors**;
- Optimize flight operations such as route planning to reduce **flight distances**.

This section describes the key factors influenced by these measures, which contribute to a fuel efficiency rebound effect as conceptualized in the existing literature.

Aircraft Fuel Efficiency

Abrantes et al. (2021) state that increasing aircraft efficiency plays a critical role in meeting carbon reduction targets by 2050. Since the beginning of the jet age, technological innovations - including the use of lighter materials, improved engine performance, and aerodynamic improvements have resulted in a 70% reduction in fuel consumption per passenger-kilometer of aircraft (Abrantes et al., 2021). Given this historical trend, further reductions are anticipated as new technological innovations continue to be introduced into the aviation sector.

Improving technological efficiency, particularly in aircraft design and engine fuel consumption, represents a viable short-term strategy, especially for airlines operating older fleets (Kettler & Walls, 2022). Owen et al. (2010); Randt et al. (2015) and Terekhov et al. (2018) have analyzed the impact of emerging conventional aircraft technologies and aircraft configurations on future CO_2 emissions in the global aviation sector. Their findings indicate that while advancements in aircraft technology contribute to fuel savings, the adoption of new aircraft generations occurs gradually due to market dynamics and industry constraints. After a new aircraft enters service, it takes several years before its widespread adoption significantly impacts the overall fleet efficiency (IATA, 2021a). On average, each new generation of aircraft achieves a 15-20% improvement in fuel efficiency over its predecessor. However, the slow pace of aircraft replacement, due to the high costs and logistical constraints of frequent fleet upgrades, results in a modest annual efficiency improvement of only 1-1.5% (Peeters & Melkert, 2024). Consequently, further fuel consumption reductions will need to be complemented by the implementation of operational efficiency improvements.

Operational Efficiency

In addition to the impact of aircraft fuel efficiency, Ploetner et al. (2017) and Hassan and Mavris (2020) estimate that fleet-level fuel burn could be further reduced by 7-8% by 2050 as a result of increasing passenger load factors. Ploetner et al. (2017) highlight that achieving climate targets cannot rely solely on short-term advancements in aircraft technology, as the slow integration of new technologies at the fleet level limits their impact. While substantial improvements in operational efficiency may enable immediate benefits in the short term (Hassan & Mavris, 2020), emissions are projected to remain approximately 10% higher than the IATA targets set for 2035 (Ploetner et al., 2017). Increasing passenger load factors and reducing flight distances enhance fuel usage efficiency on a per passenger-kilometer basis (Wadud, 2015), which is a critical metric for evaluating the environmental performance of individual flights. Passenger load factor is a measure of how efficiently the maximum seating capacity of an aircraft is utilized:

$$\text{Passenger Load Factor} = (\text{RPK} / \text{ASK}) * 100\%$$

Where RPK refers to revenue passenger-kilometers and ASK refers to available seat-kilometers. Reducing flight distances can further improve efficiency since shorter distances typically result in less fuel consumption due to reduced time in the air and lower total distance traveled per passenger.

Fuel Costs and Fare Prices

To achieve financial success, airlines must perform well in both productive efficiency and fare pricing (Oum et al., 2005). The highly competitive nature of the passenger aviation market compels airlines to continuously enhance efficiency and reduce operational costs. A key indicator of cost competitiveness is an airline's ability to maintain lower unit costs than its competitors on a sustainable basis (Oum & Yu, 1998). Given that fuel constitutes a substantial share of airline operating expenses (Zou et al., 2014), jet fuel efficiency is frequently analyzed as a critical input factor in assessing productive efficiency (Adler et al., 2013; Arjomandi & Seufert, 2014). Fuel efficiency is typically expressed as a ratio metric, indicating the amount of fuel consumed per unit of output. In the literature, this output is commonly measured in terms of fuel consumption per seat-kilometer or passenger-kilometer. An improvement in fuel efficiency, defined as a reduction in fuel consumption per passenger-kilometer, implies that less fuel and therefore lower costs are required to produce the same level of output and revenue. Since passenger-kilometers are the core output of airlines in passenger aviation, improvements in fuel efficiency per passenger-kilometer are inherently linked to operational cost savings (Miyoshi & Fukui, 2018).

The benefits allow airlines to reduce unit operating costs and enabling them to offer lower and more competitive airfares to passengers (Zou et al., 2014). However, a key concern for regulators is the extent to which airlines are able to pass through cost changes to fare prices. Empirical evidence on this pass-through effect remains limited. A pass-through rate of 100% is often assumed, based on the premise that the aviation sector is highly competitive. However, Koopmans and Lieshout (2016) found that sector-wide cost changes are passed through at a rate of more than 50 %. In this research, a default pass-through rate of 45% is assumed as the average value for the entire passenger aviation industry, serving as the baseline input for the reference scenario in the initial experiments presented in 5. This rate is chosen because it is considered reasonable to expect that the average pass-through rate lies between a minimum of 10% and a maximum of 100%, with 45% representing the midpoint of this range. For the scenario analysis in Chapter 6, the pass-through rate is varied across different scenarios to assess the impact of potential actual values on the magnitude of the rebound effect.

Global Passenger Demand

Aviation's contribution to climate change would be immediately halted by either a sustained annual 2.5% decrease in air traffic under the existing fuel mix (Klöwer et al., 2021). However, the likelihood of air traffic in 2050 being reduced depends strongly on the stringency of climate policies, changes in passenger behavior, and economic developments within the aviation sector. Improvements in fuel efficiency alone are unlikely to significantly reduce aviation's climate impact, as past gains have been outpaced by continued traffic growth, and the potential for further improvements is becoming increasingly limited.

Airbus forecasts a continued annual growth rate of 4.4% in revenue passenger-kilometers (RPK) over the next two decades, as outlined in its Global Market Forecast (Airbus, 2018). Similarly, Boeing's Commercial Market Outlook anticipates an annual growth rate of 4.6% (Boeing, 2019). However, both projections are primarily driven by expected increases in GDP per capita and largely rely on a single baseline scenario that estimates future passenger demand based on income elasticities and the corresponding number of required aircraft. While useful for planning fleet size and capacity, such single-scenario models are insufficient for assessing the robustness of emerging technologies (Kölker, Bießlich, & Lütjens, 2016). Projected aviation emissions are frequently estimated using aggregated approaches, as seen in previous studies (Miyoshi & Fukui, 2018), which typically model multiple scenarios by varying the assumed rates of fuel efficiency improvements.

While GDP is a key predictor in air transport forecasts (Martins et al., 2017), with established models typically projecting RPK growth at 20% - 40% faster than GDP (Smyth & Pearce, 2008), this research contributes to these projections by conceptualizing fuel efficiency improvements as additional drivers of passenger demand - an element typically excluded from traditional aviation forecasts.

Fare Elasticity of Demand

Demand elasticities quantify the change in passenger-kilometers demanded in response to variations in airfare, with elasticity values dependent on the specific focus of the analysis. The sensitivity of aggregated demand varies across different route levels, as well as national or even supra-national scales (Smyth & Pearce, 2008). Elasticities have been estimated in various contexts, with a general consensus that they are influenced by traveler motives and haul segments (Brons et al., 2002). Studies have reported fare elasticities of ranging from -0.27 to -1.52, with a mean fare elasticity of -1.146 , indicating that fare price changes can result in a proportional change in demand (Gillen, 2020). For this research, three[1] representative fare elasticities (-0.82; -1.06; -1.28) are used as baseline inputs[2] for the reference scenario of initial experiments in Chapter 5. Due to the lack of consensus on elasticity values by haul segment and the aggregate nature of the model, the scenario analysis in Chapter 6 explores the implications of applying different average fare elasticity assumptions per haul segment.

3.2. Problematic System Behavior

Efficiency gains from the introduction of newer, more fuel-efficient aircraft are expected to average $\pm$1.5% per year, reflecting long-term historical trends (Peeters et al., 2016; IATA, 2023). In addition, improvements in operational efficiency enhance overall fuel use per revenue passenger-kilometer (RPK) (Grewe et al., 2021). While these developments reduce fuel use per unit of output, they also risk triggering a rebound effect: lower per-RPK fuel costs can stimulate increased demand, which may lead to a net rise in total aircraft activity and, ultimately, fuel consumption and emissions.

[1] The modeling approach distinguishes five haul segments, but applies only three distinct elasticity values across them, while excluding traveler motives from the scope of analysis

[2] The estimations of the three high-level elasticities based on existing literature, can be found in the Excel file on GitHub

The contrasting effects on passenger-kilometers traveled create a challenge for regulating overall aviation fuel consumption and emissions (Wadud, 2015). Across the industry, airlines are expected to collectively respond to demand growth by fully accommodating increased passenger volumes, regardless of the market structure. Fleet management flexibility enables airlines to meet rising demand, indicating that, sector-wide future demand growth is likely to be fully met (Pitfield et al., 2010). Moreover, empirical studies suggest that for all market structures, supply-side decisions (e.g., frequency and aircraft size) are primarily driven by demand across the broader network rather than by local market characteristics (Abrahams, 1983; Wei & Hansen, 2005).

While improved load factors, flight distances and aircraft technology can enhance fuel efficiency on a per-passenger basis, they must be evaluated in the context of broader system dynamics and their impact on total emissions and operational efficiency. Therefore, the model incorporates the feedback-loop complexities that cause additional demand growth and fuel consumption resulting from reductions in fuel consumption per revenue passenger-kilometer (RPK). Figure 3.1 presents a synthesis of the key factors driving the feedback mechanisms underlying the problematic behavior associated with a fuel efficiency rebound effect in a Causal Loop Diagram (CLD). For clarity, the diagram presents a simplified structure in which certain detailed variables - though included in the SD model - have been omitted. The conceptualization of the underlying behavioral feedback mechanisms highlights two dynamics that deserve attention:

- **R1:** Efficiency-induced revenue passenger-kilometers (RPK)
- **B1:** Efficiency-induced fuel consumption

It is assumed that total RPK demand ultimately determines the number of aircraft-kilometers flown (AKF) required to meet this demand, as indicated in the literature. Operational efficiency can play a mitigating role in this relationship, for example through flight distance, while the passenger load factor (PLF) influences the number of passengers (PAX) per flight. Together, these factors determine how many aircraft-kilometers are needed on average to achieve a given RPK output.

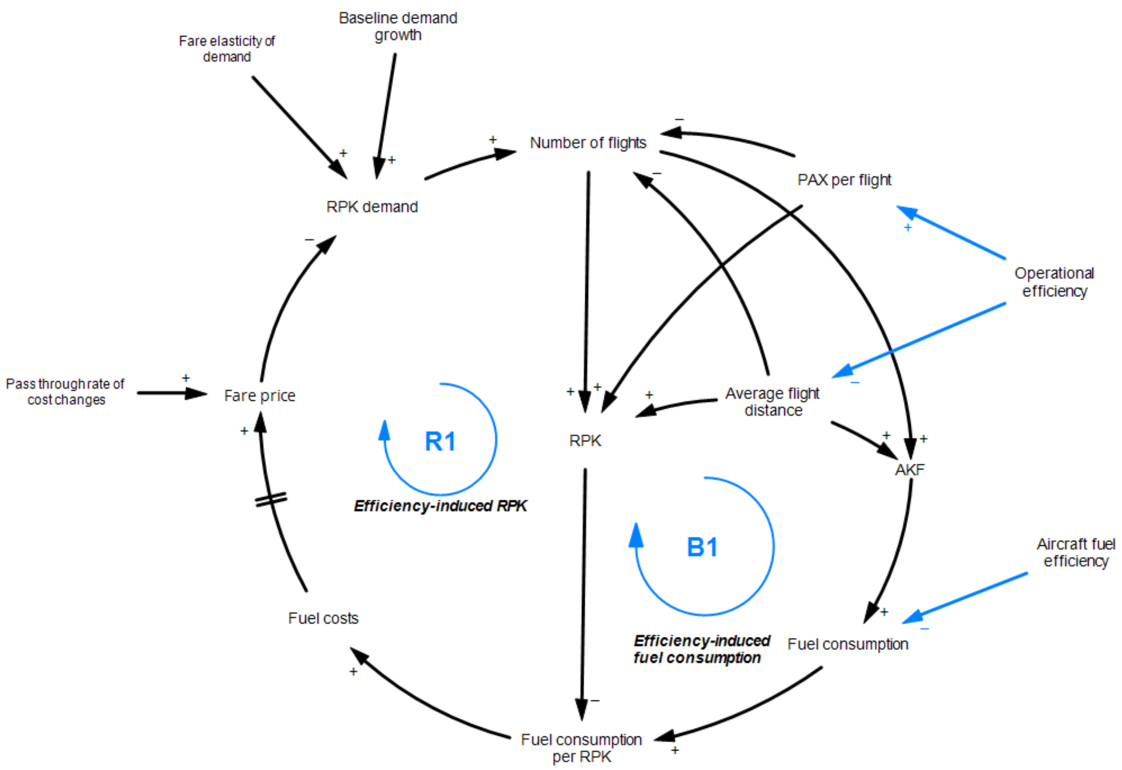

Figure 3.1: Causal Loop Diagram illustrating the hypothesized feedback mechanisms driving the problematic behavior. Positive causal relationships are indicated with a "+" sign at the arrowhead, denoting that an increase in one variable leads to an increase the connected variable, *ceteris paribus*. Negative causal relationships are marked with a "-"sign, indicating that an increase in one variable leads to a decrease in the other, *ceteris paribus*. Delay between variables is presented by a "||" symbol. The reinforcing feedback loop is labeled "R1", and the balancing feedback loop is labeled "B1".

Efficiency-induced revenue passenger-kilometers

The first feedback mechanism, *efficiency-induced revenue passenger-kilometers* (R1), is a reinforcing feedback loop that emerges when fuel consumption per RPK decreases as a result of improvements in operational and aircraft fuel efficiency. Lower total fuel consumption leads to reduced fuel costs per unit of output (RPK), enabling fare reductions depending on the cost pass-through rate. The extent to which these lower fares stimulate additional RPK demand, depends on the fare elasticity of demand. This additional rise in demand, amplified by baseline growth trends, contributes to a higher volume of RPKs being generated relative to fuel consumption. This feedback loop represents the core mechanism behind the fuel efficiency rebound effect: the improved efficiency lowers costs, which in turn simulates increased demand and flight operations in terms of passenger-kilometers.

Efficiency-induced fuel consumption

The second feedback mechanism, *efficiency-induced fuel consumption* (B1), captures the dynamic where fuel efficiency improvements initially lead to a reduction in total fuel consumption. Both through decreased aircraft-kilometers flown (AKF), enabled by operational efficiencies, and through lower fuel use per AKF, achieved via aircraft fuel efficiency. However, the resulting decline in fuel consumption per RPK stimulates additional RPK demand, ultimately leading to an absolute increase in the number of aircraft-kilometers required. This, in turn, can offset the initial fuel savings and lead to an overall rise in fuel consumption. These dynamics, in which the market responses counteract initial benefits, are conceptualized as a balancing feedback-loop.

3.3. Dynamic Hypothesis

The dynamic hypothesis of the problematic system behavior simulated in this research is supported by the identification of archetypical feedback structures, as conceptualized in the CLD shown in Figure 3.1. This system behavior is hypothesized based on the structure used in the rebound simulation, as presented in the experimental design for this research outlined in Chapter 2. Since the behavior observed in this extended structure builds upon the dynamics of the baseline simulation, the behavioral hypothesis is first presented for the baseline system structure. Subsequently, the emergence of problematic behavior in the rebound configuration is hypothesized, supported by the theory of system archetypes as proposed by (Senge, 1990).

When considering only the baseline system structure, there are no feedback mechanisms present from efficiency improvements that reduce fuel consumption per RPK to additional RPKs or aircraft-kilometers. Existing projections in the literature suggest that baseline RPK demand is expected to grow at an almost exponential rate, along with a corresponding increase of aircraft-kilometers flown. Despite efficiency improvements, this accelerated growth pattern outpaces[3] the gains in fuel efficiency, leading to an increase in emissions up to 2040[4].

System archetypes, as proposed by Senge (1990), represent common underlying structures that give rise to recurring patterns of problem behavior. Such archetypical behaviors typically emerge from specific configurations of reinforcing and/or balancing feedback loops within a highly aggregated system structure. The feedback dynamics driving the fuel efficiency rebound effect closely align with the system archetype referred to as *Fixes that Fail*. This archetype describes situations in which a seemingly effective solution generates significant unintended consequences over time. This may cause the system to revert to its original problematic state leading to even greater challenges, rather than resolving the issue. In the problem behavior examined in this research, fuel efficiency improvements intended to achieve a potential emission reduction, trigger a rebound effect resulting in unintended consequences that lead to even higher fossil fuel consumption and a similar trend in overall emissions.

The hypothesized problematic behavior of the rebound structure is linked to the behavior of the baseline structure. The baseline RPK demand growth and corresponding aircraft-kilometers are amplified by the feedback mechanisms triggered by efficiency improvements, which accelerates fuel consumption and result in higher CO_2 emissions compared to the baseline simulation. The difference in total accumulated emissions between the baseline simulation and the rebound simulation is expected to be small initially, as both simulations start with the same initial values. However, this difference will progressively expand over time due to the cumulative effects of the rebound feedback. The hypothesized dynamic behavior of both system structures is illustrated in Figure 3.2.

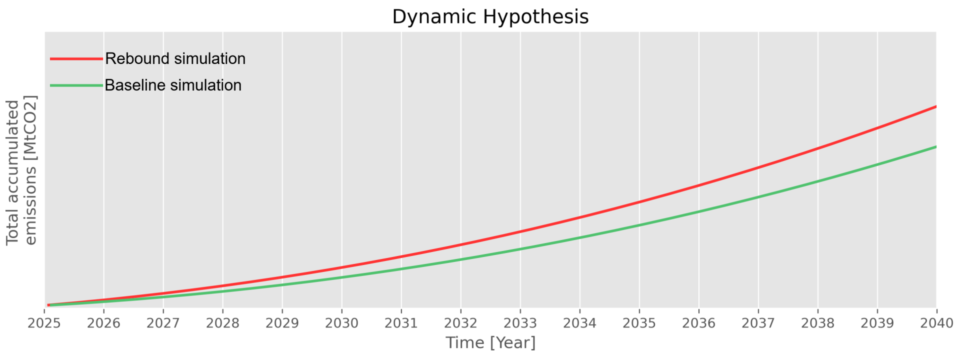

Figure 3.2: Hypothesized system behavior expressed in terms of total accumulated emissions for both the baseline and rebound simulations. The hypothesis illustrates the expected relative behavior of the system in a rebound scenario compared to the baseline over time. Emissions are set to zero at initial time, as they are tracked cumulatively from 2025 onward. The baseline simulation incorporates projected demand growth and efficiency improvements, while the rebound simulation includes the same conditions with the addition of rebound feedback mechanisms and resulting additional demand growth and emissions.

[3]Efficiency improvements lead to lower emissions compared to a scenario with no efficiency gains. However, despite these improvements emissions are expected to continue to rise

[4]The literature covers a range of scenarios, with more recent studies increasingly assuming that the introduction of disruptive aircraft technologies and alternative fuels will not occur until after 2040. This timeline assumption is also adopted in this research

4
Model

After establishing the key concepts and interactions related to the fuel efficiency rebound effect in Chapter 3, this chapter presents the System Dynamics (SD) model developed in this research to address the following sub-question:

How can a System Dynamics model effectively capture and integrate the key factors and interactions of the fuel efficiency rebound effect?

Section 4.1 defines the model boundaries, followed by a high-level overview of the model structure in Section 4.2. Section 4.3 discusses the subsystems and main assumptions of the model, while Section 4.4 introduces the Key Performance Indicators (KPIs). Baseline input values, used consistently across all experiments in the subsequent chapters, are detailed in Section 4.5. The chapter concludes with a discussion on model validation in Section 4.6.

4.1. Model Boundaries

The selection of model boundaries is guided by the research scope, the purpose of the model and the key factors identified in Chapter 3. Given the global scope of this research, the model operates at a high level of aggregation. Consequently, variables representing detailed operational phases of passenger aviation are excluded, and only those directly relevant to the fuel efficiency rebound effect are considered.

The model is designed to specifically capture the demand increase directly resulting from lower fare prices, driven by improvements in both operational fuel efficiency and aircraft fuel efficiency. Consequently, the model operates under a *ceteris paribus* assumption, meaning that all other factors influencing operating costs, fare prices and passenger demand remain constant and are excluded from the model boundaries.

To account for expected future growth, the model incorporates projected baseline demand, reflecting the anticipated doubling of total passenger demand. Establishing this baseline is essential for assessing the rebound effect, as it enables a comparison between passenger demand under baseline conditions - where the rebound effect is not considered - and a scenario in which the rebound effect is accounted for.

Figure 4.1 provides an overview of the included and excluded variables. Finally, Chapter 8 explores significant potential model expansions for future research.

Main Assumptions

- The model operates under a *ceteris paribus* assumption, meaning that all other factors influencing relevant variables and not driven by the fuel efficiency rebound effect are excluded.

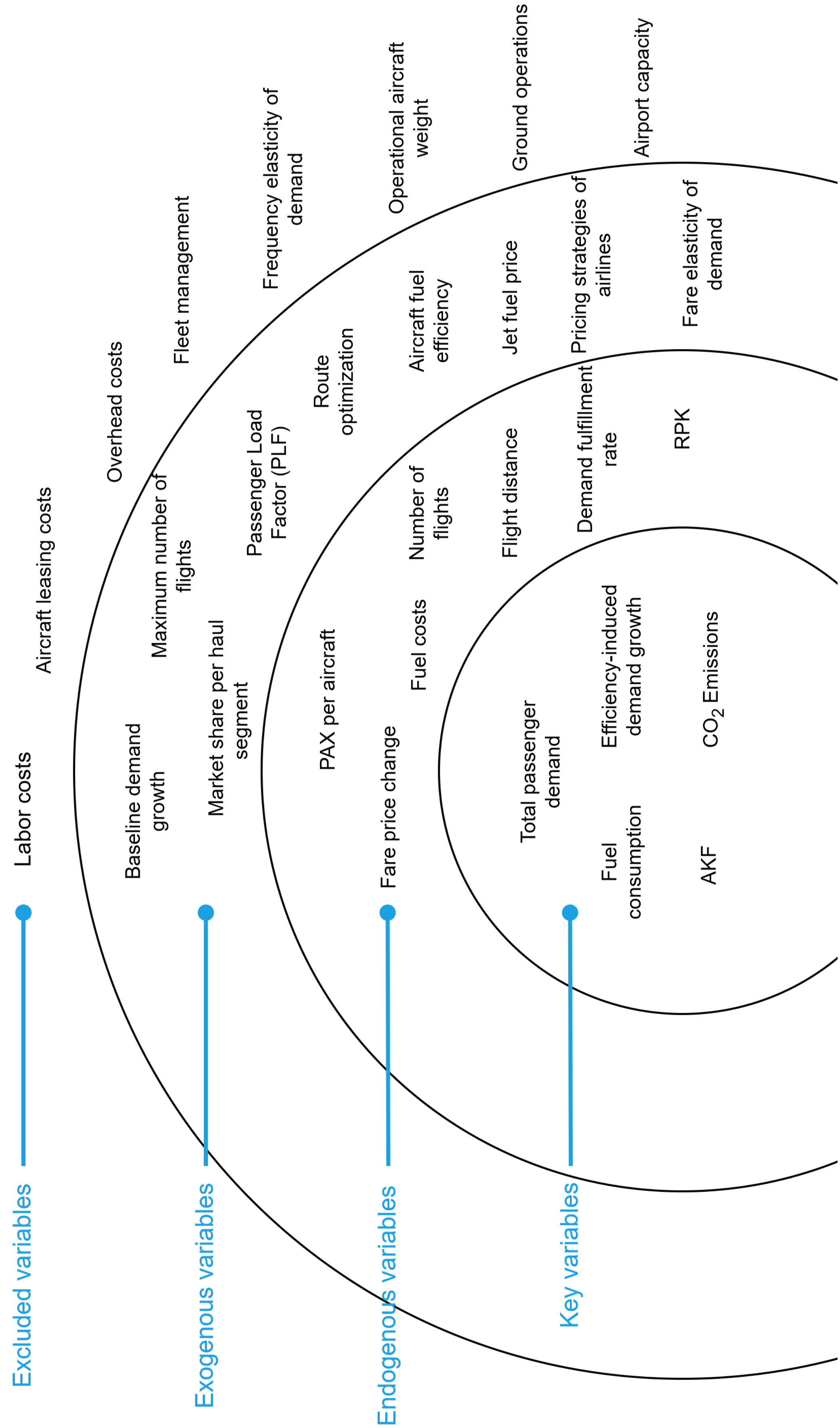

Figure 4.1: Bulls-eye diagram for the visualization of model boundaries

4.2. Model Structure

Figure 4.2 provides a high-level overview of the model structure, illustrating how key variables and subsystems interact through the assumed causal relationships within the rebound loops. Given that the fuel efficiency rebound effect is the primary focus of this research, these feedback loops form the core of the model. Accordingly, the model is built on the key assumption that a causal relationship exists between fuel efficiency, fuel consumption, fuel costs, fare price, and demand growth - specifically in that sequence. Unlike the null simulation and baseline simulation, the rebound simulation of the experimental design includes rebound feedback and incorporates the variables and relationships highlighted in red, completing the rebound loops. The baseline simulation and rebound simulation include baseline variables (blue) along with efficiency improvements (green). The null simulation only includes the baseline variables (blue).

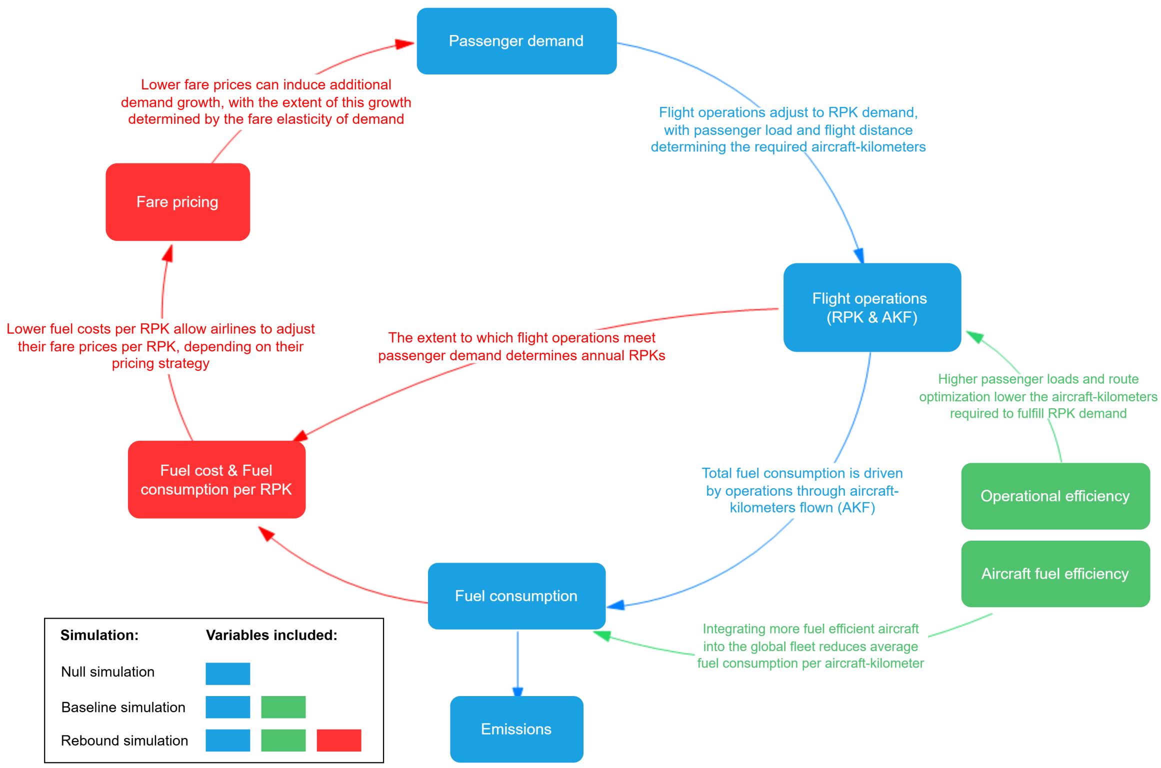

Figure 4.2: High-level overview of the System Dynamics model showing subsystems, key variables, and their connections. Blue subsystems are common to all simulations, green subsystems represent efficiency improvements included in the baseline and rebound simulations, and red subsystems complete the feedback loops driving the hypothesized problematic behavior, included only in the rebound simulation.

Given the model's high level of aggregation and in line with the common approach in SD modeling, most variables represent industry-wide averages. However, the industry-average variables *flight distance* and *maximum seating capacity of aircraft* vary significantly across haul segments (see Chapter 3). Since these variables are crucial for determining flight operations, the model is subscripted across five haul segments. In SD modeling, subscripts are used to represent and simulate multiple similar entities within a single model structure (Vensim documentation, 2025). This approach enables the model to generate distinct outputs for each subscripted entity. The subscripted model enables more precise estimations of flight operations, thereby improving the accuracy of other key variables dependent on flight operations. As a result, most variables are calculated separately for each of the five haul segments. Industry-wide KPI values are obtained by summing the values across all haul segments. Table 4.1 presents the adopted haul segment classification and the corresponding industry-wide averages used as input data for the model. A detailed explanation of how these industry-wide averages were estimated can be found in Appendix A.

Table 4.1: Estimations of industry-wide averages per haul segment

Haul segment	**Flight distance**	**Maximum seating capacity of aircraft**
Short haul	600 km	108.75
Short-medium haul	1000 km	126.25
Medium haul	1600 km	146.43
Long haul	3250 km	183.33
Ultra-long haul	12000 km	308.33

Main Assumptions

- An indirect causal relationship between fuel efficiency and demand growth forms a feedback loop that captures the dynamics of a potential fuel efficiency rebound effect;
- The model operates under a *business as usual* scenario, meaning that unforeseen events are not considered and are assumed not to significantly disrupt the dynamics within the rebound feedback.

4.3. Subsystems & Assumptions

The model comprises the following subsystems: *Passenger demand*, *Flight operations*, *Fuel consumption*, *Operational & Aircraft fuel efficiency*, and *Fare pricing*. The following subsections outline the structure, the most important equations and the main assumptions of each subsystem. The subsystems presented in this section reflect the model configuration used in the full rebound simulation. The rebound simulation includes all modeled variables, while in the null simulation and baseline simulation certain variables were excluded. The underlying equations are disaggregated and modified where necessary to account for the inclusion or exclusion of variables in simulations. Several variables are formalized using an integral approach to accurately represent the common stock-flow relationship in SD modeling. The complete file of the model developed for this research can be accessed via Github[1].

4.3.1. Passenger Demand

The dynamics of consumer behavior contributing to the fuel efficiency rebound effect are reflected in the way total annual passenger demand accumulates over time. Given that a *business as usual* scenario is assumed, and projections in the literature consistently indicate an increasing trend in demand, passenger demand is modeled as a stock-flow system with two inflows and no outflows, as visualized in Figure 4.3. The two inflows distinguish between baseline demand growth and fuel efficiency-induced demand growth, enabling comparison of null and baseline scenarios to the rebound scenario. Consequently, in the null simulation and the baseline simulation, where the rebound is not accounted for, total annual passenger demand is determined solely by the inflow of baseline demand growth. In the rebound simulation, where the rebound feedback mechanisms are included, total annual passenger demand is modeled as the sum of both contributing inflows:

$$D_t = D_0 + \int_0^t \begin{cases} [D_t * \beta_t]\,dt & \text{Null simulation \& Baseline simulation} \\ [D_t * (\beta_t + \lambda_t)]\,dt & \text{Rebound simulation} \end{cases} \tag{4.1}$$

Where:

D_t = Total annual passenger demand at time t [RPK/year]

D_0 = Initial total annual passenger demand at time $t = 0$ [RPK/year]

β_t = Baseline prediction demand growth rate at time t

[1] GitHub Repository

λ_t = Fuel efficiency-induced demand growth rate at time t

The baseline growth rate operates independently of the rebound feedback and depends on the baseline prediction of the yearly demand growth rate. The fuel efficiency-induced growth rate is driven by rebound feedback and therefore depends on the fare price change and the fare elasticity of demand. Fare elasticity of demand in general represents the degree to which consumers respond to changes in fare prices (Belobaba, 2009):

$$\varepsilon_p = \frac{\Delta D}{\Delta p} \qquad \rightarrow \qquad \Delta D = \varepsilon_p * \Delta p \tag{4.2}$$

Where:

ε_p = Fare elasticity of demand

ΔD = Percentage change of demand

Δp = Percentage change of fare price

Applying this formula to the specific fare price change due to fuel efficiency in this model, gives the following equation for the fuel efficiency-induced demand growth rate:

$$\lambda_t = \rho_t * \varepsilon_p \tag{4.3}$$

Where:

ρ_t = Fare price change ratio at time t

ε_p = Fare elasticity of demand

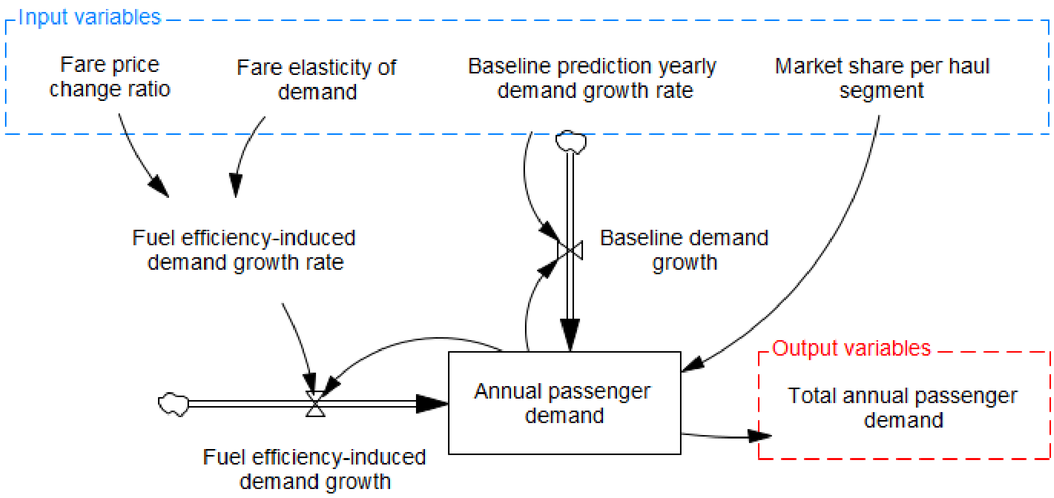

Figure 4.3: Simplified visualization stock-flow structure of subsystem for passenger demand

Main Assumptions

- The predicted passenger demand growth values found in the literature serve as the baseline for passenger demand growth, which is assumed to increase over the years in line with existing projections;

- Higher passenger load factors do not result in a decrease of passenger demand;
- The values for fare elasticity of demand remain constant over the entire simulation time.

4.3.2. Flight Operations

Passenger demand is met through flight operations performed by airlines. An increase in demand, whether from baseline growth alone or from a combination of baseline growth and the rebound feedback, leads to a higher number of flights. This, in turn, results in an increase in revenue passenger-kilometers (RPK) and total aircraft-kilometers flown (AKF) on average. Figure 4.4 illustrates how annual revenue passenger-kilometers and aircraft-kilometers depend on other variables within the subsystem.

The model assumes that the airline industry will capitalize on growth opportunities (Abrahams, 1983; Wei & Hansen, 2005; Pitfield et al., 2010), and therefore will adjust its supply to match increasing passenger demand in the long term. Consequently, the model initially assumes that airlines collectively fulfill 100% of the demand. However, to enable scenario testing under a flight restriction, the model incorporates an upper limit on the annual number of flights:

$$\eta_t = \begin{cases} 1 & \text{IF } N_{d,t} \leq N_{\text{max}} \\ N_{\text{max}}/N_{d,t} & \text{ELSE} \end{cases} \tag{4.4}$$

Where:

η_t = Demand fulfillment rate at time t

$N_{d,t}$ = Demand for annual number of flights at time t

N_{max} = Maximum annual number of flights

The annual number of flights is determined by total annual passenger demand (measured in RPK), average flight distance, number of passengers (PAX) per flight and the demand fulfillment rate:

$$N_t = \frac{D_t}{p_t * PAX_t} * \eta_t \tag{4.5}$$

Where:

N_t = Annual number of flights at time t

D_t = Total annual passenger demand at time t [RPK/year]

PAX_t = Average number of passengers per flight at time t [passengers]

d_t = Average flight distance at time t [km]

The number of annual aircraft-kilometers flown (AKF) is then calculated as follows:

$$AKF_t = N_t * d_t \tag{4.6}$$

In principle, the total annual revenue passenger-kilometers performed by airlines matches the total annual passenger demand. If the maximum allowable number of annual flights is reached, only a portion of the demanded revenue passenger-kilometers will be fulfilled (see equation 4.4).

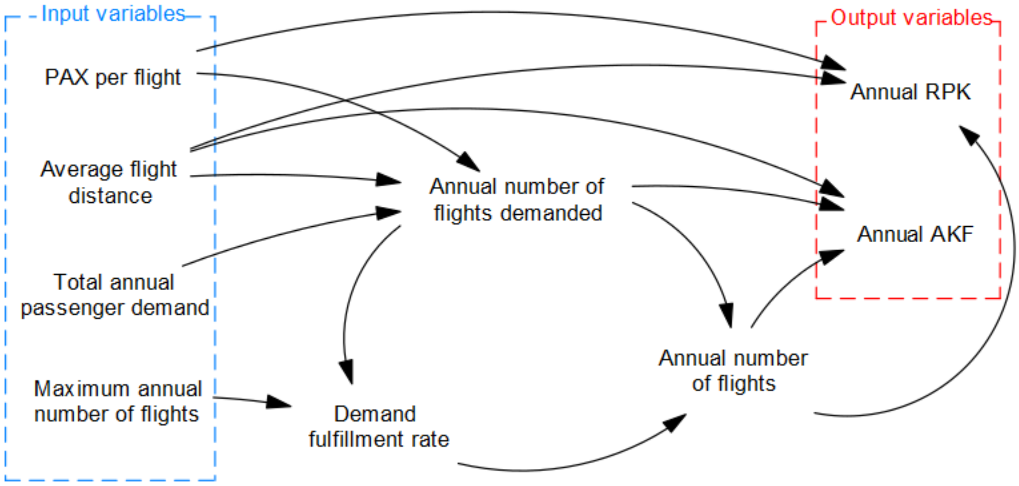

Figure 4.4: Simplified visualization stock-flow structure of subsystem for flight operations

Main Assumptions

- Passenger demand dictates the volume of flight operations, meaning the supply of airline services is adjusted to meet the level of demand, rather than demand being influenced by the available supply of flights;
- The degree of demand fulfillment is only limited by an industry-wide maximum annual number of flights.

4.3.3. Fuel Consumption

Fuel consumption is calculated based on total aircraft-kilometers flown (AKF) multiplied by fuel consumption per aircraft-kilometer, instead of using revenue passenger-kilometers (RPK) multiplied by fuel consumption per passenger-kilometer. This approach allows aircraft-kilometers flown to adjust in response to operational efficiency via the number of passengers (PAX) per flight and optimizing flight distances. These changes, which affect the number of flights required to meet the same RPK-demand, enable fuel consumption to decrease as a result of operational efficiency. Consequently, fuel consumption per revenue passenger-kilometer is treated as an endogenous variable in the model, rather than as an external fixed value. This approach aligns with how fuel efficiency metrics are commonly presented in aviation literature, reflecting the dynamics between operational fuel efficiency, aircraft fuel efficiency and fuel consumption.

The fuel consumption rate is assumed to be constant across all kilometers flown, meaning that fuel consumption is expressed on a per-distance basis. Consequently, fuel consumption during different phases of flight (such as taxi, takeoff, cruising, and landing), is not separately accounted for in this model. Instead, total fuel consumption is a stock that accumulates over time, considering the level of aircraft fuel efficiency (measured as fuel consumption per AKF) and the total aircraft-kilometers flown (4.5). The annual fuel consumption is then calculated as follows:

$$F_{\text{annual},t} = \int_{t-1}^{t} \left[F_{\text{AKF},t} * AKF_t\right] dt \tag{4.7}$$

Where:

$F_{\text{annual},t}$ = Annual fuel consumption at time t [L]

$F_{\text{AKF},t}$ = Fuel consumption per AKF at time t [L/km]

AKF_t = Aircraft-kilometers flown at time t [km]

Annual fuel consumption per revenue passenger-kilometer is calculated as follows:

$$F_{\text{RPK},t} = \frac{F_{\text{annual},t}}{RPK_t} \tag{4.8}$$

Where:

$F_{\text{RPK},t}$ = Annual fuel consumption at time t [(L/RPK)/year)]

RPK_t = Annual RPK at time t (RPK/year)

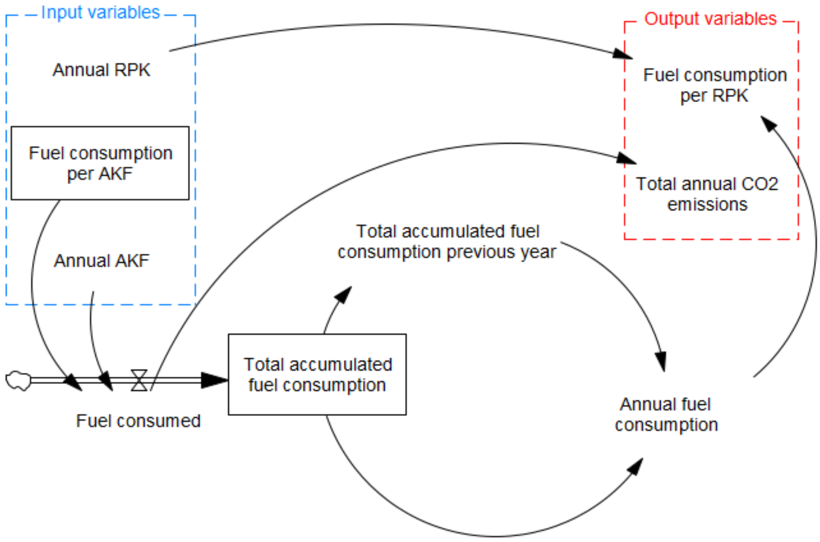

Figure 4.5: Simplified visualization stock-flow structure of subsystem for fuel consumption

Main Assumptions

- The fuel consumption rate is consistent across all kilometers flown;
- There is no significant relationship between the increase in aircraft operational weight due to higher passenger loads and fuel consumption.

4.3.4. Operational & Aircraft Fuel Efficiency

Fuel efficiency is assumed to improve continuously through advancements in operations and aircraft technology. The adoption of these improvements across the whole aviation sector is inherently slow and gradual (Abrantes et al., 2021). In the model, this behavior is captured in a stock-flow structure, where changes occur continuously each year (Figure 4.6). Enhancing operational efficiency reduces the total number of aircraft-kilometers required to meet passenger demand. This is achieved by increasing passenger load factors (PLF) and optimizing flight routes to shorten travel distances. These continuous improvements are reflected in small annual percentage changes, ultimately contributing to long-term reductions in fuel consumption. Improving aircraft fuel efficiency directly decreases the fuel consumption per aircraft-kilometer flown. The initial value of fuel consumption per aircraft-kilometer, used as input for the model, is determined by current fuel consumption per available seat kilometer (ASK), which accounts for differences in aircraft sizes across the haul segments.

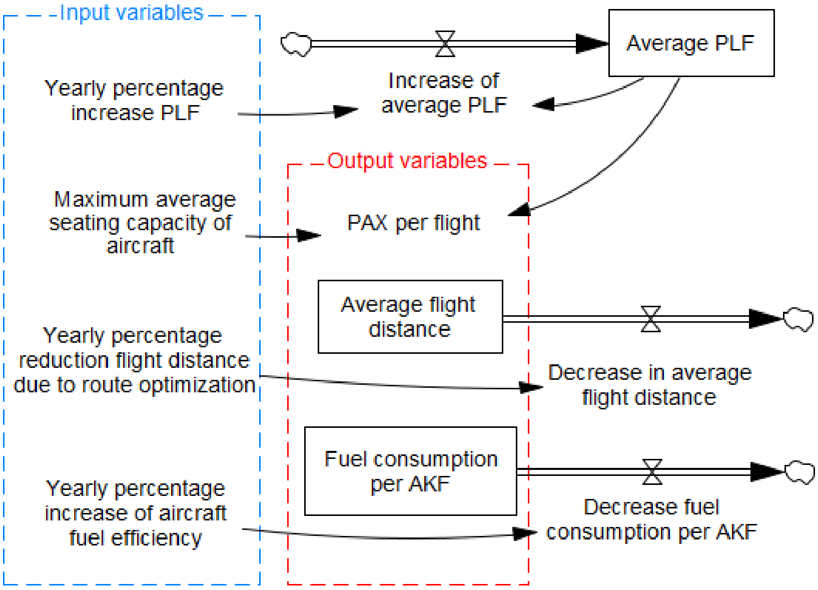

Figure 4.6: Simplified visualization stock-flow structure of subsystem for operational and aircraft fuel efficiency

Main Assumptions

- The fuel efficiency improvement rate is consistent over all types of aircraft, and therefore the same for each haul segment;
- Jet fuel price does not affect passenger load factor;
- On average, efficiency improvements gradually and continuously spread across the entire sector, causing the stock-flow structures to accurately reflect this development.

4.3.5. Fare Pricing

Fuel costs represent a significant portion of airlines' overall expenses (Kettler & Walls, 2022). As fuel efficiency improves, fuel costs per revenue passenger-kilometer are expected to decline. In the model, fuel costs are captured by multiplying fuel costs per revenue passenger-kilometer by a fixed jet fuel price. The jet fuel price remains constant throughout the simulation time to isolate and capture the direct effect of improved fuel efficiency on passenger demand through fare price changes. The change in fuel cost per revenue passenger-kilometer is calculated based on the fuel cost one year previous, resulting in a year-over-year change ratio. The structure of this subsystem is visualized in Figure 4.7.

A reduction in fuel cost per revenue passenger-kilometer directly influences fare prices through the pricing strategy factor. This factor, which ranges between zero and one, determines the extent to which airlines pass fuel cost savings on to consumers. The change in fare prices is calculated as follows:

$$\rho_t = \alpha * \gamma_{C_{\text{fuel}},t} \tag{4.9}$$

Where:

ρ_t = Fare price change ratio at time t

α = Pricing strategy factor

$\gamma_{C.t}$ = Change ratio fuel cost per RPK at time t

The fare price change ratio, combined with fare elasticity, is used to determine the fuel efficiency-induced demand growth rate in Equation 4.3. This relationship completes the rebound loop by linking fare reductions driven by fuel savings to subsequent increases in passenger demand in Equation 4.1.

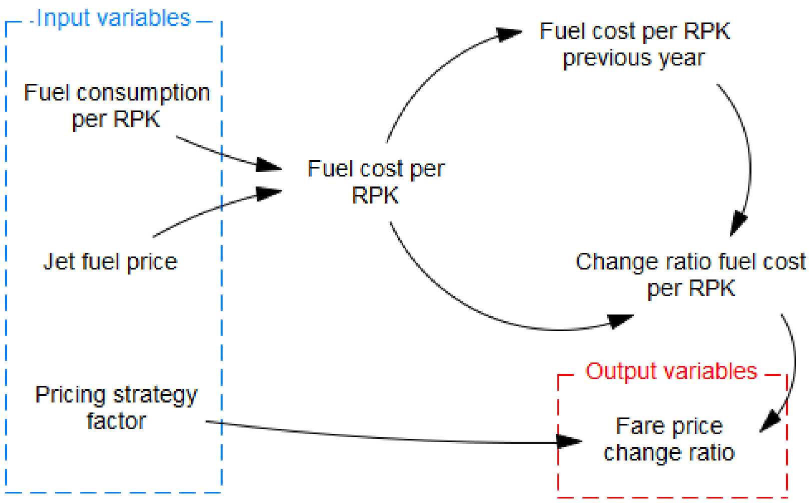

Figure 4.7: Simplified visualization stock-flow structure of subsystem for fare pricing

Main Assumptions

- Fare price change is only driven by fuel savings;
- Price fluctuations in both jet fuel prices and ticket fares can be approximated by a linear trend, as they average out over the long term.

4.4. Key Performance Indicators

The model calculates total CO_2 emissions, based on scenario's where the rebound loop was included or excluded. CO_2 emissions accumulate over time as a stock, depending on the total fuel consumed throughout the simulation time and the emissions produced per unit of jet fuel. Since the model is structured in subcategories, the total emissions are obtained by summing the accumulated fuel consumption - multiplied by emissions per unit of jet fuel - across all market haul categories:

$$E_{\text{total},t} = \sum_c \int_0^t [F_{c,t} * e] \, dt \tag{4.10}$$

Where:

$E_{\text{total},t}$ = Total accumulated CO_2 emissions at time t [Mt]

$F_{c,\tau}$ = Fuel consumed for haul segment c at time t [L/year]

e = CO_2 emissions per unit of jet fuel [Mt/L]

When rebound feedback is included in simulation (rebound simulation), the model calculates total CO_2 emissions in a scenario where both baseline demand growth and additional demand growth are considered, accounting for a rebound effect. Conversely, When rebound feedback is excluded from simulation (null simulation & baseline simulation), the model estimates total CO_2 emissions expected based solely on baseline demand growth, without factoring in a potential rebound effect:

$$KPI = \begin{cases} E_{\text{total},t}(\text{no efficiency}) & \text{Null simulation} \\ E_{\text{total},t}(\text{baseline}) & \text{Baseline simulation} \\ E_{\text{total},t}(\text{baseline+rebound}) & \text{Rebound simulation} \end{cases}$$

Main Assumptions

- Emissions are constant per liter of fuel consumed across all flight phases;
- Jet fuel consists solely of fossil fuels for the entire simulation time.

4.5. Baseline Parameter Values

Operational and aircraft fuel efficiency improvements serve as the primary drivers of the rebound feedback. The parameter values representing these variables are derived from projections in existing literature (see Table 4.2). These efficiency parameters serve as baseline inputs for the model, alongside the projected demand growth rate, which is treated separately from the additional demand growth induced by efficiency improvements. This approach allows for data-driven estimations of CO_2 emissions in the baseline simulation and null simulation, which include no rebound. The same standard parameter values are then used for the rebound simulation, enabling a clear comparison between the no-rebound and with-rebound simulations. The baseline demand growth rate is set at 4.4 % per year, while the annual efficiency improvement of the global fleet due to new generations of aircraft is set at 1.5%, both derived from projections in the literature. Improvements in operational efficiency, via average flight distance and passenger load factors, are based on literature-supported estimations.[2]

Table 4.2: Baseline parameter values for passenger demand, operational efficiency improvements, and aircraft fuel efficiency improvements.

Parameter Category	Variable	Annual Change Rate
Passenger demand	Baseline demand growth	+4.4%
Operational efficiency	Passenger load factor Average flight distance	+0.317% -0.349%
Aircraft fuel efficiency	Fuel consumption per AKF	-1.5%

4.6. Model Verification & Validation

Model verification is conducted by assessing the model's behavior across various numerical integration methods and step sizes, as well as performing error checks on all equations and units. Given the presence of multiple fixed delays in the model, Euler's method is identified as most robust and suitable numerical integration technique. A relatively small timestep of 0.0078125 year is selected for the simulations to ensure accuracy. Additionally, the alignment between the CLD and SFD representations was verified to ensure consistency in the model's structure and logic. The correctness of the equations and dimensional consistency are thoroughly verified, as no unit- or equation errors were found.

The model's purpose, as specified in Chapter 2 is to generate strategic insights for policy development by:

- Integrating the dynamics of the key factors related to the fuel efficiency rebound effect
- Reflecting the difference in the rate of increase in passenger demand and resulting emissions between the baseline scenario and the rebound scenario
- Estimating the emission reduction potential and the magnitude of the rebound effect by simulating the model in alignment with the experimental design.

[2]A detailed justification and the references supporting the chosen parameter values can be found in the Excel file on GitHub.

The validation and verification process established confidence in the model's suitability for its intended purpose and its correct implementation. While several improvements are reserved for future research, these limitations do not detract from the model's current utility for informing strategic policy design. The literature on SD model validation outlines a range of tests to evaluate the validity of the model. A selection of validation tests from each of the three main categories discussed in Chapter 2 are executed. The results of the tests can be found in Table 4.3.

Table 4.3: Validation tests and results

Category	Validation test	Results and comments
Direct structure tests	Boundary adequacy test	Requirements are satisfied, subject to certain assumptions
Structure-oriented behavior tests	Sensitivity analysis Extreme conditions test	Model behavior is slightly numerically sensitive, but not behaviorally sensitive to parameter values
Behavior reproduction tests	Historical and future emissions data check	Model behavior and order of magnitude of estimations align with historical and future emissions data

Boundary adequacy testing ensures that the model's structure endogenously represents the most critical elements of the system required to achieve its purpose (Sterman, 2000). Key elements of the system relevant to the model's purpose are explicitly modeled within the system's boundaries, which have been carefully and deliberately defined during the modeling process.

Model behavior is validated through behavioral sensitivity and extreme condition testing. The results of these tests can be found in Appendix B. The model is found to exhibit slight numerical sensitivity to rebound-related parameters and keeps functioning within the boundaries of plausible parameter ranges, while simulating logical model behavior. The model behavior and underlying mechanisms align with expectations, which implies that the structural validity of the model is sufficient.

The behavior reproduction evaluation confirmed that the model's output aligns closely with historical data and is consistent with other future projections of passenger demand and emissions reported in the literature. In both simulations, passenger demand exhibits a strong upward trend, while annual emissions increase at a slower rate. When accumulated over the entire simulation time, emissions still follow a similarly steep upward trend. This aligns with other projections in the literature and reflects patterns observed in historical data. Furthermore, the order of magnitude of the model's estimations corresponds with both historical data and future projections, further supporting the validity of the results. A historical and future emissions data check, based on a comprehensive study by the Air Transportation Association Group (ATAG), is provided in the box on the following page.

Historical and Future Emissions Data Check

Figure 4.8 presents both the historical emissions trend and projected emissions under several future scenarios, based on a comprehensive study by the Air Transport Association Group (ATAG).

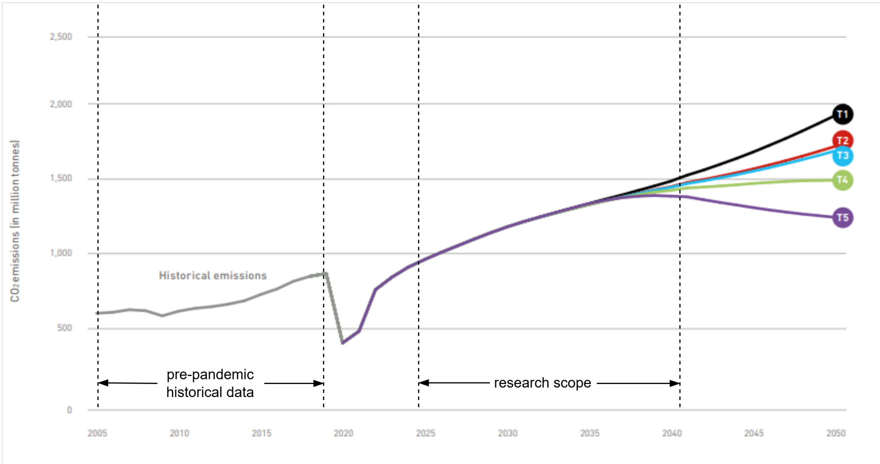

Figure 4.8: Historical CO_2 emission trends and projected emissions in various future scenarios for passenger aviation. Scenario T1 illustrates a baseline with no further improvements in fuel efficiency or adoption of new technologies. T2 assumes a gradual introduction of more fuel-efficient aircraft generations (note: without considering the rebound). Scenarios T3-T5 depict more transformative shifts, including revolutionary aircraft designs and transitions to electric and hydrogen propulsion. From: ATAG (2021).

The alignment between the model's behavior depicted below (Figure 4.9) and the pre-pandemic historical data[a] in Figure 4.8 supports the model's ability to reasonably replicate past dynamics. Additionally, the projected emissions in the model remain within the same range and order of magnitude when compared with scenario-based estimates in T1 and T2[b]. This consistency builds confidence in the model's reliability for subsequent problem exploration.

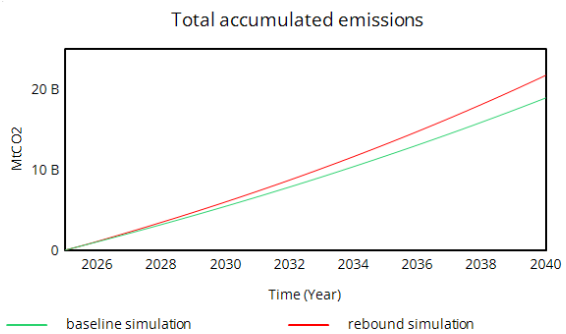

Figure 4.9: Model-projected future CO_2 emissions, for comparison with historical and projected future emissions data for validation purposes.

[a]Only pre-pandemic historical data was used for comparison, as the sharp decline in emissions in 2019 and the subsequent recovery through 2024 were driven by exceptional, disruptive events. These deviations do not align with the business-as-usual assumption underpinning the research.

[b]Scenarios T3-T5 fall outside the scope of this research, as it is assumed that disruptive technologies will not become commercially viable before 2040, which marks the end of the research time horizon.

5

Initial Experiment Results

This chapter aims to present an initial projection of the fuel efficiency rebound effect, using a reference scenario. The focus is on validating and quantifying the rebound, before proceeding to scenario analysis. The simulation and the interpretation of its results in this chapter address the following sub-question:

What is an initial projection of the magnitude of the fuel efficiency rebound effect and the corresponding actual emission reduction through 2040 in the reference scenario?

First, the experiment design input values for uncertain sector-based parameters located in the middle of the uncertainty range are established in Section 5.1. Next, the experiment results based on these values are presented in Section 5.2, followed by final calculations in Section 5.3 to provide a clearer interpretation of the results and their implications. Section 5.5 then analyzes the extent to which the model behavior aligns with the hypothesized behavior formulated in the dynamic hypothesis (Chapter 3). The chapter concludes with additional remarks on the findings.

5.1. Experimental Setup

The variables and subsystems driving the key dynamics of the rebound model structure (highlighted in red in Figure 4.2) depend on market-specific parameters for which no clear consensus exists in the literature, as discussed in Chapter 3. To gain an initial understanding of the potential magnitude and implications of the fuel efficiency rebound effect and its underlying dynamics, simulations will be conducted under a reference scenario before proceeding to the full scenario analysis. The reference scenario is built using the standard parameter values for efficiency and baseline demand growth, along with market-specific parameter values positioned at the midpoint of the defined uncertainty range (see Table 5.1). An explanation of how these uncertainty ranges were estimated or chosen based on the literature, can be found on Github[1].

Table 5.1: Midpoint values for uncertain parameters

Parameter	Midpoint value
Fare elasticity of demand	-0.83, -1.06, -1.28
Pricing strategy factor	0.45
Market share per haul segment	20%

Fare elasticity of demand varies by haul segment, ranging from -0.83 for long- and ultra-long-haul flights to -1.28 for short- and short-medium-haul flights. The fare elasticity for medium-haul flights

[1] GitHub Repository.

is assumed to be -1.06; the average of these minimum and maximum values. The pricing strategy factor ranges from 0.1 (minimal pass-through of fuel savings) to 1 (full pass-through of fuel savings to consumers), with 0.45 as the midpoint within the uncertainty range. Additionally, due to a lack of data on actual market shares, the market share per haul segment is set to an equal distribution (e.g. 20% per segment) in the reference scenario.

5.2. Experiment Results

With the midpoint parameter values established, the three simulations are executed in accordance with the experimental design outlined in Chapter 2, using these values and baseline parameter values presented in Chapter 4 as input. Figure 5.1 demonstrates that in this reference scenario, passenger demand increases more rapidly in the rebound simulation compared to the baseline. This significant difference indicates that passenger demand is responsive to fuel savings, as shown in Figure 5.2. In the initial years, fuel efficiency-induced demand growth rises sharply. However, the model behavior stabilizes relatively quickly into a linear trend. Evidently, fuel efficiency-induced demand growth remains zero in the baseline simulation, as the rebound feedback is not included.

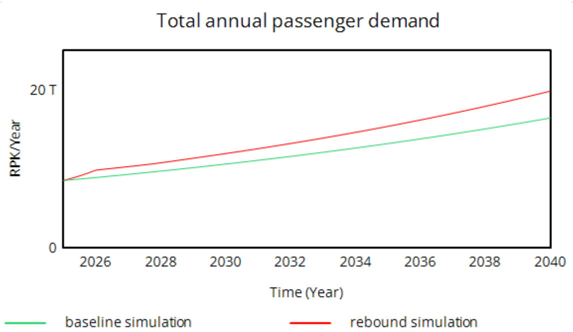

Figure 5.1: Total annual passenger demand in the baseline simulation and rebound simulation, showing the difference in demand growth resulting from rebound feedback between 2025-2040.

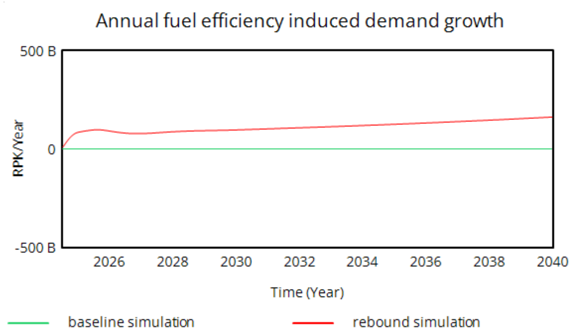

Figure 5.2: Annual fuel efficiency-induced demand growth in the baseline and rebound simulation, representing the additional demand growth resulting from rebound feedback between 2025-2040.

As expected, a similar problematic pattern can be observed in the total accumulated emissions over the entire simulation time (see Figure 5.4). Initially, the difference in total emissions is too small to be noticeable in this graph's scale. However, as emissions accumulate over time, the difference becomes increasingly apparent, amounting to several billion metric tons of CO_2.

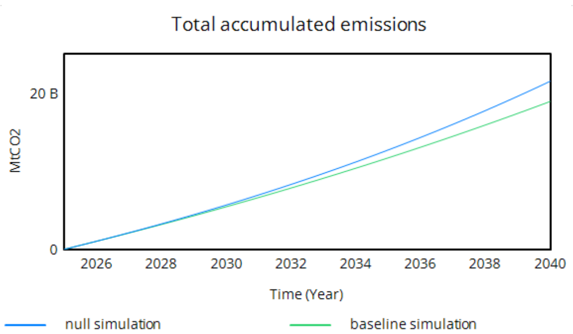

Figure 5.3: Total accumulated emissions in the null simulation and baseline simulation, representing the emission reduction potential between 2025-2040.

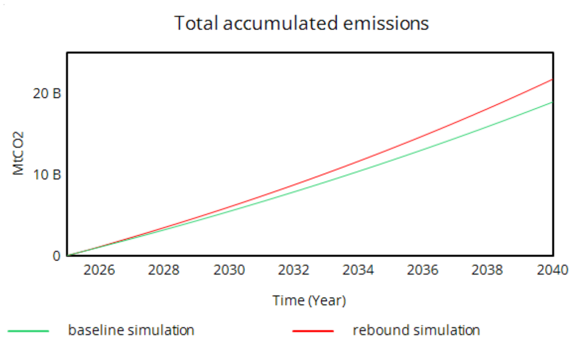

Figure 5.4: Total accumulated CO_2 emissions in the baseline simulation and rebound simulation, representing the magnitude of the rebound between 2025-2040.

The additional increase in passenger demand in the rebound simulation can be attributed to the decline in fare prices. Consequently, the rise in CO_2 emissions results from the increase in aircraft-kilometers driven by higher passenger demand, which offsets the benefits of improved operational efficiency and reduced fuel consumption per aircraft-kilometer (see Appendix C).

5.3. Final Calculations

To quantify the overall magnitude of the fuel efficiency rebound effect through 2040 and to interpret the implications of observed behaviors in the reference scenario, final calculations are required. Table 5.2 presents the total accumulated emissions by 2040 for each simulation within the experimental design described in Section 2.4.

Table 5.2: Emission results per simulation in the reference scenario by 2040 (all values reported in billion metric tons of CO_2.

Simulation	KPI	KPI Value
Null simulation	$E_{\text{total},T}$(no efficiency)	22.06
Baseline simulation	$E_{\text{total},T}$(baseline)	18.96
Rebound simulation	$E_{\text{total},T}$(baseline+rebound)	21.78

Based on these results, the emission reduction potential in the reference scenario is calculated as follows:

Emission reduction potential = $E_{\text{total},T}$(no efficiency) - $E_{\text{total},T}$(baseline) = 3.09e+09 $MtCO_2$

Where:

$E_{\text{total},T}$(no efficiency) = Total accumulated emissions at the end of the null simulation

$E_{\text{total},T}$(baseline) = Total accumulated emissions at the end of the baseline simulation

The rebound observed in the reference scenario is calculated relative to the baseline as the difference between total accumulated emissions in the baseline simulation and total accumulated emissions in the rebound simulation:

Rebound = $E_{\text{total},T}$(baseline+rebound) - $E_{\text{total},T}$(baseline) = 2.82e+09 $MtCO_2$

Where:

$E_{\text{total},T}$(baseline+rebound) = Total accumulated emissions at the end of the rebound simulation

The actual emission reduction that can be attributed to operational and aircraft fuel efficiency improvements when the rebound is accounted for, is:

Actual emission reduction = Emission reduction potential - Rebound = 2.8e+08 $MtCO_2$

Based on the accumulated KPI values shown in Table 5.3, and the final calculations performed using these results, the total CO_2 emissions rebound relative to the baseline is estimated at 2.82 billion metric tons, despite operational and aircraft fuel efficiency improvements. Table 5.3 provides an overview of the KPI values obtained from the final calculations based on the simulation results of the reference scenario.

Table 5.3: Emission reduction potential, rebound and resulting actual emission reduction in the reference scenario by 2040 (all values reported in billion metric tons of CO_2).

Derived KPI	KPI Value
Emission reduction potential	3.09
Rebound	2.82
Actual emission reduction	0.28

5.4. Implications

This section evaluates two key rebound implications: (1) the **rebound effect** itself, defined as the share of the emission reduction potential that is offset due to rebound dynamics, and (2) the **actual emission reduction**, representing the remaining percentage reduction in emissions, relative to a scenario without any efficiency improvements. The actual emission reduction is derived by applying the rebound effect to the estimated emission reduction potential.

The final calculations reveal that emissions in the rebound simulation exceed emission levels in the baseline simulation by 14.9%:

$$\text{Baseline-relative rebound} = \frac{\text{Rebound}}{E_{\text{total},T}(\text{baseline})} * 100\% = \frac{2.82\text{e+09}}{18.96\text{e+09}} * 100\% = 14.9\%$$

Where:

$E_{\text{total},T}$(baseline) = Total accumulated emissions at the end of the baseline simulation

The rebound effect quantifies the extent to which expected emission reductions from efficiency improvements are offset by increased consumption of air travel and it expresses the percentage of emission reductions actually realized (Sorrell & Dimitropoulos, 2008; Berkhout et al., 2000). According to this theory, the rebound effect, expressed as the percentage offset of the emission reduction potential is calculated as follows:

$$\text{Rebound effect} = \frac{\text{Rebound}}{\text{Emission reduction potential}} * 100\% = \frac{2.82\text{e+09}}{3.09\text{e+09}} * 100\% = 91.3\%$$

This indicates that, within the central range of uncertainty, the increase in passenger demand driven by fuel savings offsets $\pm$91.3% of the potential emission reductions. Table 5.4 provides an overview of these implications. The findings highlight the significant potential mitigating impact of the rebound effect on intended emission reductions.

In the baseline simulation, efficiency improvements lead to a 14% reduction in emissions compared to a scenario without efficiency improvements:

$$\frac{\text{Emission reduction potential}}{E_{\text{total},T}(\text{no efficiency})} * 100\% = \frac{3.09\text{e+09}}{22.06\text{e+09}} * 100\% = 14\%$$

Where:

$E_{\text{total},T}$(no efficiency) = Total accumulated emissions at the end of the null simulation

However, when accounting for the rebound effect, the actual emission reduction achieved is only:

$$\frac{\text{Actual emission reduction}}{E_{\text{total},T}(\text{no efficiency})} * 100\% = \frac{2.8\text{e}{+}08}{22.06\text{e}{+}09} * 100\% = 1.3\%$$

Table 5.4 presents the implications derived from the outcomes of the three simulations in the reference scenario. Although the scenario shows an emission reduction potential of 14%, this potential is largely offset by a baseline-relative rebound of 14.9%, which negates 91.3% of the potential reduction. As a result, only a modest actual emission reduction of 1.3% remains.

Table 5.4: Rebound implications in the reference scenario by 2040.

Implications	Percentage
Emission reduction potential	14%
Rebound effect	91.3%
Actual emission reduction	1.3%

5.5. Comparison to Dynamic Hypothesis

The behavioral patterns of both the baseline and rebound simulations for the reference scenario align with the hypothesized dynamics outlined in Chapter 3. As anticipated, both simulations exhibit accelerated growth of both passenger demand and emissions, while the rebound simulation demonstrates a steeper trajectory. A key dynamic is the linear decline of fuel consumption per RPK, which activates the efficiency-induced RPK loop and continuously generates additional demand. Over time, this reinforcing loop becomes dominant over the efficiency-induced fuel consumption loop, as the additional demand drives up total fuel consumption. While the rebound simulation mirrors the behavioral patterns of the baseline trajectory, a divergence in cumulative emissions emerges and progressively widens over time.

5.6. Concluding Remarks

The initial experiment results confirm the occurrence of a fuel efficiency rebound effect and, moreover, highlight its significant magnitude and implications in the reference scenario. The findings indicate that fuel consumption per RPK plays a critical role in shaping overall emissions when accounting for the rebound effect. A decrease in fuel consumption per RPK, driven by higher fuel efficiency induces additional demand growth via resulting fare price changes. This phenomenon can occur alongside an overall increase of total fuel consumption, driven by the associated rise in RPK demand and flight operations, where both RPKs and aircraft-kilometers exhibit an upward trend. Despite the industry appearing more efficient when evaluated solely based on fuel consumption per RPK, a commonly used efficiency metric in aviation, this system behavior highlights a paradox: efficiency gains at the unit level contribute to greater aggregate environmental impact. However, for this reference scenario, a demand fulfillment rate of 100% was reached as there was no annual flight limit in this experiment.

6
Scenario Analysis

It remains uncertain whether the fuel efficiency rebound effect estimations and implications presented in Chapter 5 are accurate. To gain a deeper understanding of the system's behavior, this scenario analysis will explore the plausible range of potential fuel efficiency rebound effects within the identified range of uncertainty. It also analyzes how the market-specific uncertainties may influence the magnitude of the rebound effect. This chapter addresses the following sub-question:

How do market-specific uncertainties influence the potential magnitude of a fuel efficiency rebound effect?

First, Section 6.1 outlines the experimental setup, detailing the uncertainty ranges of market-specific parameters. Section 6.2 then presents the results of the scenario runs and PRIM analysis. Finally, Section 6.3 concludes with additional remarks on the findings. The file with the code that was used for the scenario runs in this chapter can be found at Github[1].

6.1. Experimental Setup

The parameter values used in the simulations in Chapter 5 represent the midpoints of the selected minimum and maximum values. The minimum and maximum parameter values defining the parameter uncertainty range for input combinations in this scenario analysis are presented in Table 6.1. The experimental scenarios were generated using the LHS-Sampler tool in the EMA Workbench, with the exception of the market shares per haul segment, which were sampled using the Dirichlet-sampling method[2] to ensure the sum constraint of 100% was satisfied.

To gain an initial understanding of the progression of the rebound effect and resulting emissions under conditions where airlines' tendency to capitalize on demand growth is constrained, the same experiments are also conducted in a scenario that imposes a cap on the annual number of flights. This constraint ensures that the demand fulfillment rate remains within a certain threshold, rather than reaching 100% over the entire simulation time. The maximum is set at 125% of the annual number of flights at initial time, allowing for a maximum total annual number of flights increase of 25% over the simulation time.

[1] GitHub Repository

[2] Dirichlet sampling in Python is a method used to sample from a Dirichlet distribution, which is commonly used to model the distribution of probabilities across multiple categories. In Python, this can be done using the 'numpy.random.dirichlet' function, where a vector of parameters (called concentration parameters) is passed to generate random samples that sum to 1.

Table 6.1: Minimum and maximum values for uncertain parameters and categorical parameters

Uncertain parameters	Minimum	Maximum
Fare elasticity of demand	-1.5	-0.6
Pricing strategy factor	0.1	1.0
Market share per haul segment	10%	30%
Categorical parameters		
Maximum annual number of flights	125% of initial value	No restriction

The experiments are conducted according to the experimental design described in Chapter 2. The first baseline simulation consists of a single run to serve as a reference point from which the rebound will emerge to varying extents. The rebound simulation consists of 1000 runs. These runs will explore various parameter combinations within the specified uncertainty ranges. The baseline input values remain constant in both simulations to prevent changes in variables not directly related to the rebound effect from influencing its magnitude. The focus remains on independently examining the dynamics of the rebound effect itself, rather than its dependency on baseline inputs.

6.2. Experiment Results

The temporal model behavior for key outcomes, as illustrated in the following figures, demonstrates that in the worst-case scenarios, the rebound effect can manifest in quite extreme forms. Figure 6.1 shows that, in terms of emissions - the main KPI in this research - the rebound can lead to more than a 100% offset of the potential emission reductions. The initial results of the reference scenario are also presented in the plots to provide context against which the implications of scenario outcomes can be assessed. The density plot on the right illustrates the distribution of the final time outcomes for the generated scenarios over 1000 runs.

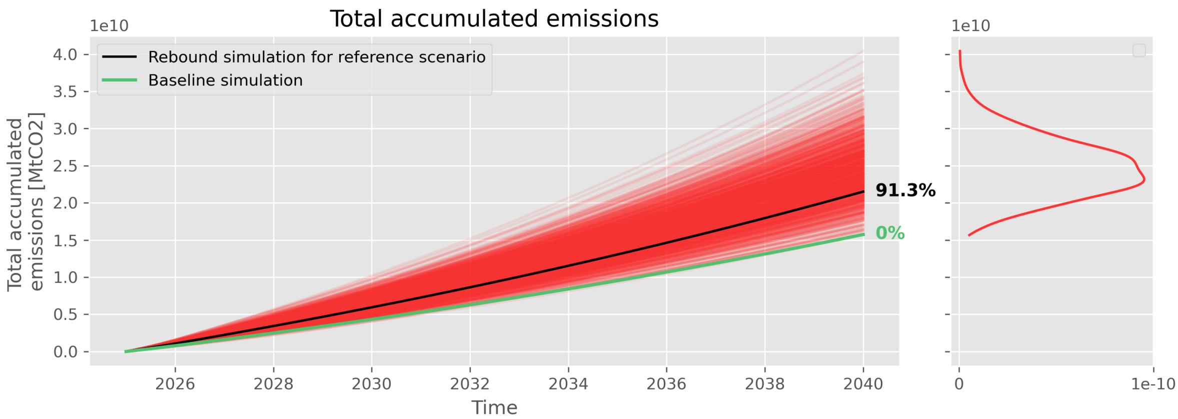

Figure 6.1: The red lines represent CO_2 emissions in an ensemble of 1000 rebound simulation runs, without a constraint on the cumulative growth in flight volume. The density plot in the right section of the figure visualizes the distribution of the final time outcomes. The black line represents emissions in the rebound simulation for the reference scenario and the corresponding rebound effect. The green line represents emissions in the baseline simulation, which implies a 0% offset and full realization of the emission reduction potential, as rebound feedback was excluded.

However, it is questionable whether the number of flights can realistically increase sufficiently to accommodate the growing passenger demand. For this reason, a trade-off analysis was conducted to illustrate that if rebound dynamics are allowed to unfold without constraints, the system will respond accordingly. Yet, when policy or infrastructural limitations impose constraints on the increase of the annual number of flights, the plausible range of potential rebound effects remains limited. The results are visualized in Figure 6.2.

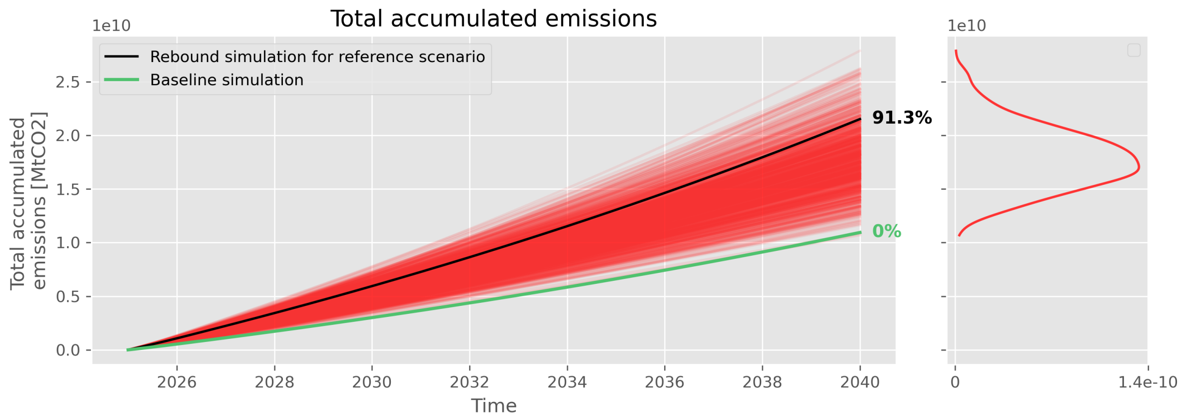

Figure 6.2: The red lines represent CO_2 emissions in an ensemble of 1000 rebound simulation runs, under a flight restriction of 125% of the initial annual number of flights in 2025. The density plot visualizes the distribution of the final time outcomes. The black line represents emissions in the rebound simulation for the reference scenario and the corresponding rebound effect. The green line represents emissions in the baseline simulation, which implies a 0% offset and full realization of the emission reduction potential, as rebound feedback was excluded.

At the same time, as highlighted in Figure 6.3, airlines will increasingly fail to meet the rising demand for revenue passenger-kilometers (RPKs) under this flight restriction. This highlights a critical trade-off: while constraints on capacity can mitigate environmental rebound effects, they may also lead to unmet demand.

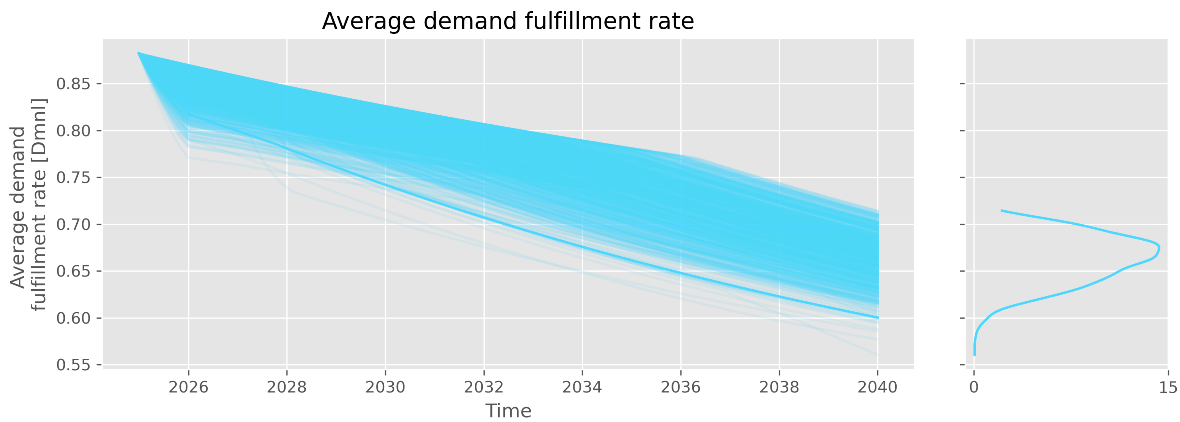

Figure 6.3: Average demand fulfillment rate under a flight restriction of 125% of the initial annual number of flights in 2025, across 1000 rebound scenario runs. The density plot visualizes the distribution of the final time outcomes.

The PRIM algorithm has been applied to analyze the results and identify the most critical uncertain parameters driving variations in the final outcomes of the 1000 scenario runs. Appendix C presents a visual representation of the PRIM results. As expected, the market shares of all haul segments were included in the PRIM box, which indicates that the system is sensitive to the distribution of market shares, rather than to any market share alone. Market shares of the longer-haul segments are constrained more tightly than that of the short-haul segment. This suggests a greater influence of these segments on the magnitude of the rebound effect. The sensitivity analysis presented in Section 4.6 further supports this observation by demonstrating that the system is responsive to increases in market shares of longer haul segments. Additionally, the PRIM analysis conducted on a subset of parameters within the ultra-long-haul segment reveals a particularly narrow range for the market share parameter. This indicates that specific values within this segment are strongly associated with a higher rebound magnitude compared to the reference scenario. Based on these findings, it can be concluded that a higher market share of longer haul segments has a more significant impact on the system's problematic behavior than the short-haul segment. The extent to which fuel cost savings are passed on to consumers appeared to be less influential, as the pricing strategy factor was not included in the PRIM boxes. This indicates that even at its lowest assumed value (0.1), a substantial rebound effect of over 91.3% can occur. Nevertheless, higher pass-through rates remain undesirable, given their association with a more pronounced rebound effect as revealed by the sensitivity analysis (appendix B). Although pricing strategy factor is highly influential, it doesn't help identify the conditions under which the rebound effect exceeds the 91.3% in the reference scenario. On the other hand, fare elasticity and market share distribution are less influential overall, but help define the boundary of scenarios that exceed the rebound threshold.

Combining the findings of the scenario runs and the PRIM analysis, the main conclusions of the scenario analysis are summarized below:

The magnitude of the rebound effect exceeds the 91.3% observed in the reference scenario, under the following conditions:

- Consumers exhibit a **high sensitivity to fare price reductions** per RPK;
- A relatively **high market share of longer-haul segments** compared to that of shorter-haul segments;
- Airlines can fully capitalize on demand growth, i.e. the potential **amount of flights is unrestricted.**

6.3. Concluding Remarks

The scenario analysis results indicate that, compared to the reference scenario in Chapter 5, the rebound effect exhibits significant variability in its potential magnitude, depending on the scenarios used to represent plausible sets of critical parameters. The density plots indicate that, assuming the boundaries of the selected scenario set are chosen correctly, the majority of the potential rebound magnitudes slightly exceed those observed in the reference scenario. The reference scenario demonstrated a 14% rebound relative to the baseline scenario, offsetting 91.3% of potential emission reductions. This implies that a significant portion of the plausible scenario sets approaches a complete offset of $\pm$100% of the potential emission reductions. The influence of fare elasticity of demand on problematic system behavior is found to be more pronounced for longer-haul flights than for shorter-haul flights. When the annual number of flights is constrained, the plausible range of rebound effects and resulting emissions narrows to fall between the baseline and the reference scenarios. This indicates that under a flight restriction, a larger share of the emission reduction potential is likely to be realized. However, the demand fulfillment rate progressively declines, indicating that a portion of passenger demand remains unmet. These findings highlight a trade-off between limiting emissions and maintaining economic accessibility of transport services, offering valuable insights for policy recommendations and future research directions as discussed in Chapter 8.

7 Discussion

This chapter discusses the results presented in Chapter 5 and Chapter 6 in relation to the methodological choices made throughout the research and explores their societal and scientific implications. Section 7.1 discusses important modeling choices, their implications, and outlines the next steps in model development to enhance the estimation of the fuel efficiency rebound effect, enabling a more accurate evaluation of the true environmental benefits of fuel efficiency improvements in global passenger aviation. Section 7.3 highlights the limitations of SD as a modeling approach, followed by a discussion on the scope and applicability of the findings in Section 7.2. The chapter concludes with a description of the broader societal and scientific implications of the results in Sections 7.4 and 7.5.

7.1. Reflection on Modeling Choices

While the developed SD model effectively captures the feedback dynamics of the fuel efficiency rebound effect, it remains relatively compact with sharply defined boundaries. This approach follows Sterman (2000), emphasizing the importance of focusing on the core problem rather than attempting to model every detail of a complex system. By prioritizing the essential dynamics of the issue over unnecessary complexity, this research establishes a solid foundation for future studies on the integration of fuel efficiency rebound effects in policy evaluation models. This section outlines several potential model extensions to better capture the system's complexity.

One of the most important modeling choices in this research is the application of a *ceteris paribus* assumption, which confines the model to include only the key factors and interactions directly related to the rebound effect. It is important to acknowledge that estimating the exact trajectory of future fare prices is inherently complex. Airline fare prices are influenced by a range of factors, and the price charged to the passengers does not always reflect the underlying costs (ATAG, 2021). Furthermore, while sustainable aviation fuel (SAF) is expected to be significantly expensive compared to fossil fuels, the future evolution of fossil fuel prices remains uncertain, particularly when future international policies mandate SAF blending with conventional fossil fuels. While it is also conceivable that energy costs for aviation may rise and result in less consumption of air travel, this research suggests that such effects could be counteracted by advances in fuel efficiency through technological innovations and improvements in operational performance. Regardless of future developments, aviation is expected to continue playing a crucial role in global efforts to address climate change, even if fare prices increase. Future modeling steps should integrate additional dynamics influencing fare prices and passenger demand, with particular attention to the fluctuations in jet fuel prices and their impact on fare price variations. In the current model, fare price per RPK exhibits a slight downward trend, which may approximate long-term averages. However, over shorter time periods, fare prices in passenger aviation are subject to significant fluctuations, leading to corresponding variations in passenger demand (Hsu & Eie, 2013). In contrast, this research assumes that passenger demand follows a consistent upward trend throughout the entire simulation period.

This assumption leads to another important modeling consideration: the model and its estimations are based on a *business-as-usual* scenario. While it is likely that passenger demand will generally follow a steep upward trend over the long term, as indicated by existing literature, it could be beneficial to extend the model to account for scenarios involving disruptive events or economic downturns. Although this research assumes that the feedback dynamics of the rebound effect persist continuously, without disruption or counteraction, incorporating the likelihood of global events or changes in economic health, as well as other market dynamics that may counteract the rebound effect at certain times, would provide a more comprehensive and accurate evaluation of the impact of fuel efficiency improvements on actual emission reductions.

The current model estimates future flight operations based on the assumption that the airline industry will capitalize on growth opportunities (Abrahams, 1983; Wei & Hansen, 2005; Pitfield et al., 2010). Consequently, projected passenger demand is used as a model input, while the supply of RPKs and flights is treated as an endogenous variable, under the assumption that supply will align with passenger demand in the long term. Although existing literature supports this approach for long-term projections, future model expansions should integrate more comprehensive economic principles to capture the dynamic interplay between supply and demand in the passenger aviation market. For instance, an increase in the supply of RPKs distributed across multiple flights may stimulate additional passenger demand through the mechanism of frequency elasticity of demand (Gillen, 2020). For this research, this mechanism was excluded from the model.

While the model incorporates five haul segments to capture market diversity in passenger aviation, it does not account for the distinct business strategies of different carrier types. The extent to which fuel savings are reflected in fare prices is represented by the pricing strategy factor, acknowledging that not all carriers pass on fuel cost reductions to consumers. However, in reality, each carrier type may adopt a different pricing strategy. While this research initially aimed to differentiate pricing strategies across carrier types, the lack of market-specific data limited this approach. Future modeling efforts should therefore focus on airlines' fuel management policies and strategies, with an emphasis on first understanding their market share and role in each haul segment before assessing their influence on pricing dynamics on the global passenger aviation market.

Additionally, it is important to distinguish between different traveler motives, such as leisure and business travel, as these categories are typically associated with varying demand elasticities (Alderighi et al., 2016). Market-specific characteristics also differ between domestic and international flights, further influencing demand patterns and price sensitivities (Njegovan, 2006). While an attempt was made to incorporate these distinctions into the model, the lack of market-specific data limited the implementation of a more detailed differentiation. Future modeling steps should prioritize obtaining empirical data to refine these distinctions and improve the accuracy of demand elasticity estimations in the model.

7.2. Scope and Applicability Limitations

This research adopts a global scope, as the availability of input data and modeled interactions are largely generalized at a global level. Moreover, given that climate change is a global challenge with far-reaching implications, addressing the implications of a fuel efficiency rebound effect from a worldwide perspective enhances the relevance of the findings. However, the generalizability of this research and its findings to specific regional markets is subject to limitations. Context-specific variations may lead to differences in parameters and interactions at the regional level (Wittmer & Bieger, 2021), diverging from the aggregated global market dynamics of passenger aviation. These contextual factors include regulatory differences, geographical and infrastructural constraints, the pace of new technology adoption, and varying sensitivities to fare prices due to the availability of alternative transportation options.

7.3. Limitations of System Dynamics Modeling

The discussion on modeling choices in Section 7.1 further highlights the potential of the SD modeling approach to generate strategic insights without requiring extensive empirical data. Despite these strengths, its application in this research also posed limitations related to individual decision-making processes of actors, dynamic price-demand relationships, capturing market shocks, diverse business models and multiple scale levels. Actor preferences and behaviors vary across market segments, contributing to the heterogeneity of airline passengers (Huse & Evangelho, 2007). While SD models effectively capture system-level dynamics, they are constrained in their ability to integrate psychological factors and economic interests that influence individual decision-making processes. This application of an SD approach applied a static price-demand relationship, relying on constant elasticity values. SD models typically assume smooth, long-term trends (Forrester, 1987), making them less effective at modeling sudden market disruptions and their effects on demand, operations, and emissions. Passenger aviation operates across multiple scales - local, regional and global. Beyond the challenge posed by limited transparency in traffic data across these layers, SD models cannot effectively integrate the complex interconnections across multiple scales (Pruyt, 2013). Agent-Based Modeling (ABM) enables the integration of heterogeneous components at multiple levels, addressing the limitations related to individual actor behavior and interests, diverse business models and multiple scale levels. Agents are modeled as autonomous entities that perceive and act upon their environment, enabling ABM to manage dependencies between multiple actors such as passengers, airlines, air traffic controllers and airports (Bouarfa et al., 2013). Although ABM could complement SD in capturing the complexity of the passenger aviation system, this research affirms that SD is particularly effective for analyzing industry-wide structural relationships and long-term trends due to its aggregated approach. The findings of this study offer significant potential to generate strategic insights for policy formulation.

7.4. Societal Implications

This research offers several important contributions to the development of robust and sufficiently stringent policies aimed at achieving climate targets for global passenger aviation. First, this research introduces a method for quantifying the fuel efficiency rebound effect in future emission projection models, which can also be applied in policy evaluation frameworks. Second, this research underscores the political relevance of the fuel efficiency rebound effect by estimating the magnitude of the effect over a 15-year time horizon in a reference scenario. It further identifies the implications of this effect and provides a plausible range in which it may occur. Third, this research examines role of critical market-specific factors for which there is no consensus in the literature about their actual values. This section elaborates on these contributions by examining the specific results and their associated implications.

To the best of current knowledge, policy evaluation models do not incorporate feedback mechanisms related to the fuel efficiency rebound effect in aviation. However, unintended consequences of policy measures aimed at stimulating fuel efficiency in aviation must be considered in policy evaluation frameworks (Kettler & Walls, 2022). A review of previous work on rebound effects in aviation shows that such effects are primarily estimated retrospectively, based on empirical data. This research conceptualizes key factors and feedback mechanisms underlying the fuel efficiency rebound effect and, in combination with the experimental design outlined in Chapter 2, establishes an approach for estimating the rebound effect in future scenarios. Furthermore, the model formulation offers insights into which aviation metrics should be used to express key factors to capture their real impact in the system.

Total accumulated emissions is a Key Performance Indicator (KPI) selected in this research, as it enables the quantification of the difference in CO_2 released into the atmosphere by the end of the simulation time. This metric ultimately represents the critical environmental impact of passenger aviation. The initial experimental results for the reference scenario highlight the substantial impact of a fuel efficiency rebound effect, leading to several billion metric tons of additional CO_2 emitted compared to the baseline scenario, within a period of just 15 years. The implications of this effect in the reference scenario amount to an almost complete offset of potential emission reductions. The scenario analysis further demonstrates that the rebound effect could reach even greater magnitudes, leading to more severe consequences. In fact, additional emissions compared to a scenario in which no efficiency improvements are implemented, are undesirable but likely in a substantial number of scenarios.

The research highlights that when consumers are highly sensitive to incentives that reduce fare prices, the fuel efficiency rebound effect can take on extreme forms, in theory. The extent of these incentives is determined by airlines, who have the ability to pass on cost reductions to consumers either partially or fully. These findings underscore the need for complementary policies that mitigate the incentives driving this behavior of actors within the system.

7.5. Scientific Implications

The research provides valuable contributions to future predictive studies on rebound effects and broader emission reduction efforts in aviation. First, it conceptualizes the key drivers and feedback mechanisms of the rebound effect through a systems thinking approach. Second, it captures these dynamics in a compact SD model, that operates without relying on extensive empirical datasets. Third, it estimates the rebound effect and its implications within a reference scenario, and explores a range of plausible scenario outcomes. Fourth, it analyzes these outcomes to identify influential combinations of market-specific uncertain parameters. Finally, the research highlights critical market-specific empirical data gaps that must be addressed to narrow the plausible range of model results. This section elaborates on these contributions.

In the absence of a comprehensive conceptualization of the underlying dynamics of the fuel efficiency rebound effect in existing literature, this research adopts a systems thinking approach to enhance understanding of the system structure and its underlying behavior. By translating this conceptualization into a quantitative SD model, it extends previous studies on the rebound effect in aviation by introducing a predictive, forward-looking model, rather than relying on empirical, retrospective analyses. This approach enables the estimation of the potential future rebound effect in passenger aviation and the identification of its implications and key contributing market-specific factors, while using a data-light method. While broadly aligned with earlier studies on rebound effects in aviation, this research estimates a significantly higher rebound effect for the reference scenario (91.3%) than reported previously. Specifically, the estimated rebound effect exceeds the 49% and 18.8% values reported in previous research by Miyoshi and Fukui (2018). This discrepancy can be attributed to key methodological differences, including the use of a *ceteris paribus* approach in this research that isolates behavioral feedback effects, and the exclusive focus on passenger aviation, whereas previous research also included cargo operations.

This research addresses key limitations of traditional transport modeling approaches by adopting an exploratory modeling and analysis approach to investigate the plausible range of rebound effects and associated emissions under various alternative future scenarios. Rather than attempting to predict a single future outcome, the exploratory approach systematically examines how the system behaves across a broad set of plausible combinations of uncertain parameters. Through this process, the research identifies which market-specific uncertainties are most critical in shaping the outcomes. These parameters remain uncertain due to the limited transparency and availability of empirical data in the aviation sector. By addressing the knowledge gaps in available market-specific data, this research enables future research to produce insights with reduced uncertainty and stronger empirical foundations.

7.5.1. Academic Context

Climate change can be described as a wicked problem[1] (Walls, 2018), a phenomenon that has been examined across various contributing domains within the MSc. Engineering & Policy Analysis program. Although aviation is a major contributor to climate change, it is not an extensively covered sector within this master's program. While policymaking in this sector is becoming a global priority, the systematic policy evaluation in this field remains relatively underexplored. This research enhances informed international policy development by exploring the fuel efficiency rebound effect and its implications, while also establishing a setup to integrate these dynamics into policy evaluation models. Consequently, this thesis fulfills the requirements of a final research project for the Master of Science degree in Engineering & Policy Analysis.

[1] A 'wicked problem' is the term used to describe some of the most challenging and complex issues of our time, many of which threaten human health (Walls, 2018).

8

Conclusion & Recommendations

Actual emission reductions in passenger aviation are often overestimated, due to the absence of a comprehensive analysis of how future fuel efficiency rebound effects might affect projected reductions over time. The objective of this research was to uncover fuel efficiency rebound effects in passenger aviation and generate strategic insights to support effective policymaking for achieving substantial global emission reductions. Two primary knowledge gaps were addressed: (1) the lack of a conceptual and quantitative understanding of how future rebound effects could undermine projected emission reductions, and (2) the dearth of an analysis of how this quantification is influenced by market-specific uncertainties.

This chapter begins by presenting answers to each sub-question, followed by an answer to the main research question. Finally, these findings - together with the discussion on key insights, limitations and implications in Chapter 7 - form the basis for the policy recommendations and recommendations for future research.

SQ1: What factors contribute to a fuel efficiency rebound effect and how do they interact?

In addition to the already growing baseline demand for air travel, further passenger demand can be stimulated by ongoing reductions in fuel consumption per revenue passenger-kilometer (RPK). These reductions lead to lower fuel costs per passenger-kilometer, a portion of which is typically passed on to consumers, resulting in lower fare prices per passenger-kilometer. This trend can, in turn, induce additional demand, depending on the fare elasticity of passenger demand. Although there is uncertainty surrounding the precise interactions between airlines and between pricing dynamics and consumer behavior, the highly competitive nature of the aviation sector and limited availability suggest that both pass-through rates and fare elasticities are sufficiently high to trigger a fuel efficiency rebound effect. While fuel consumption per revenue passenger-kilometer is likely to exhibit a downward trend due to ongoing operational and aircraft fuel efficiency improvements, total fuel consumption may still rise. This is driven by the increase in overall RPK demand, which necessitates additional aircraft-kilometers. Despite improvements in aircraft technology that reduce fuel use per aircraft-kilometer, aggregate fuel consumption can still increase due to the volume of aircraft-kilometers required to meet growing demand.

SQ2: How can a System Dynamics model effectively capture and integrate the key factors and interactions of a fuel efficiency rebound effect?

Quantifying the rebound effect within a SD model is inherently complex, as it cannot be fully captured by a single variable. Instead, constructing a model that explicitly incorporates the feedback mechanisms driving the rebound effect is required. These feedback loops must be designed in a way that allows them to be activated or deactivated between simulation runs, enabling a comparison of total emissions over the simulation time, with and without the rebound effect. This approach is implemented through the following steps:

1. Defining the model purpose and experimental design
2. Establishing the model boundaries by including or excluding relevant variables
3. Developing the SD model to represent the rebound-inclusive structure of the experimental design
4. Including a rebound switch in the model to (de-)activate the rebound feedback loop
5. Including an efficiency switch in the model to (de-)activate efficiency improvements

When the rebound switch is set to zero, no additional demand induced by efficiency improvements is added to the total passenger demand projections. When the efficiency switch is set to zero, the model runs with a constant fuel consumption per RPK, to effectively simulate a scenario without fuel efficiency improvements and without a rebound effect. This allows for the estimation of potential emission reductions in the baseline simulation, serving as a reference point to assess the extent to which this potential is offset by the rebound effect.

The model is subscripted across five haul segments to enhance predictive accuracy. As discussed in Chapter 7, future modeling efforts would benefit from extending this approach by introducing additional dimensions, such as carrier types, traveler motives and the distinction between domestic and international flights.

SQ3: What is an initial projection of the magnitude of the fuel efficiency rebound effect and the corresponding actual emission reduction through 2040 in the reference scenario?

Within the time horizon of 2025-2040, the baseline scenario - with efficiency improvements but without accounting for rebound - offers a potential emission reduction of 14%. In the reference scenario, total accumulated emissions in the rebound scenario exceed those in the baseline scenario by 14.9% (see Figure 8.1).

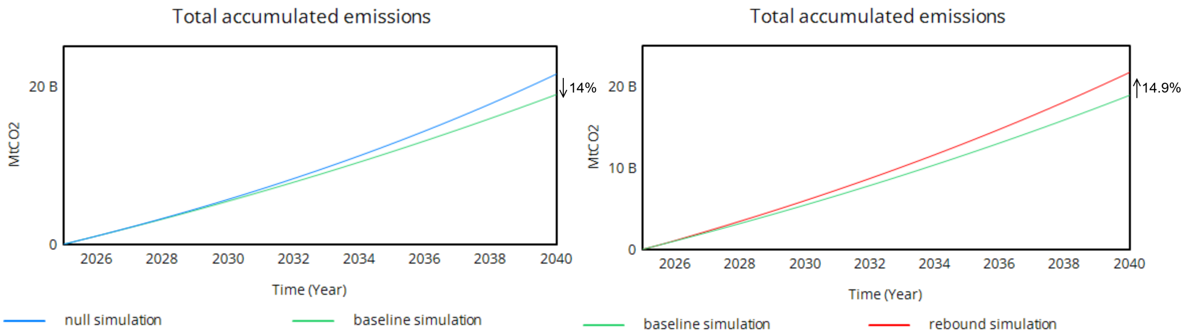

Figure 8.1: The left panel shows total accumulated emissions from 2025-2040 in a baseline scenario with efficiency improvements relative to a null scenario without efficiency improvements, indicating a 14% emission reduction potential. The right panel compares the baseline scenario to a scenario with rebound feedback, indicating a 14.9% rebound relative to the baseline.

These additional emissions offset 91.3% of the emission reduction potential. As a result, only a modest actual emission reduction of 1.3% remains.

Table 8.1: Rebound implications in the reference scenario by 2040.

Implications	Percentage
Emission reduction potential	14%
Rebound effect	91.3%
Actual emission reduction	1.3%

SQ4: How do market-specific uncertainties impact the potential magnitude of a fuel efficiency rebound effect?

Market specific factors and their associated uncertainty ranges contribute significantly to the variability in the potential magnitude of a fuel efficiency rebound effect. The key uncertainties that determine the extent to which this effect offsets the potential for emission reductions are as follows:

- **Consumer sensitivity to fare price reductions**. This key uncertainty is captured by the fare elasticity of demand. A high (absolute) elasticity value indicates that consumers are highly responsive to fare price reductions, strengthening the rebound feedback mechanism and leading to increased additional demand.
- **Market share distribution across haul segments**. This uncertainty reflects the relative market share of long-haul and ultra-long haul segments compared to shorter-haul segments. A greater share of long-distance flights results in significantly higher additional fuel consumption, due to the greater number of aircraft-kilometers flown (AKF).
- **Flight restrictions**. The stringency of regulatory measures or airport capacity constraints influences the extent to which airlines can accommodate growing demand. In the absence of such constraints, additional demand induced by efficiency improvements is more likely to be met. This means that the rebound effect reaches its full potential.

  Although **pass-through rate of cost reductions** is highly influential, it doesn't help identify the conditions under which the rebound effect exceeds the 91.3% in the reference scenario. Even at its lowest assumed value, a substantial rebound effect of over 91.3% can occur.

In summary: when consumers are highly responsive to the resulting fare price reductions, the rebound effect becomes particularly problematic in long-haul and ultra-long haul market segments, and in the absence of restrictions on flight volume.

Research Question: What is the potential impact of a future fuel efficiency rebound effect on the environmental benefits from efficiency improvements in passenger aviation?

Although the annual CO_2 emissions in passenger aviation are not expected to decline solely as a result of efficiency improvements[1], these improvements still offer a desirable means to slow the growth rate of emissions. However, the rebound effect in passenger aviation can partially or even fully offset the potential emission reductions achieved through operational and aircraft efficiency gains in the reference scenario. In the majority of other scenarios, it may even lead to additional emissions, further amplifying the already increasing trend in aviation-related emissions. It is therefore an oversimplification for policymakers and international organizations to assume that fuel efficiency improvements alone will reduce the amount of CO_2 emitted in the environment by 2040. This is especially relevant given that the short-term measures outlined in IATA's four-pillar strategy, which emphasize advancements in operational and aircraft fuel efficiency, primarily target efficiency gains without addressing the demand side of the equation. As this research shows, such measures do not necessarily result in environmental benefits in passenger aviation, due to fuel efficiency rebound effects. There is a significant risk that the sector's contribution to global emission reduction targets is overestimated. Even if other sectors succeed in decarbonizing, aviation could account for an increasingly larger share of global emissions,

[1] The anticipated annual efficiency gains are smaller than the projected baseline demand growth, meaning that demand growth outpaces efficiency improvements in the baseline scenario already.

while creating a false sense of progress. This false idea of progress can undermine future efforts to decarbonize the sector.

8.1. Policy Recommendations

Promoting sustainable mobility remains a central objective in transport policy, aiming to ensure that transport systems continue to meet society's economic and social needs. This section proposes several policy recommendations to prevent or mitigate the fuel efficiency rebound effect in passenger aviation. These recommendations are based on the research findings, discussion of the results and the overall conclusions drawn in this research.

Integrate rebound feedback mechanisms into policy evaluation models. The quantitative results of this research underscore the relevance of the fuel efficiency rebound effect and its potential implications. Ex ante transport policy evaluations should incorporate all unintended negative impacts and align outcomes with established goals and government targets (van Wee et al., 2013). Accordingly, policymakers should systematically consider rebound feedback mechanisms that may offset anticipated efficiency gains when evaluating the effectiveness of proposed measures.

Stimulate the adoption of Sustainable Aviation Fuels (SAF). As this research highlights, a critical trade-off emerges in the design of aviation emission reduction policies, balancing demand growth, technological innovation and the need for substantial emission reductions. The results of the scenario analysis show that imposing a cap on the annual number of flights can effectively mitigate the rebound effect. However, such a policy measure would also constrain the sector's capacity to meet growing passenger demand. Supporting SAF uptake through subsidies can help decouple emissions from air traffic growth and reduce reliance on efficiency improvements alone. The complete replacement of fossil fuels with sustainable alternative fuels is physically achievable, but would require substantial policy support to become commercially viable (ICAO, 2019).

Strengthen carbon pricing mechanisms. As outlined in the conceptual model of this research, both baseline demand growth and additional demand induced by fuel efficiency improvements contribute to a continued upward trajectory in total fuel consumption. Existing literature suggests that decarbonization of the aviation sector requires stronger integration into emission reduction schemes (Muehlberger et al., 2024). While such a demand-side strategy may impose constraints on the sector's economic expansion, it does hold potential to mitigate the rebound driven increase in total fuel consumption and related emissions.

Implement fiscal measures to manage demand and limit fare reductions. The quantitative SD model developed in this research operates under a *ceteris paribus* assumption. Within this framework, the fuel efficiency rebound effect emerges as a significant dynamic. Consumer sensitivity to fare price reductions and the pass-through rate of fuel cost savings were identified as critical leverage factors. However, policy interventions can influence such key determinants of fuel efficiency-induced passenger demand, thereby counteracting the mechanisms that drive the rebound effect. Price-based instruments such as taxes and minimum fare thresholds can compensate for fare reductions triggered by efficiency improvements, preventing additional demand growth. Moreover, tax incomes can be used to commercialize Sustainable Aviation Fuels (Kettler & Walls, 2022).

Industry stakeholders and regulators often dismiss demand reduction as unrealistic, citing the essential role of aviation in a highly mobile and interconnected world (Kettler & Walls, 2022). However, policy measures aimed at demand reductions need to remain on the table in the near term to benefit from fuel efficiency improvements and address climate change, at least until viable alternatives to kerosene-powered aircraft become available. Fare elasticities in aviation are generally higher than in other transport sectors (Miyoshi & Fukui, 2018), and the quantitative findings in this research indicate a significant potential for a rebound effect over a 15-year period. This highlights the importance of sustained policy interventions for aviation, particularly when combined with efficiency investments to mitigate the risk of rebound (Druckman et al., 2011).

8.2. Recommendations for Future Research

The scenario analysis in this research explored plausible future scenarios of the occurrence of the rebound effect. While robust transport futures research explicitly incorporates uncertainty (Annema et al., 2013), this section categorizes the recommendations for future research into three key areas: (1) addressing knowledge gaps in data availability, (2) refining traditional emission projection models, and (3) future modeling efforts for meaningful expansion or integration of the current model. These recommendations stem from uncertain factors identified in model conceptualization, key findings and the reflection on modeling choices.

To reduce uncertainty around key factors and move towards a more data-driven modeling approach, future empirical research should focus on **addressing existing knowledge gaps in data availability**. Specifically, empirical data collection is needed on:

- market share distributions across different haul segments;
- fare elasticities of demand, differentiated by haul segment and traveler motives;
- pass-through rates of fuel cost savings by carrier type;
- market share distributions across carrier types.

To better assess the potential benefits of fuel efficiency improvements and the impact of rebound effects on total emissions, **future emission projection models** for aviation should be **refined** by:

- Integrating rebound feedback mechanisms into traditional emission projection models to account for behavioral responses to efficiency gains;
- Differentiating emission forecasts by haul segments to capture varying rebound intensities.

The current model offers a solid foundation for future studies on the fuel efficiency rebound effect, both in aviation and in other sectors where such effects may arise. To enhance reliability and policy relevance of results, **future modeling efforts** can improve the current model by:

- Capturing the dynamic interplay between supply and demand over time;
- Embedding the model into existing air transport system models to reflect a more comprehensive context, thus moving beyond the *ceteris paribus* assumption;
- Incorporating context-specific heterogeneity by integrating multiple spatial and market scale levels.

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A

Model Variables & Data

The model file, along with the Excel file containing parameter estimations and the supporting references, can be found on the GitHub Repository. Most variables are subscripted across five haul segments, which differ in average flight distance and maximum average seating capacity of aircraft (Table A.1).

Table A.1: Estimations of industry-wide averages per haul segment

Haul segment	Initial average flight distance	Maximum average seating capacity of aircraft
Short haul	600 km	108.75 seats
Short-medium haul	1000 km	126.25 seats
Medium haul	1600 km	146.43 seats
Long haul	3250 km	183.33 seats
Ultra-long haul	12000 km	308.33 seats

A.1. Variables

The model variables presented in this section reflect the model configuration applied in the full rebound simulation. For the uncertain input parameters, the values corresponding to the reference scenario are used.

Initial total value passenger demand = 8.5e+12

UNIT[(Passengers*km)/Year]

Initial value passenger demand = Initial value passenger demand sector wide*Market share per haul segment[Haul segment]

UNIT[(Passengers*km)/Year]

Market share per haul segment = 0.2

UNIT[Dmnl]

Annual passenger demand = INTEG(Baseline demand growth[Haul segment]+Fuel efficiency induced demand growth[Haul segment])

UNIT[(Passengers*km)/Year]

Total annual passenger demand = SUM(Annual passenger demand[Haul segment!])

UNIT[(Passengers*km)/Year]

Baseline demand growth = Annual passenger demand[Haul segment]*Baseline prediction yearly demand growth rate[Haul segment]

UNIT[(Passengers*km)/(Year*Year)]

Baseline prediction yearly demand growth rate = 0.044

UNIT[1/Year]

Total annual change of passenger demand = SUM(Annual passenger demand[Haul segment!])-Annual passenger demand previous year

UNIT[(Passengers*km)/Year]

Annual passenger demand previous year = DELAY FIXED(SUM(Annual passenger demand[Haul segment!]) , 1 , SUM(Annual passenger demand[Haul segment!]))

UNIT[(Passengers*km)/Year]

Current value annual number of flights demanded = (Current value annual passenger demand[Haul segment])/(PAX per flight[Haul segment]*Average flight distance[Haul segment])

UNIT[1/Year]

Demand fulfillment rate = IF THEN ELSE(Maximum annual number of flights[Haul segment]>=Current value annual number of flights demanded[Haul segment], 1 , (Maximum annual number of flights[Haul segment]/Current value annual number of flights demanded[Haul segment]))

UNIT[Dmnl]

Maximum annual number of flights = Market share per haul segment[Haul segment]*Maximum total annual number of flights sector wide

UNIT[1/Year]

Maximum total annual number of flights sector wide = 5e+09

UNIT[1/Year]

PAX per flight = Average PLF*Maximum average seating capacity of aircraft[Haul segment]

UNIT[Passengers]

Initial average flight distance = [600, 1000, 1600, 3250, 12000]

UNIT[km]

Average flight distance = INTEG(-Decrease in average flight distance[Haul segment])

UNIT[km]

Decrease in average flight distance = Average flight distance[Haul segment]*Yearly percentage route optimization

UNIT[km/Year]

Yearly percentage route optimization = 0.00349*Unit*Efficiency Switch

UNIT[1/Year]

Efficiency Switch = [0 OR 1]

UNIT[Dmnl]

Maximum average seating capacity of aircraft = [108.75, 126.25, 146.43, 183.33, 308.33]

UNIT[Passengers]

Annual ASK = Maximum annual number of flights[Haul segment]*Maximum average seating capacity of aircraft[Haul segment]*Average flight distance[Haul segment]

UNIT[(Passengers*km)/Year]

Total annual ASK = SUM(Annual ASK[Haul segment!])

UNIT[(Passengers*km)/Year]

Initial value average PLF = 0.834
UNIT[Dmnl]

Average PLF = INTEG(Increase of average PLF)

UNIT[Dmnl]

Increase of average PLF = Yearly percentage increase PLF*Average PLF

UNIT[Dmnl/Year]

Yearly percentage increase PLF = 0.00317*Efficiency Switch

UNIT[1/Year]

Current annual RPK = Average flight distance[Haul segment]*PAX per flight[Haul segment]*Current value annual number of flights[Haul segment]

UNIT[(Passengers*km)/Year]

RPK = Current annual RPK[Haul segment]

UNIT((Passengers*km)/Year)

Total accumulated RPKs = INTEG(RPK[Haul segment])

UNIT[Passengers*km]

Current value annual number of flights = Current value annual number of flights demanded[Haul segment]*Demand fulfillment rate[Haul segment]

UNIT[1/Year]

Current value annual AKF = Current value annual number of flights[Haul segment]*Average flight distance[Haul segment]

UNIT[km/Year]

AKF = Current value annual AKF[Haul segment]

UNIT[km/Year]

Total accumulated AKF = INTEG(AKF[Haul segment])

UNIT[km]

Initial value total fuel consumption = Initial value total fuel consumption sector wide*Market share per haul segment[Haul segment]

UNIT[Ltrs]

Initial value total fuel consumption sector wide = 3.59575e+11

UNIT[Ltrs]

Fuel consumed = Current value annual AKF[Haul segment]*Fuel consumption per AKF[Haul segment]

UNIT[Ltrs/Year]

Total accumulated fuel consumption = INTEG(Fuel consumed[Haul segment])

UNIT[Ltrs]

Initial value fuel consumption per AKF = Initial value fuel consumption per ASK*Maximum average seating capacity of aircraft[Haul segment]

UNIT[Ltrs/km]

Initial value fuel consumption per ASK = 0.0315

UNIT[Ltrs/(Passengers*km)]

Fuel consumption per AKF = INTEG(-Decrease fuel consumption per AKF[Haul segment])

UNIT[Ltrs/km]

Decrease fuel consumption per AKF = Fuel consumption per AKF[Haul segment]*Average yearly percentage increase of aircraft fuel efficiency

UNIT[Ltrs/(km*Year)]

Average yearly percentage increase of aircraft fuel efficiency = 0.0125*Unit*Efficiency Switch

UNIT[1/Year]

Annual fuel consumption = IF THEN ELSE(Time=INITIAL TIME, Initial value total fuel consumption[Haul segment], Total accumulated fuel consumption[Haul segment]-Total accumulated fuel consumption previous year[Haul segment])

UNIT[Ltrs]

Total accumulated fuel consumption previous year = DELAY FIXED(Total accumulated fuel consumption[Haul segment], 1 , Total accumulated fuel consumption[Haul segment])

UNIT[Ltrs]

Fuel consumption per RPK = Annual fuel consumption[Haul segment]/Current annual RPK[Haul segment]

UNIT[Ltrs/((Passengers*km)/Year)]

Fuel cost per RPK = Jet fuel price*Fuel consumption per RPK[Haul segment]

UNIT[euro/(Passengers*km)/Year]

Jet fuel price = 0.541

UNIT[euro/Ltrs]

Initial value fuel cost per RPK = Jet fuel price*Initial value fuel consumption per RPK[Haul segment]

UNIT[euro/(Passengers*km)/Year]

Initial value annual RPK = Initial value passenger demand[Haul segment]*Market share per haul segment[Haul segment]

UNIT[(Passengers*km)/Year]

Initial value fuel consumption per RPK = Initial value total fuel consumption[Haul segment]/Initial value annual RPK[Haul segment]

UNIT[Ltrs/((Passengers*km)/Year)]

Change ratio fuel cost per RPK = IF THEN ELSE(Time=INITIAL TIME, (Fuel cost per RPK[Haul segment]-Initial value fuel cost per RPK[Haul segment])/Initial value fuel cost per RPK [Haul segment] , (Fuel cost per RPK[Haul segment]-Fuel cost per RPK previous year[Haul segment])/Fuel cost per RPK previous year[Haul segment])

UNIT[Dmnl]

Fuel cost per RPK previous year = DELAY FIXED(Fuel cost per RPK[Haul segment], 1 , Fuel cost per RPK[Haul segment])

UNIT[euro/(Passengers*km)/Year]

Fare price change ratio = Change ratio fuel cost per RPK[Haul segment]*Pricing strategy factor[Haul segment]

UNIT[Dmnl]

Pricing strategy factor = 0.45

UNIT[Dmnl]

Fuel efficiency induced demand growth rate = MAX(0,Fare elasticity of demand[Haul segment]*Fare price change ratio[Haul segment])

UNIT[1/Year]

Fare elasticity of demand = [-0.83, -0.83, -1.06, -1.28, -1.28]

UNIT[1/Year]

Fuel efficiency induced demand growth = Fuel efficiency induced demand growth rate[Haul segment]*Annual passenger demand[Haul segment]*RE Loop Switch

UNIT[(Passengers*km)/(Year*Year)]

RE Loop Switch = [0 OR 1]

UNIT[Dmnl]

Total annual CO2 emissions = Fuel consumed[Haul segment]*CO2 emissions per liter jet fuel

UNIT[MtCO2/Year]

CO2 emissions per liter jet fuel = 0.00316

UNIT[MtCO2/Ltrs]

Accumulated CO2 emissions = INTEG(Total annual CO2 emissions[Haul segment])

UNIT[MtCO2]

Total accumulated CO2 emissions = SUM(Accumulated CO2 emissions[Haul segment!])

UNIT[MtCO2]

A.2. Data

Seating capacity of aircraft per haul segment are estimated based on Figure A.1.

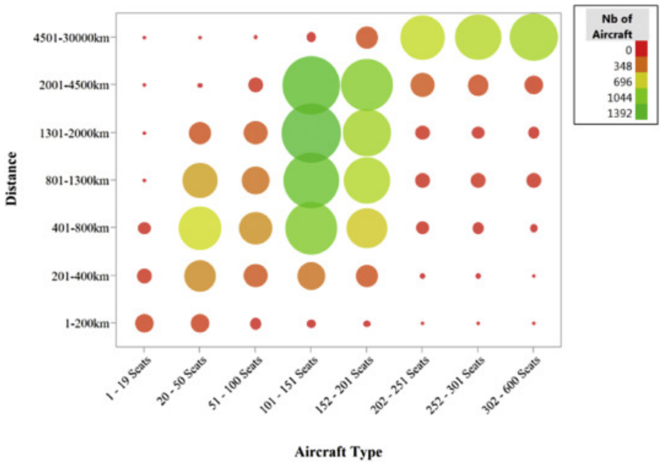

Figure A.1: Demand of aircraft per distance and aircraft size based on empirical data

For example, a major quantity of medium size aircraft with a capacity from 101 up to 150 seats are used for a distance range of 801–2000 km (Kölker et al., 2016). A detailed justification and references supporting the chosen parameter values and industry-wide averages can be found in the Excel file on GitHub.

B

Model Validation

This appendix presents the results of the selected validation tests, including sensitivity analysis and extreme conditions testing. A historical and future emissions data check is provided in a textbox within the main text.

B.1. Sensitivity Analysis

For sensitivity testing, the baseline input variables were varied within a range of -10% to +10% relative to their values in the reference scenario, defined in Chapter 5. This approach helps assess the model's validity by testing the robustness of its outcomes. The baseline input parameters tested include baseline demand growth, annual increase of passenger load factor, annual reduction of flight distance and annual increase of aircraft fuel efficiency. 200 sensitivity simulations are conducted using the full model configuration, consistent with the structure applied in the rebound simulations. Values for each baseline input parameter were sampled from the specified range using a uniform random distribution, with a fixed random seed of 1234 to ensure reproducibility. The corresponding results are presented in Figures B.1 and B.2.

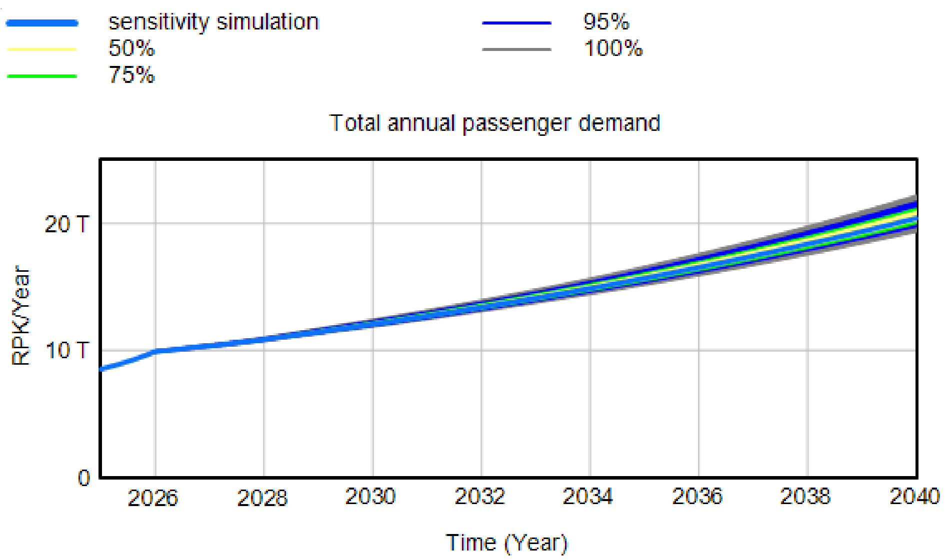

Figure B.1: Results of 200 sensitivity simulations for baseline input parameters, illustrating the sensitivity of projected annual passenger demand.

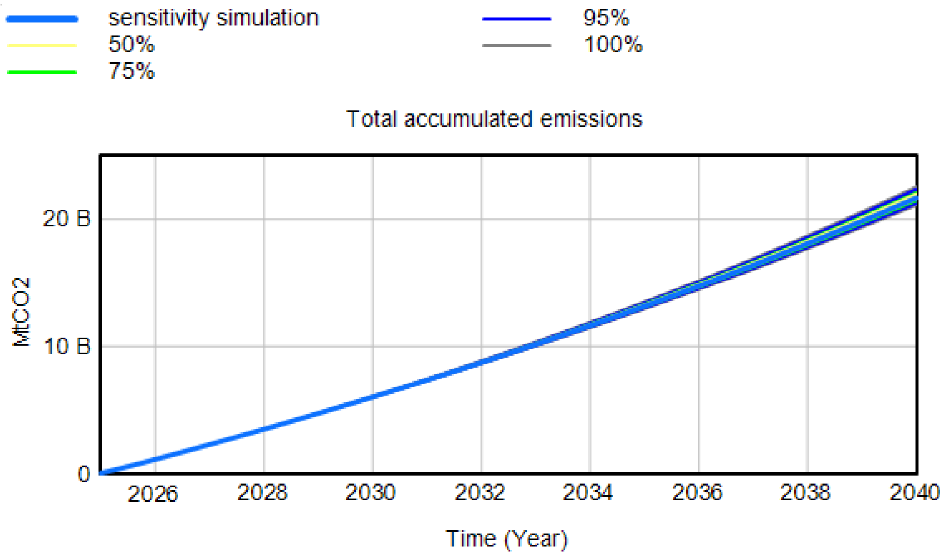

Figure B.2: Results of 200 sensitivity simulations for baseline input parameters, illustrating the sensitivity of projected accumulated emissions.

The relatively narrow range of resulting outcomes indicates that the model is not highly sensitive to small changes in the baseline input parameters, suggesting internal consistency and stability in the model's structure.

To conduct a more comprehensive sensitivity analysis, the parameters related to rebound feedback are also included. Because these parameters are associated with variables and subsystems that close critical feedback loops, even small changes in their values can produce significant systemic effects. These parameters are considered highly uncertain due to limited empirical consensus and data availability. This approach allows for an exploration of how sensitive model outcomes are to parameters that may significantly affect the rebound effect. The parameters tested include the pricing strategy factor and fare elasticity of demand.

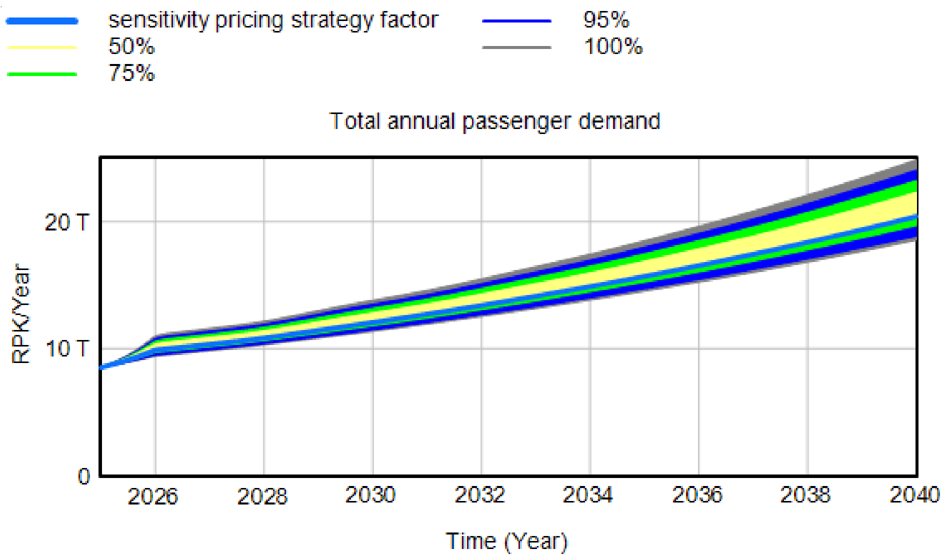

Figure B.3: Results of 200 sensitivity simulations for pricing strategy factor input, illustrating the sensitivity of projected annual passenger demand.

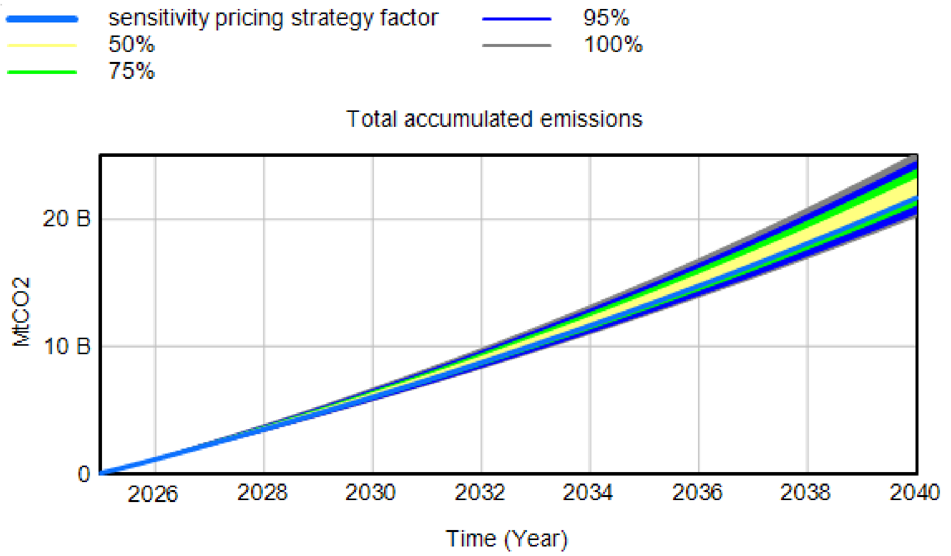

Figure B.4: Results of 200 sensitivity simulations for pricing strategy factor input, illustrating the sensitivity of projected accumulated emissions.

The sensitivity analysis shows the model is more sensitive to the pricing strategy factor. Even small changes in this parameter have a strong effect on output variability. The model is less sensitive to fare elasticity, meaning changes in this parameter do not have a strong effect on output variability. The results are presented in Figures B.5 and B.6.

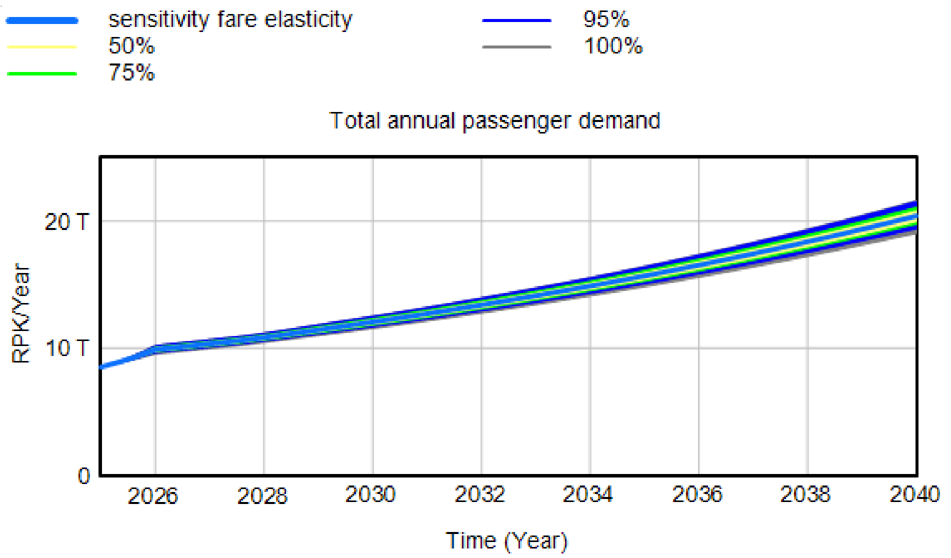

Figure B.5: Results of 200 sensitivity simulations for fare elasticity of demand input, illustrating the sensitivity of projected annual passenger demand.

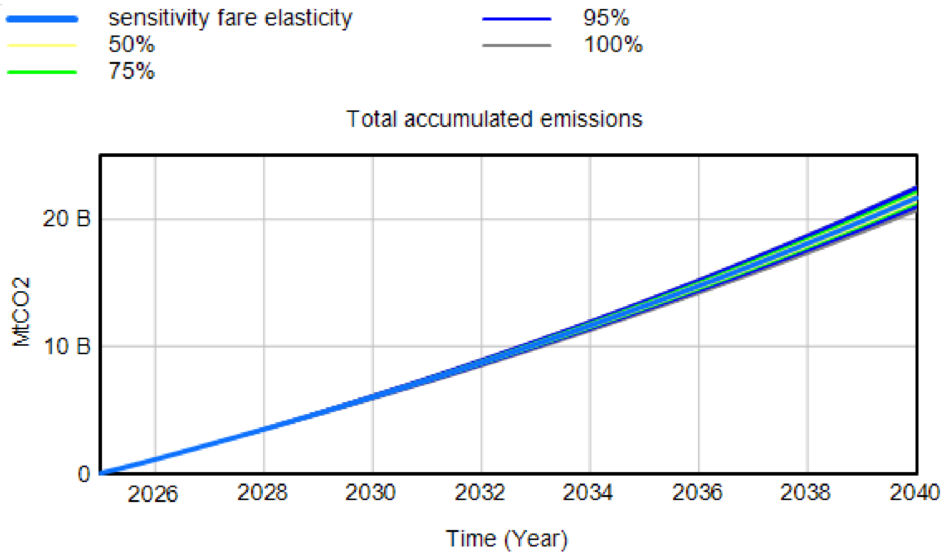

Figure B.6: Results of 200 sensitivity simulations for fare elasticity of demand input, illustrating the sensitivity of projected accumulated emissions.

B.2. Extreme Conditions Test

Extreme conditions testing was conducted to evaluate the model's robustness by applying extreme input values and assessing whether it continues to produce consistent and logical behavior. Simulations are conducted with both the parameter values of the reference scenario and with extreme values using the full model configuration, consistent with the structure applied in the rebound simulations. Once again, extreme values were assigned to rebound-related parameters for testing, as these parameters influence variables and subsystems that close critical feedback loops. This approach provides insight into whether the full model structure behaves consistently and logically. The results are presented in Figures B.7 and B.8.

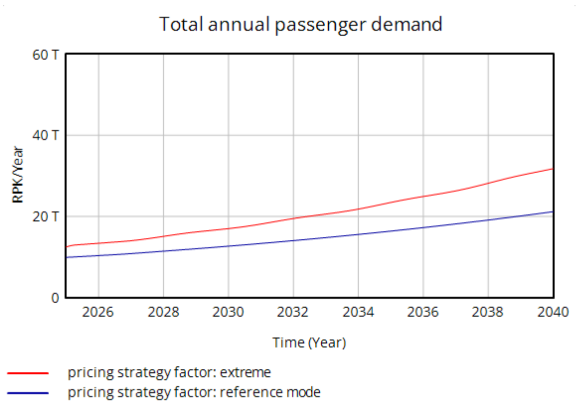

Figure B.7: Difference in total annual passenger demand over time between the reference scenario and an extreme scenario in which the pricing strategy factor is set to a high value of 1.5, representing an unrealistically high pass-through rate of fuel cost savings.

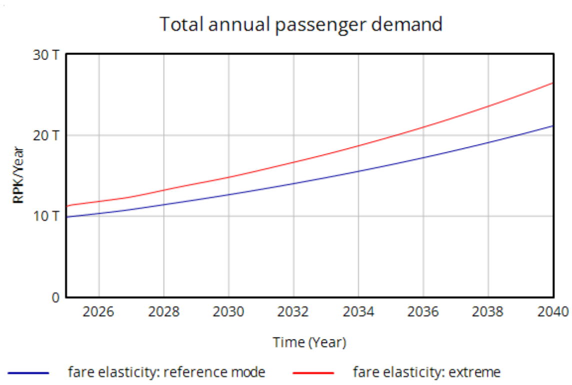

Figure B.8: Difference in total annual passenger demand over time between the reference scenario and an extreme scenario in which the fare elasticity of demand is set to a high absolute value of -2, representing a highly elastic demand response.

For the tests of the rebound-related parameters, total annual passenger demand was expected to increase, and the model reflected this behavior accordingly. To assess whether the subsystem of flight operations produces logical outputs under extreme conditions, the impact of a stringent flight restriction was tested. Specifically, the effects on the demand fulfillment rates and total accumulated emissions were evaluated to confirm that a forced reduction in flight operations leads to a corresponding decrease in accumulated emissions, as would be expected. The results are presented in Figures B.9 and B.10.

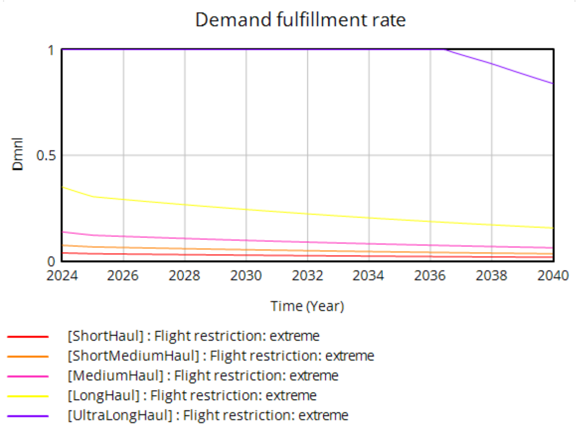

Figure B.9: Effect of demand fulfillment rates by haul segment over time in an extreme scenario imposing a stringent flight restriction, allowing only 90% of initial annual flight operations.

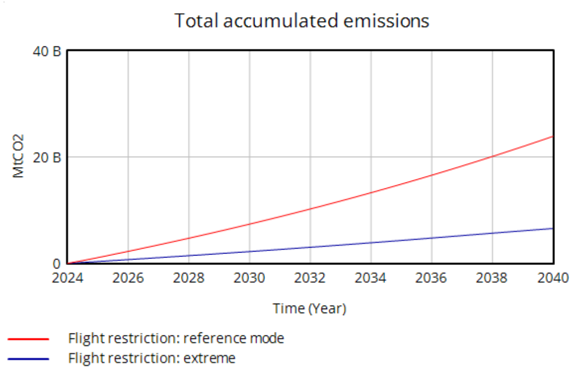

Figure B.10: Difference in total accumulated emissions over time between the reference scenario and an extreme scenario imposing a stringent flight restriction, allowing only 90% of initial annual flight operations.

C

Initial Experiment Results

This appendix presents additional results not included in the main text. These results cover variables related to efficiency improvements, baseline estimates of flight operations, and rebound-related variables that close the key feedback loops. The results of the rebound simulations are based on the reference scenario.

C.1. Efficiency Improvements

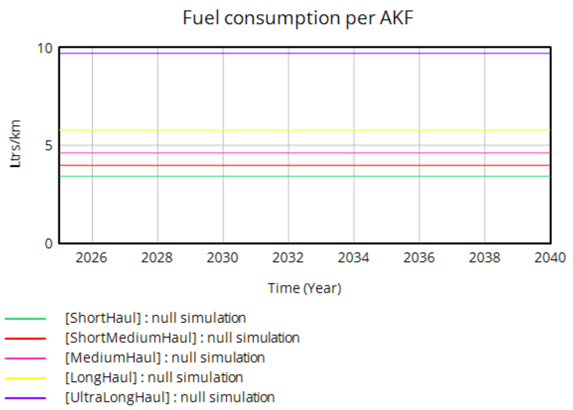

Figure C.1: Fuel consumption per aircraft-kilometer flown from 2025-2040 in the null simulation, which excludes efficiency improvements.

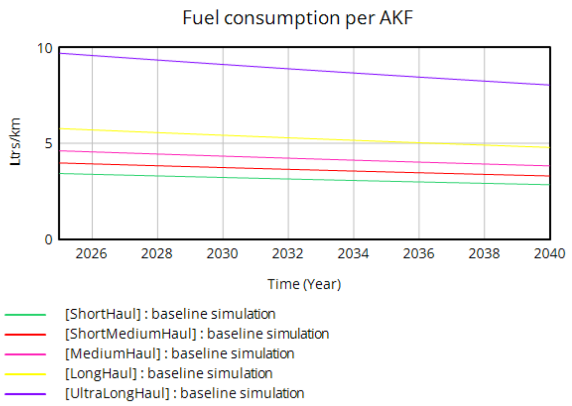

Figure C.2: Fuel consumption per aircraft-kilometer flown from 2025-2040 in the baseline simulation, which includes efficiency improvements.

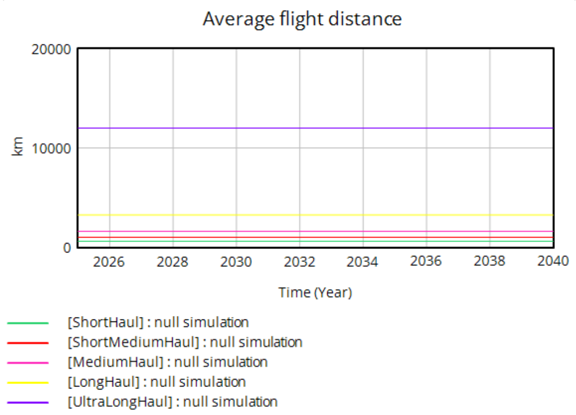

Figure C.3: Average flight distance from 2025-2040 in the null simulation, which excludes efficiency improvements.

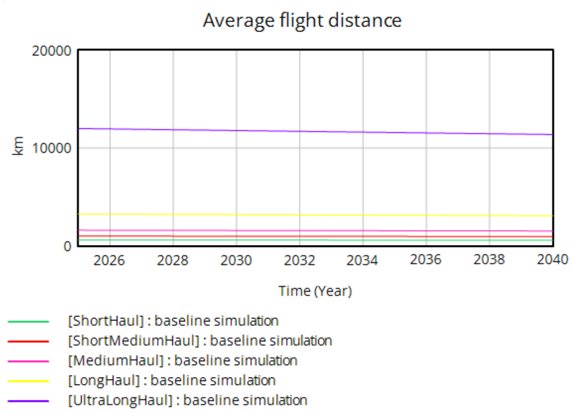

Figure C.4: Average flight distance from 2025-2040 in the baseline simulation, which includes efficiency improvements.

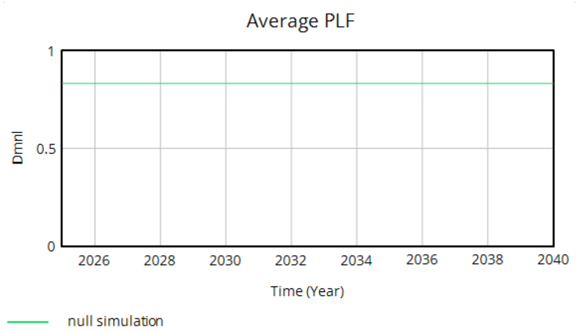

Figure C.5: Average passenger load factor from 2025-2040 in the null simulation, which excludes efficiency improvements.

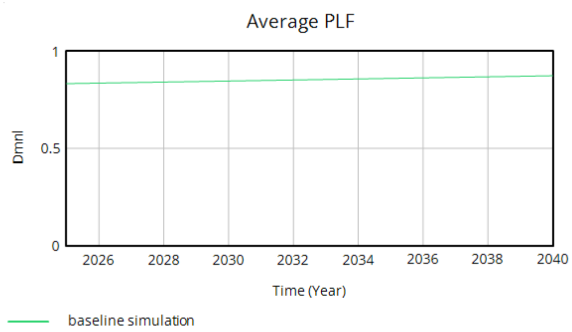

Figure C.6: Average passenger load factor from 2025-2040 in the baseline simulation, which includes efficiency improvements.

C.2. Baseline Variables

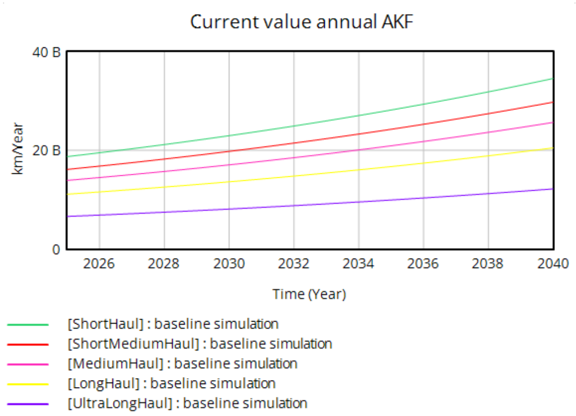

Figure C.7: Annual aircraft-kilometers flown from 2025-2040 in the baseline simulation, which excludes rebound feedback.

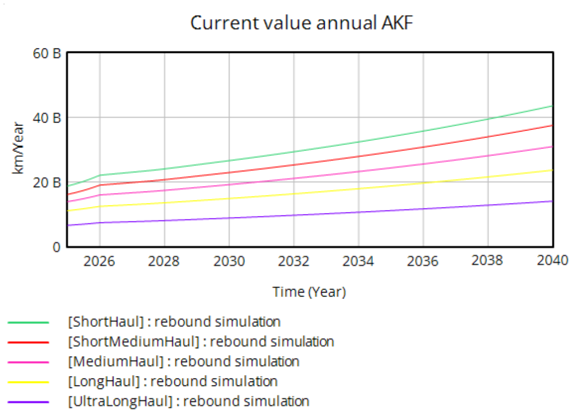

Figure C.8: Annual aircraft-kilometers flown from 2025-2040 in the rebound simulation, which includes rebound feedback.

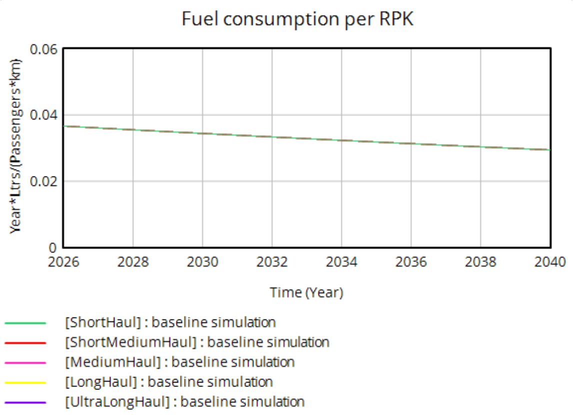

Figure C.9: Fuel consumption per RPK from 2025-2040 in the baseline simulation, which corresponds with the rebound simulation as both simulations include efficiency improvements.

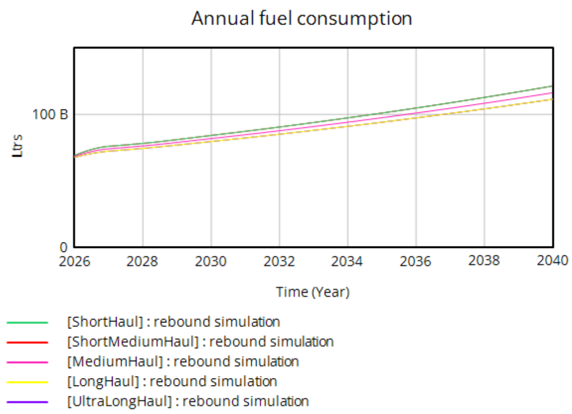

Figure C.10: Annual fuel consumption from 2025-2040 in the rebound simulation, which includes both efficiency improvements and rebound feedback.

C.3. Rebound Variables

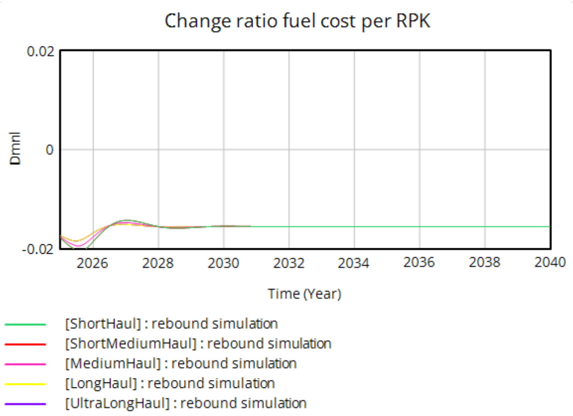

Figure C.11: Change ratio of fuel costs per RPK from 2025-2040 in the rebound simulation, which includes rebound feedback.

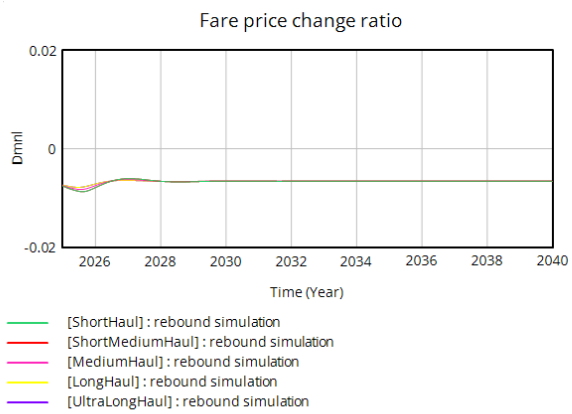

Figure C.12: Fare price change ratio from 2025-2040 in the rebound simulation, which includes rebound feedback.

D

Scenario Analysis Results

This appendix presents the results of the PRIM analysis. The complete Scenario Analysis, conducted using the EMA Workbench in Python, is available in the ipynb-files on GitHub.

D.1. PRIM

To apply PRIM, the market-specific uncertain parameters were first grouped into experiment subsets, and the algorithm was run separately for each subset. This approach reduces correlations and allows for a clearer understanding of how each category of uncertain parameters affects the outcome. The first subset includes all market shares across haul segments to identify which market segments most strongly affect the results. Figure D.1 presents the outcomes of the PRIM analysis for scenario outcomes where the rebound threshold of the reference scenario was exceeded. Parameters that appear in the box with narrower value ranges are considered more influential in shaping the magnitude of the fuel efficiency rebound effect.

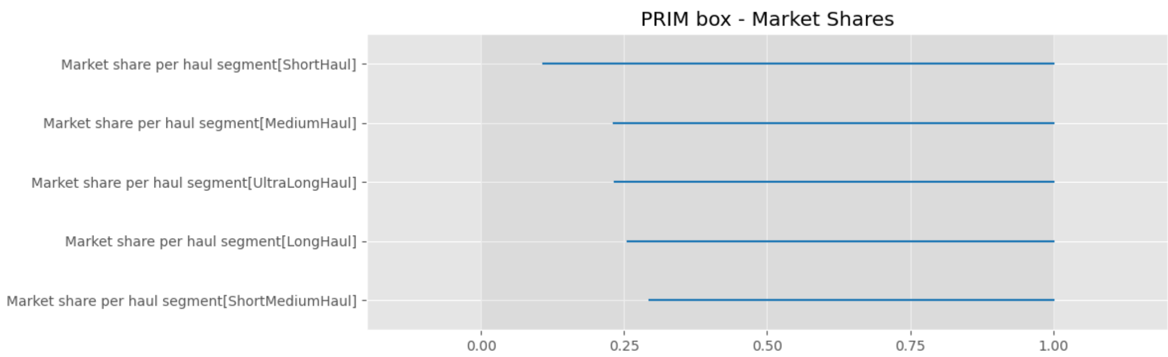

Figure D.1: Input spaces of market share parameters per haul segment that explain higher rebound magnitudes than that of the reference scenario.

Figure D.2 displays the algorithm's peeling trajectory, showing how the trade-off between scenario coverage and density evolves as the market shares per haul segment are progressively constrained.

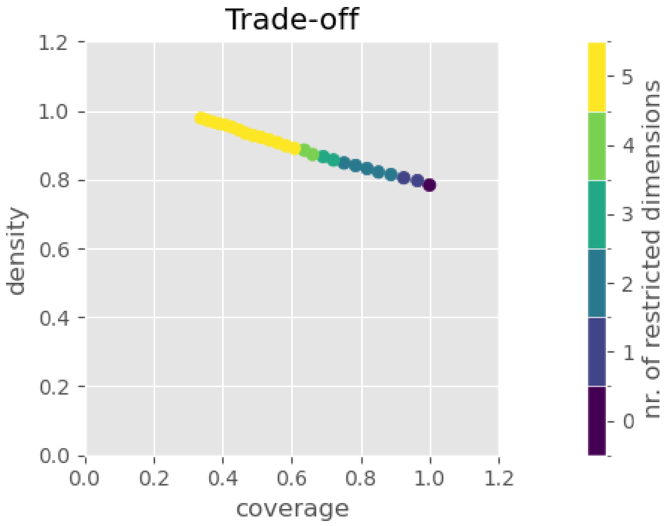

Figure D.2: Peeling trajectory of the PRIM algorithm applied to the market share subset, where the rebound threshold exceeds the rebound in the reference scenario.

Based on the PRIM results from the first experiment subset, the longer haul segments emerged as particularly influential. Consequently, a second subset of experiments was analyzed, focusing specifically on how ultra-long-haul-related parameters affect the outcomes of interest. This approach allows to focus on interactions across parameter types within a single haul segment. Figure D.3 presents the results.

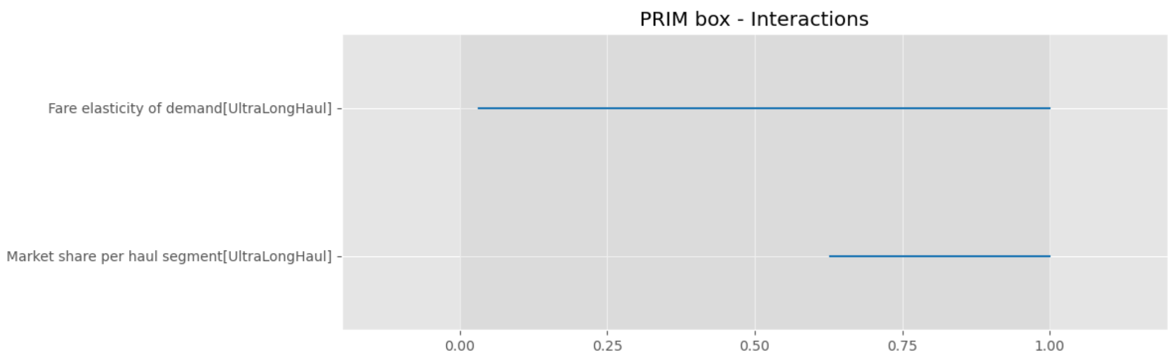

Figure D.3: Input spaces of market-specific parameters within the ultra-long-haul segment that explain higher rebound magnitudes than that of the reference scenario.

Figure D.4 displays the algorithm's peeling trajectory, showing how the trade-off between scenario coverage and density evolves as the market-specific parameters within the ultra-long-haul segment are progressively constrained.

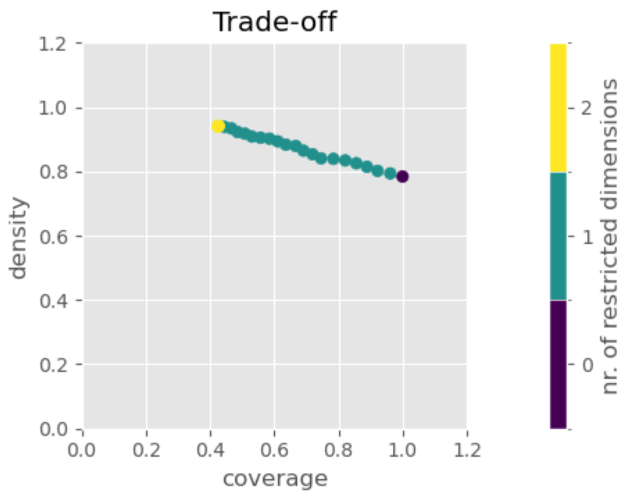

Figure D.4: Peeling trajectory of the PRIM algorithm applied to the ultra-long-haul subset, where the rebound threshold exceeds the rebound in the reference scenario.