SUSTAINABILITY OF MULTIMODAL INTERCITY TRANSPORTATION USING A HYBRID SYSTEM DYNAMICS AND AGENT-BASED MODELING APPROACH

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SUSTAINABILITY OF MULTIMODAL INTERCITY TRANSPORTATION USING A HYBRID SYSTEM DYNAMICS AND AGENT-BASED MODELING APPROACH

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LIST OF SYMBOLS AND ABBREVIATIONS

μ_m Cost of travel with mode m

τ_m Time of travel with mode m

A_m Attractiveness of mode m

U_m Disutility of mode m

V_m Demand for mode m

X Exogenous variable

x_k Mode design variables

C_nH_m Hydrocarbon

CH_4 Methane

CO_2 Carbon Dioxide

CO Carbon Monoxide

H_2O water vapor

N_2O Nitrous Oxide

NO_x Nitrogen Oxides

O_3 Ozone

SO_x Sulfur Oxide

Mi   Agent-Based Model for multimodal transportation demand

AAOD   Absorption Aerosol Optical Depth

ABM	Agent-Based Modeling
ALN	Commercial Air Transportation (Airline) Mode
AVHRR	Advanced Very High Resolution Radiometer
BC	Black Carbon
CAFE	Corporate Fuel Economy
CONUS	Continental United States
DG	Distance Group
DOE	Design of Experiments
eGAME	environmental Ground and Air Mode Explorer
EPA	Environmental Protection Agency
EV	Electric Vehicle
GAME	Ground and Air Mode Explorer
GDP	Gross Domestic Product
GND	Ground Mode
GOES	Geostationary Operational Environmental Satellite
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
IAM	Integrated Assessment Model
ICAO	International Civil Aviation Organization
IDEA	Integrated Dynamics Environmental Analysis

IPCC	Intergovernmental Panel on Climate Change
IRF	Impulse Response Function
LDV	Light-Duty Vehicle
LW	Longwave
MADM	Multi-Attribute Decision Making
MBM	Market-Based Measures
MCSI	Michigan Consumer Sentiment Index
MMG	Metro Market Group
MOVES	MOtor Vehicle Emission Simulator
mpg	miles per gallon
MSA	Metropolitan Statistical Area
NOAA	National Oceanic and Atmospheric Administration
P2P	Point to Point air transportation
PM	Particulate Matter
ppb	parts per billion
ppm	part per million
RF	Radiative Forcing
RFE	Radiative Forcing Efficiency
RPM	Revenue Passenger Miles
RT	Radiative Transfer

SCC	Social Cost of Carbon
SD	System Dynamics
SoS	System-of-Systems
SW	Shortwave
SZA	Solar Zenith Angle
TAR	IPCC's Third Assessment Report
TOA	Top Of the Atmosphere
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UHC	Unburned Hydrocarbon
VMT	Vehicle Miles Traveled
VOC	Volatile Organic Compound

SUMMARY

Demand for intercity transportation has increased significantly in the past decades and is expected to continue to follow this trend in the future. In the meantime, concern about the environmental impact and potential climate change associated with this demand has grown, resulting in an increasing importance of climate impact considerations in the overarching issue of sustainability. This results in discussions on new regulations, policies and technologies to reduce transportation's climate impact. Policies may affect the demand for the different transportation modes through increased travel costs, increased market share of more fuel efficient vehicles, or even the introduction of new modes of transportation. However, the effect of policies and technologies on mobility, demand, fleet composition and the resulting climate impact remains highly uncertain due to the many interdependencies. This motivates the creation of a parametric modeling and simulation environment to explore a wide variety of policy and technology scenarios and assess the sustainability of transportation. In order to capture total transportation demand and the potential mode shifts, a multimodal approach is necessary.

The complexity of the intercity transportation System-of-Systems calls for a hybrid Agent-Based Modeling and System Dynamics paradigm to better represent both micro-level and macro-level behaviors. Various techniques for combining these paradigms are explored and classified to serve as a hybrid modeling guide. A System Dynamics approach is developed, that integrates socio-economic factors, mode performance, aggregated demand and climate impact. It is used to explore different policy and technology scenarios, and better understand the dynamic behavior of the intercity transportation System-of-Systems. In order to generate the necessary

data to create and validate the System Dynamics model, an Agent-Based model is used due to its capability to better capture the behavior of a collection of sentient entities. Equivalency of both models is ensured through a rigorous cross-calibration process. Through the use of fleet models, the fuel burn and life cycle emissions from different modes of transportation are quantified. The radiative forcing from the main gaseous and aerosol species is then obtained through radiative transfer calculations and regional variations are discussed. This new simulation environment called the environmental Ground and Air Mode Explorer (eGAME) is then used to explore different policy and technology scenarios and assess their effect on transportation demand, fleet efficiencies and the resulting climate impact. The results obtained with this integrated assessment tool aim to support a scenario-based decision making approach and provide insight into the future of the U.S. transportation system in a climate constrained environment.

CHAPTER I

INTRODUCTION

"Most persons think that a state in order to be happy ought to be large; but even if they are right, they have no idea of what is a large and what is a small state... To the size of states there is a limit, as there is to other things, plants, animals, implements; for none of these retain their natural power when they are too large or too small, but they either wholly lose their nature, or are spoiled."

(Aristotle, 322 BC, cited in Limits to Growth, 1972)

"The benefit derived from the modeling efforts of large scale systems [using dynamic systems modeling techniques invented by Forrester] suggests that the techniques may be beneficially applied to other large-scale systems. Transportation provides many problems of a large scale where new and more effective approaches are needed."

(Hansen and Kahne, 1975)

1.1 Motivation

Over the past decades, the issue of sustainability has gained a lot of momentum. The most widely cited definition of sustainability was from Norway's Prime Minister in 1987: "sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [3, 164]. Sustainability is increasingly discussed in the field of transportation, and the definitions of sustainable transportation derive from the concept of sustainable development. It comes with multiple objectives and should equally account for the sector's impact on local society, economy, and the environment [184]. With a sustainable transportation system, the basic access needs of individuals and societies are met safely, at a reasonable price, and with limited emissions [10]. It is related to a large number of variables such as overall economy, employment, operators', manufacturers' and airports' economic viability, passenger comfort, travel cost, travel time, safety, energy consumption, climate impact, local air quality and noise emissions. To achieve sustainability, the proper balance between current and future environmental, social, and economic qualities must be found [156]. Due to the multiple objectives of sustainability, and the many variables and stakeholders involved, which result in significant complexity, specific modeling methods are needed. Both micro-level types of behaviors (such as individual decisions to travel) and macro-level behaviors (such as overall system's performance and the effects of policies) must be captured.

1.1.1 A New Set of Constraints for Sustainability

As the carbon dioxide concentration in the atmosphere recently passed the milestone level of 400 parts per million (ppm), concern about climate change keeps growing. The Intergovernmental Panel on Climate Change (IPCC) goal of 450 ppm could be reached as early as 25 years from today [166]. This results in an increasing importance given to climate impact among sustainability considerations. In developed countries,

transportation is one of the major sources of greenhouse gases. In the United States, it is the second main emitter behind electricity generation, and the first end-use sector, as illustrated in Figure 1. With the expected increase in demand for inter-city transportation, emissions are likely to keep increasing if no new technologies are introduced. Technological improvements supported by regulations and policies are proposed to address the concern for transportation climate impact and reach specific given targets. The relevance of the target and the potential environmental and economic consequences is beyond the scope of this research. However the transportation system might be affected by new policies that aim to reduce emissions in an attempt to reach a given target. Therefore tools are needed to assess these effects and appropriately design a sustainable transportation system. In this research, the focus will be on mobility and climate impact of transportation. Through scenario exploration and future demand and climate impact forecasts, transportation designers and decision makers can gain valuable insight in terms of policy and technology impacts.
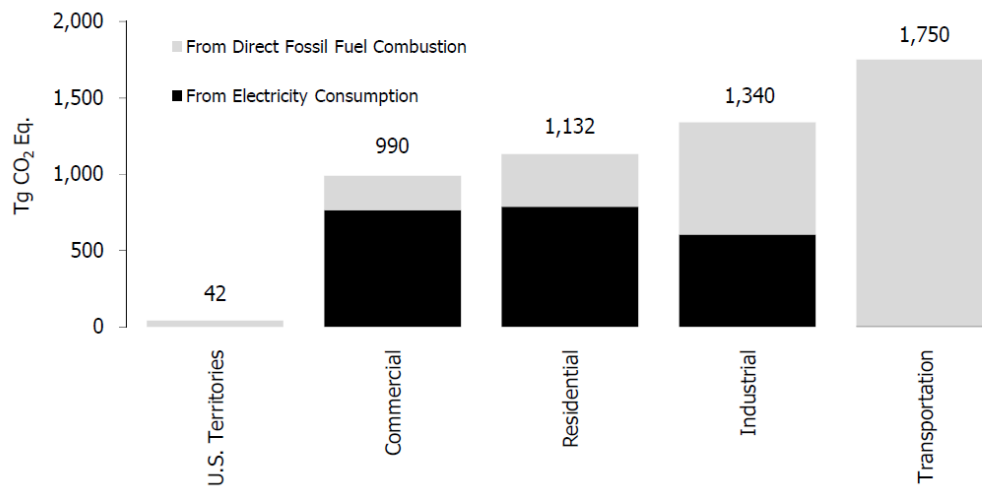
Figure 1: 2009 End-Use Sector Emissions of CO_2, CH_4 and N_2O from Fossil Fuel Combustion [43]

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1.1.2 Mobility under Climate Constraints

The transportation system is essential to the social and economic welfare of the society. It is often viewed as a creator of jobs and a catalyst for economic growth. Throughout history, it has been an enabler for many of the nation's developments. In the second half of the 19th century, the railroad system linked different parts of the country into a single national market, in which goods could be shipped across the nation. With the democratization of the automobile, the national highway system expanded, culminating with the interstate system, shaping the society and urban areas. Finally, the air transportation system became more affordable and popular, making most destinations reachable within a few hours. Long distance travel demand has grown significantly, resulting in near maximum capacity operations at some airports, and is expected to grow further. In the meantime a new set of constraints has appeared exemplified by the Kyoto protocol and the European trading scheme. The International Civil Aviation Organization (ICAO), Committee on Aviation Environmental Protection (CAEP) plans on implementing Market-Based Measures by 2020 [48]. Market-based measures are policy intruments that aim to provide incentives for environmental impact reduction by incorporating the external cost of consumption. Limiting transportation operations would be undesirable and exploring the different scenarios to maintain mobility with limited climate impact is necessary. Technologies and policies are crucial to reach the desired system efficiency and meet the demand without exceeding future constraints. It is important to consider the transportation system as a whole, including all modes of transportation, to account for competition, mode shift as well as the introduction of new modes of transportation. Predicting the behavior of the system requires careful attention because it brings together multiple transportation systems and a myriad of stakeholders (operators, manufacturers, passengers, airports, policy makers etc.) from a variety of disciplines (such as science, engineering and law). This variety of interacting systems and stakeholders constitutes

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a transportation System-of-Systems (SoS), which exhibits typical characteristics of a complex system: autonomous agents (travelers and other stakeholders), adaptability (competition between suppliers), self-organization, emergent and dynamic behaviors, feedbacks, nonlinearity (congestion and delays) and phase transitions (introduction of a new mode).

1.2   Research Statement

Forecasting transportation demand and climate impact is a challenging task due to the many interdepedencies involved and the wide variety of possible scenarios. Furthermore, large uncertainties remain in terms of climate impact from specific sectors and species. The perception of climate change can be incorrect and may lead to non-optimum decisions [38]. In order to help decision making using a scenario based approach, modeling and simulation tools need to be developed. These tools need to capture all aspects of transportation and thus climate impacts must be integrated. A holistic view of the system including all modes is needed to fully assess transportation sustainability. Since transportation climate impact is the result of species emitted by different modes of transportation, and the amount of these species depends on the fleet fuel efficiencies and the demand for each mode of transportation, one of the most important tasks is to develop a good demand and fleet forecasting tool that considers multiple modes of transportation. This tool should be parametric to allow decision makers to explore multiple scenarios of interest. These scenarios should capture the relationships that exist between technologies, policies, demand and fleets. For example, an increase in fuel price would result in a higher cost of travel, which may in turn reduce demand, while simultaneously increase the market share of fuel efficient vehicles, and eventually result in a decrease in climate impact. The complexity associated with the integrated assessement of demand, climate impact, policies and technologies requires some specific modeling paradigms. As further discussed in the next chapter,

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micro-level behaviors at the passenger level call for Agent-Based Modeling (ABM) while macro-level policies are better represented with System Dynamics (SD).

For a given socio-economic scenario, the demand is generated, and emissions can be quantified using fleet models. Based on these emissions, climate impact can be assessed. While quantifying the impact on climate is not trivial, due to the large number of parameters and the physics involved, it is necessary to provide insight into the sustainability of the transportation System-of-Systems. Measuring the effectiveness of climate policies is a relatively new effort [161]. Policies may be implemented in an attempt to change the demand and/or the fleet efficiency and help achieve a given climate impact target. However assessing the effectiveness of some policies such as a carbon tax can be challenging due to the multiple variables involved and interactions between them. An integrated assessment tool for transportation is needed that quantifies demand and climate impact into one simulation environment. The objective of this thesis is to create a framework for scenario based assessment of transportation demand and climate impact. In particular, this research will show that **the multi-modal, hybrid ABM-SD approach provides insight into the future design of transportation SoS and the effect of technologies and policies on demand and climate impact**.

The following chapter provides some necessary background on a number of theories and modeling techniques for transportation SoS integrated assessment modeling, that include demand for different modes of transportation, fleet and emissions, and transportation climate impact. The third chapter gives an overview of the method used in this research. The fourth chapter introduces the multi-paradigm methodology used for demand modeling. The fifth chapter discusses how the climate impact is quantified through the use of fleet models and a radiative transfer code. Finally, the sixth chapter explores different policy and technology scenarios and introduces the decision-making process for sustainable transportation systems' design.

CHAPTER II

BACKGROUND AND PROBLEM DEFINITION

The goal of this research is to create a parametric modeling and simulation environment for transportation demand and climate impact forecast and scenario exploration. The scope is multimodal intercity transportation in the continental U.S. The literature provides a myriad of models and approaches which could potentially be used to achieve this goal. A demand forecasting tool including multiple modes of transportation needs to be created and integrated with fleet models of sufficient granularity to better predict the transportation system's climate impact and be able to quantify the effect of policies and technologies. A short history of policies aiming to reduce transportation emissions is presented in the following section. Then, integrated assessment models are introduced as a way to assess the effect of policies. Finally the different building blocks necessary to create the relevant integrated assessment tool are presented. They include demand and fleet models to quantify emissions, and climate models to quantify the climate impact resulting from these emissions.

2.1   Climate Policies

Climate policies are often implemented nationally and by sector. The first carbon tax was introduced in Finland in 1990. In the U.S., states have started to join forces and introduced regional programs. Nine states (Connecticut, Delaware, Maine, Maryland, Massachussets, New Hampshire, New York, Rhode Island, and Vermont) participate in the Regional Greenhouse Gas Initiative (RGGI) launched in 2009 to achieve power sector CO_2 emissions 10 percent below 1990 levels by 2018. Under the Midwest Greenhouse Gas Reduction Accord six states and one Canadian province developed a cap-and-trade system. Under the Western Climate Initiative, seven states

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and four Canadian provinces were planning to reduce emissions from electricity and large industrial and commercial sources and expand the program to emissions from transportation and residential fuel use.

The transportation sector is one of the main targets for climate policies due to its significant contribution to emissions of greenhouse gases. In the case of the U.S. air transportation system, the International Civil Aviation Organization (ICAO) Committee on Aviation Environmental Protection (CAEP) has defined Landing and takeoff (LTO) emissions standards for soot, unburned hydrocarbon (UHC), carbon monoxide (CO) and nitrogen oxides (NO_x). While no regulations for cruise emissions have been established yet, they are likely to be proposed in the future [27]. Other regions have already implemented policies on carbon dioxide (CO_2) emissions. This is the case in Europe where domestic flights have recently been added to the European Trading Scheme (ETS) in order to achieve the goals set by the Kyoto protocol. Under the Kyoto protocol, Annex-I countries (which includes the industrialized countries that were members of the Organisation for Economic Co-operation and Development (OECD) in 1992, plus countries with economices in transition) agree to maintain their emissions below a predetermined level. Emission Trading Schemes are market-based policies. They encourage efficiency improvements and technological innovation [172]. Allowances are allocated to airlines based on historic average of emissions. A large portion of these allowances are free, the rest is auctioned. Due to the recent economic crisis and the associated drop in demand, the price of carbon remained lower than expected. Studies on the impact of this cap and trade program have been conducted recently [104, 151]. Carbon taxes are policy instruments that put a price on greenhouse gas emissions. It may be argued that the gasoline tax is essentially equivalent to a carbon tax [110].

Ground vehicles are also subject to regulations. The Corporate Average Fuel Economy (CAFE) regulation was introduced in 1975 following the oil crisis. The

CAFE standards apply to car manufacturers that sell over 10,000 light-duty vehicles (LDVs) and put a limit on the fleet average fuel efficiency of the vehicles that can be sold in a year [41]. The Environmental Protection Agency (EPA) defined standards under the Clean Air Act Amendments in 1990. These amendments limit emissions of CO, NO_x, and particulate matter (PM), which consist mostly of black carbon, formaldehyde (HCHO) and non-methane organic gases or non-methane hydrocarbons. The states are responsible for implementing plans [42]. Under the Clean Air Act, fuels are better refined, car manufacturers are required to build cleaner cars, and inspection and maintenance programs are introduced in areas with high pollution [88].

The purpose of these policies is primarily to maintain a healthy level of pollution especially in highly populated regions. A transition is happening towards more global climate concerns. In both cases, policies encourage new technologies and higher fuel efficiency. Other policies might encourage mode shift. An example is suggested by Jamin et al. [76], where high speed rail transport is used as a substitute for some short-distance flights. In order to reduce the impact on climate, multiple options exist such as carbon sequestration, hydrogen based technologies, and advanced transportation technologies [39].

Observation 1: Climate policies on transportation have been implemented and future policies are actively discussed.

In this research, the focus is on transportation policies that would affect the cost of transportation, such as cap-and-trade systems and carbon taxes, which are environmental mechanisms that put a price on emissions. These policies are discussed in more detail in Section 6.1.1. They encourage more efficient travel through an increased market share of fuel efficient modes of transportation and vehicles in the fleets. Therefore there is a need to model and quantify the potential effect of policies in an integrated assessment of transportation.

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2.2 Integrated Assessments

Climate impact assessment is challenging because it requires information from various fields of study. For example in the case of transportation, socio-economics define human activity, aeronautical and automobile engineering define the efficiency of the vehicles used to perform different trips and the resulting emissions, and climate science quantifies the effects of these emissions on the energy balance of the planet. Integrated assessments gather this information and provide decision makers with the necessary knowledge. With the growing environmental concerns and the emergence of climate policies, integrated assessments are increasingly needed [35]. They can be materialized into a tool called an Integrated Assessment Model (IAM).

IAMs are a set of models that integrate different aspects of a system, including socio-economics, technologies, and policies. IAMs date back to the early seventies with the club of Rome models. The club of Rome, founded in April 1968, is a group of politicians, diplomats, scientists, economists and business leaders from around the globe. One of the first models is the World Dynamics developed by system dynamicist Jay Forrester following a meeting with the club of Rome. IAMs are widely used for climate impact assessment, climate policy, and decision making by researchers and decision makers in a wide variety of disciplines. Consequently, IAMs differ in scope. As described by Rothman and Robinson [141], they can include parts or the entire cycle: human activity, pressure exerted, change of state, impacts, response. They have sectoral and regional boundaries. Depending on their spatial and sectoral resolution, as well as the level of detail used for technology, policy representation can be uneasy because the resolution may be unsuitable for the type of policy that is to be explored. The resolution of assessment models is often coarser than the resolution required for policy making. For instance, spatial resolution at the continental scale is unsuitable for decisions made by countries. Similarly, decisions are often made by sector, which requires enough sectoral resolution. With enough detail, it becomes

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possible to introduce policies that regulate a specific metric (such as fuel efficiency, cited as an example by Parson [126]).

The main limitation of IAMs is the difficulty in establishing credibility [140], and their associated uncertainty. IAMs use approximations of the system's behavior in order to enable fast comparison of policy scenarios with relatively simple and transparent tools [40]. Many IAMs simply use an energy per GDP factor as the only technology variable. The results from IAMs are only as good as their underlying assumptions and parameter values. It is thus important to wisely select the right model for the purpose of the research. Table 1 gives a list of existing IAMs, and their scope (for a more complete description of availale IAMs, see Reference [125] and Table 1 in Reference [35]).

IAMs can help with the analysis of different climate policies. The choice of the right IAM is crucial and tradeoffs must be made between the right sectoral and regional level of detail and the ability to explore different scenarios and variables. In some cases it may be wise to use an existing IAM, in others it may be necessary to develop a new IAM with existing tools matching the scope of the research. Most IAMs are ill-suited to examine potential travel demand changes and travel mode shifts given climate policies and changes in fuel prices, as they rarely establish the link between demand and its drivers such as fuel price and technology investment decisions [30]. Furthermore there is no IAM readily available that matches the desired scope and level of detail required for this research.

Observation 2: There is a lack of IAM tools available to assess the effect of policies on the multimodal intercity transportation in the continental U.S.

Therefore a new integrated assessment model for the continental U.S. intercity transportation system needs to be created. As described by Dallara et al. [29], the following building blocks are needed to quantify climate impact:

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Table 1: Existing IAMs and their scope

IAM	Scope and goal	Reference
DICE	Global model for identification of optimal emissions reduction trajectories, valuation of information, and policy evaluation under uncertainty	[122, 45]
NICE	Critique and extension of DICE	[44, 45]
TIME	Generation and evaluation of energy sector scenarios	[33]
ICAM	Assessment of uncertainty, including implications for different regions and interest groups	[35]
IMAGE	Focuses on complex atmospheric, climatic and physical effects and feedbacks distributed in 13 World regions	[181]
FREE	Investigation of implications of bounded rationality, embodied energy requirements, depletion, and endogenous energy technology	[45]
GCAM	Long-term, global, technologically detailed, partial-equilibrium model. It has a resolution of 14 World regions and includes industrial, buildings and transportation sectors.	[115]
AIM	Policy assessment tool for aviation, environment and economic interactions at local and global levels	[2]

- A multimodal demand model to forecast the demand for each long-distance mode of transportation. Quantifying travel need is indeed the first step in the process.

- Fleet models to forecast the fuel consumption and resulting emissions due to the travel demand. Fuel burn is indeed quantified based on demand and the fleet composition.

- A climate impact module to quantify the impacts of these emissions on the atmosphere. Different metrics may be envisioned and will be discussed in detail in Section 5.2.1.

Each of these building blocks are further described in the following sections.

2.3 Transportation Demand

Transportation Demand models have been the topic of many research efforts. A wide variety of models has been proposed, which leads to the following research question:

Research Question 1: What methodology is the most suitable for Transportation System-of-Systems Demand modeling?

2.3.1 Existing Tools for Transportation Demand Modeling

2.3.1.1 Multinomial Logit Model

Mode choice decisions have been studied both at the city and intercity scales. Well established mathematical formulations are used by transportation engineers to predict mode shares and demands. The most widely used is the multinomial logit model. In this model, travelers make decisions based on the utility of each alternative. Utility is an indicator of value to an individual [83]. An alternative is chosen when its utility is higher than other alternatives' utilities. Based on utilities, it is possible to predict which mode would be chosen for a given trip, as depicted in Figure 2.
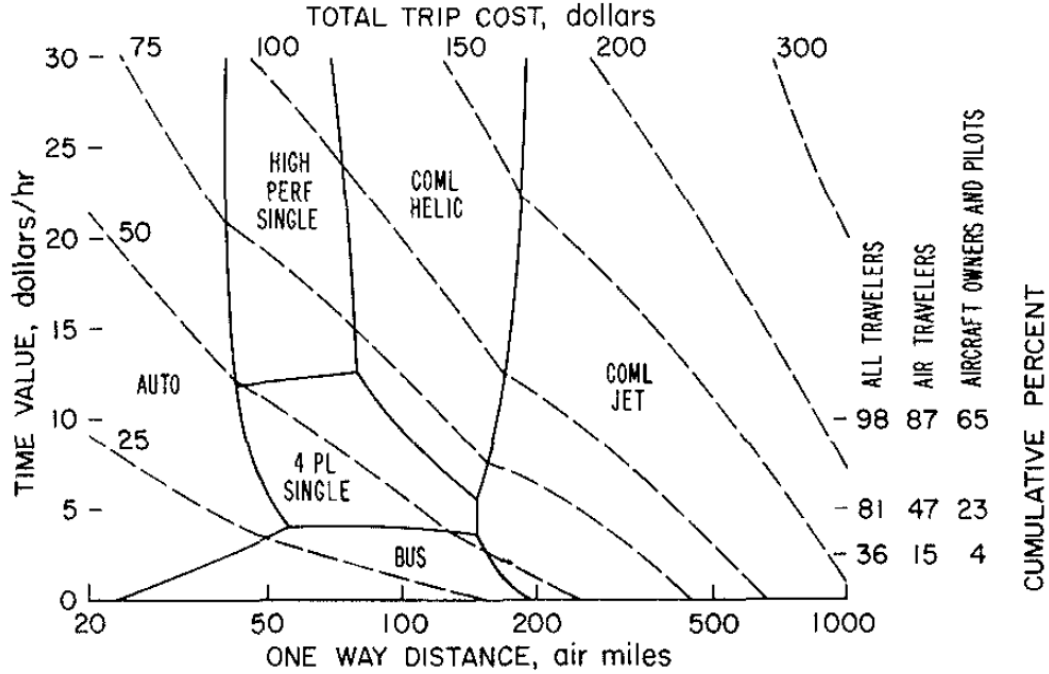
Figure 2: Example of time-value chart [36]

However, this deterministic approach does not take into account the lack of information and understanding of travelers' decisions. Therefore, probabilistic choice theory is used. The probability $P(k)$ of choosing alternative k from a set of alternatives i=1,2,...,N is:

$$P(k) = \frac{e^{U_k}}{\sum_{i=1}^{N} e^{U_i}} \tag{1}$$

where U_i is the deterministic component of the utility of alternative i.

This deterministic portion depends on individual characteristics, the attributes of the alternative and an interaction term between the attributes of the alternative and the characteristics of the individual. The attributes of the alternative are travel time, travel cost, access distance, transfers required. These attributes are weighted to generate the utility. The characteristics of the travelers include their income, age, and number of adults in the household. Interaction effects may include the value of time, which defines the importance of the cost of travel relative to the time of travel. An error term is added to account for the fact that the analyst cannot fully

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comprehend travelers' decisions. This error term captures many factors, which have relatively little impact on the value of each alternative. The central limit theorem suggests that the sum of these small errors will be distributed normally [83]. This leads to the Multinomial Probit probabilitic choice model, which is mathematically complex. Thus, an alternative model, the multinomial logit model is used. In the multinomial logit model, the error term is assumed to be Gumbel distributed, and error components are identically and independently distributed both across alternatives and individuals. The Gumbel distribution is chosen for its similarity to the normal distribution and closed form probabilistic choice model [83].

2.3.1.2   Four Step Model

A common approach to transportation forecasting is the four-step model, pioneered by Mitchell and Rapkin (1954) [116]. The four steps are trip generation, trip distribution, primary mode choice and trip assignment. Trip generation computes the trip frequency based on demographics and socio-economic factors. Trip distribution matches origin with destinations using models such as the Fratar model or a gravity model function. Mode choice computes the modal share for each origin and destination combination. These first three steps determine the transportation demand profile (origin/destination matrix for each mode of transportation). The last step determines the exact route used. This type of model has been used for a large number of studies, mostly at the intra-urban scale but also for intercity travel. For example, Stopher and Prashker (1976) [159], Koppelman (1990) [84] and Baik et al. (2008) [11] explored the US multimodal demand including automobile, commercial air transport, train and general aviation, and using different geographic granularities (metropolitan statistical areas, counties). Models using this traditional four step approach share the same structure and would thus result in predetermined volume, frequency and destination profiles of trips given socio-economic conditions.

Other models of the transportation system exist such as the Transportation System Analysis Model (TSAM) [12], which is a nationwide transportation planning model that forecasts travel behavior in the United States up to 2030, and includes multiple modes (automobile, commercial airline, air taxi and rail). It gives county-to-county passenger demand, as well as airport-to-airport passenger demand for air transportation modes [167]. On the ground side of transportation, models such as CORSIM (CORridor SIMulation) and TRANSIMS (TRansportation ANalysis SIMulation System) simulate traffic and detailed movements of people through the transportation network [90].

Recently, a new approach appeared using Agent-Based Modeling, which implements steps similar to the Four Step Model, but at the microscopic level and in a different order. This modeling approach seems particularly appropriate due to the various sentient entities that are involved in the transportation system.

2.3.2   Agent-Based Modeling

2.3.2.1   *Formulation*

Agent-based Modeling (ABM) is a bottom-up modeling technique, which aims to capture emerging behavior from a set of relatively simple rules. It is especially well suited for complex systems with interactions between agents that are difficult to fully comprehend. The main building block is the agent, which is defined as an entity that interacts with a given environment. It is adaptive, which means it can use experiences to improve its capabilities, and it is autonomous, which means it can act without guidance. As depicted in Figure 3, the agent senses its environment and makes a decision to act in a certain way, therefore potentially changing this environment. The agent then captures these changes and updates its knowledge, leading to a new action or a new goal. This results in emergent behavior, which

provides information otherwise difficult to capture.
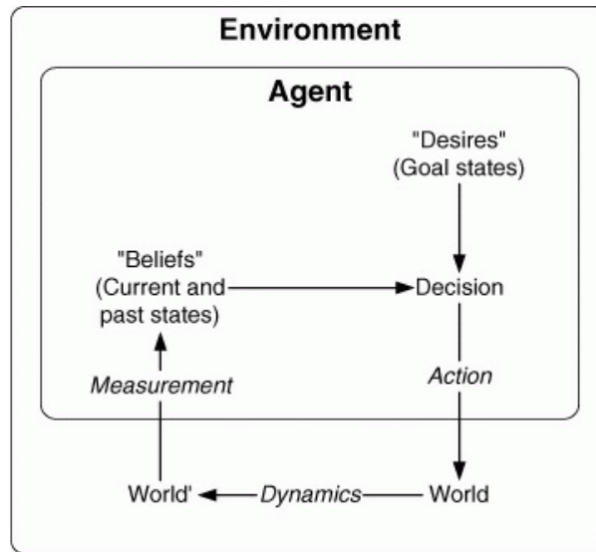
Figure 3: Agent interaction with environment [26]

Most systems are composed of multiple agents. They may be independent and only interact individually with the environment. But in many cases they interact with each other. One example of such interaction is the behavior of a flock of birds, in which case the pattern emerges from the simple interaction rules followed by each bird to avoid collision with other birds and stay within the group. This interaction between agents is called the information layer. Agents interact with the environment and the information layer. There may be multiple information layers, representing separate groups of agents. An example is the stock market where individual and institutional investors form different groups [90]. Finally in some cases, there may be a "super agent" that defines a top-level information layer through which it interacts with lower level agents as depicted in Figure 4.

2.3.2.2   Applications

Since the 1980s, Agent-Based Modeling has been increasingly applied across many different fields including natural sciences, social sciences and engineering. For example, in natural science, Fishwick et al. [47] used individual-based models (which is

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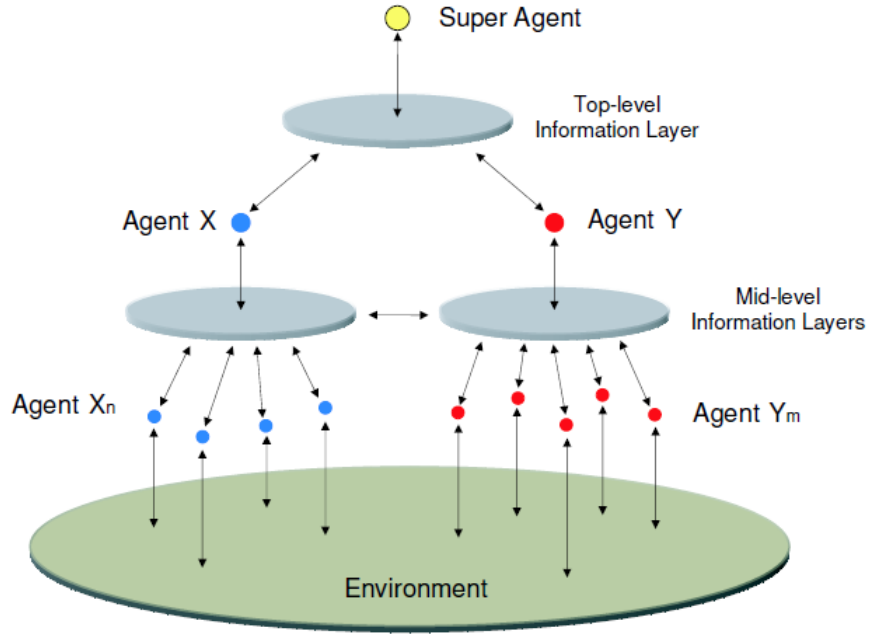
Figure 4: Multi-agent system with hierarchical organization [90]

another name for agent-based models) to model the Everglades ecosystem. In social sciences, Helbing et al. [66] modeled crowd behavior in a panic situation. An example of engineering application is the TRansportation ANalysis Simulation System (TRANSIMS) developed at the Los Alamos Laboratory. TRANSIMS is an agent-based model model that simulates traffic through urban areas. Other transportation applications include Jet:Wise and *Mi*. Jet:Wise is an agent-based model that captures the airline industry's interactions with the National Airspace System (NAS) [121]. Its outputs include fleet mix, itineraries, schedules, and fares. It models two types of passengers, business and leisure. While the focus of this model is on the airline, it can be used as a scenario generator for inputs to other simulations using models such as the Total Airport and Airspace Modeler (TAAM) [16] or the Detailed Policy Assessment Tool (DPAT) [176] that focus on traffic and trajectory. Another agent-based model, which focuses more on the passenger demand for different modes of transportation is the *Mi* model [90]. *Mi* is capable of generating the demand for

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multiple modes of transportation between Metropolitan Statistical Areas in the continental United States, based on socio-economic characteristics of agents (travelers) and mode performance. More detail is provided in the following section.

2.3.2.3 Agent-based Modeling for Transportation Demand

Many entities, subsystems and stakeholders are involved in the transportation SoS, making it suitable for an agent-based approach. In demand forecasting, the main actors are the travelers. An agent-based modeling approach is well suited to represent individual households with given geographic, demogaphic and socio-economic properties, as has been done in the model **Mi** developed at the Georgia Institute of Technology. This model was initially created for a study on the personal air vehicles under the ground rules from NASA's Small Aircraft Transportation System program [91]. It has been modified for general aviation demand [96, 90]. The most recent version of **Mi** uses the Metropolitan Statistical Area (MSA) as a node for the network of transportation and assesses commercial air transportation supply and demand [98, 97]. Each agent in the continental United States chooses a transportation mode to achieve its traveling needs, based on a given mobility budget space (which includes a time and a monetary budget). Transportation demand originates from each household's need to travel and available budget, which is represented by the budget space concept in **Mi**. Agents have unique socio-economic characteristics and have therefore their own unique budget as depicted in Figure 5. They are able to take trips until they reach a given constraint (cost or time constraint). In Figure 5, trips 1-6 can be performed, until the monetary constraint is reached before trip 7.

Mi uses the widely used logit model formulation for mode choice introduced in Section 2.3.1.1. It was calibrated against the 1995 American Travel Survey (ATS) which is the only available multimodal long distance travel survey. Multiyear calibration was performed using a set of databases including T100 [92]. Forecasts were
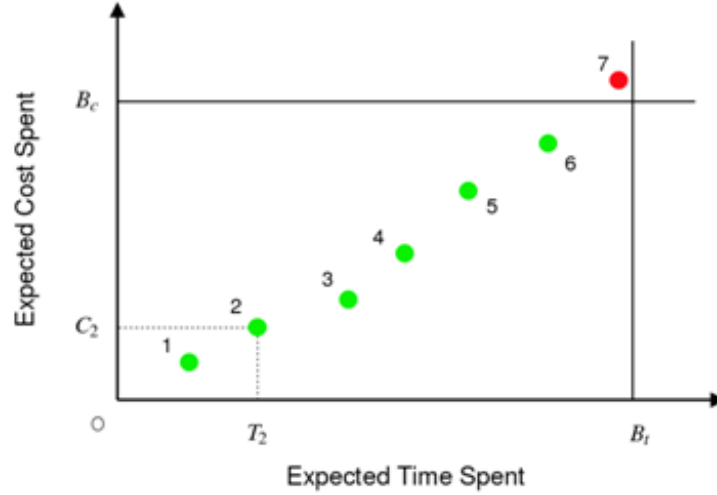
Figure 5: Mobility budget space [90]

compared to FAA's national forecast for commercial aviation, which uses a linear econometric model. Results for both calibration of past data and forecast are shown in Figure 6. Further details on $\boldsymbol{Mi}$ calibration is provided in Appendix A. A convergence study was performed to evaluate the necessary number of batches to obtain convergence of the results at the national and the market level. As mentioned in Lewe et al. [92], a compromise between convergence and simulation time was reached with 24 batches, which represents about 200,000 agents.

$\boldsymbol{Mi}$ is capable of creating the demand for multiple modes of transportations including long distance commercial air transportation and ground transportation. New mode such as general aviation can be added. As mentioned above, the MSA is chosen as the spatial resolution. 204 MSAs are considered. The model output is thus a 204 by 204 origin destination matrix (OD matrix) of total demand for each market. However this bottom-up, micro-level view of the system is inadequate for some macro-level variables such as climate impact and policies implementation. $\boldsymbol{Mi}$ is unable to capture macro-level behavior such as capacity constraints and cannot easily produce time series of demand, which is the desired output in this forecasting effort. Furthermore,

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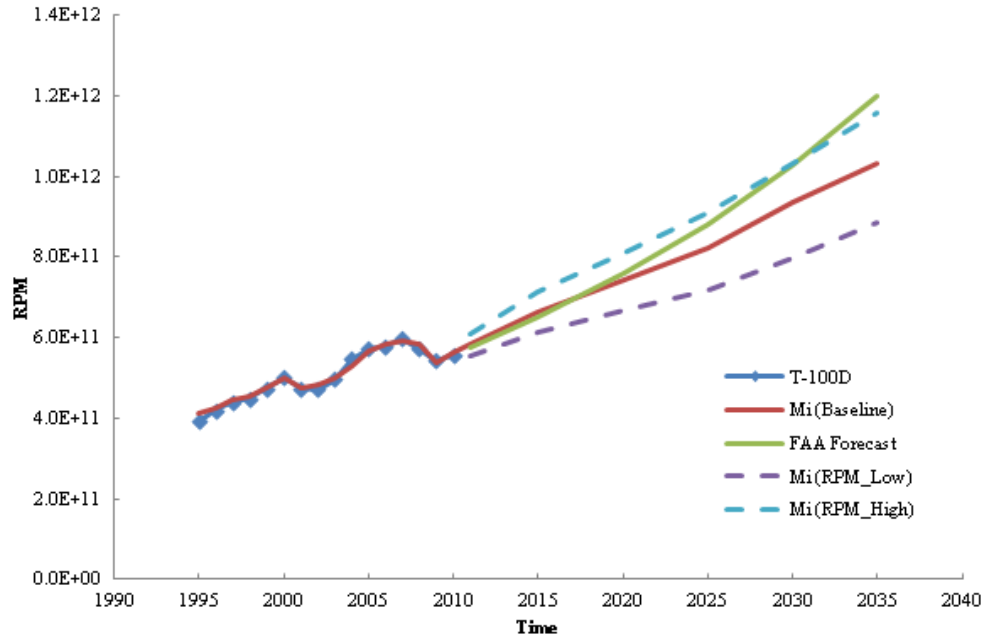
Figure 6: Demand forecast [92]

the very high fidelity modeling capability of **Mi** comes at a high computational cost, which is a showstopper for quick scenario assessment.

As a summary, **Mi**'s ABM approach, which enables to capture consumer behavior in a versatile way, scope (intercity travel in the continental U.S.), availability, and the author's experience and confidence in the model make it a potentially useful tool for this research. However its high computation time makes it unsuitable for an interactive decision-making environment.

Observation 3: An existing ABM is capable of generating the demand for each mode of transportation but its micro-level view and computation time make it unsuitable for interactive policy and technology scenario assessment.

Therefore a new model needs to be created. This model should be able to replicate the behavior of **Mi**, while enabling the assessment of macro-level behavior with limited computational cost. The following section discusses a modeling technique that

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can be leveraged to address these issues.

2.3.3 System Dynamics

As previously introduced, the transportation system is a complex system, with potential feedback loops and nonlinear behavior. Feedback loops describe the fact that a decision changes the state of the surrounding system and results in new information provided for future decisions. Many systems are complex and may therefore be difficult to understand and control. This is the case for the management structure of a corporation, an urban area, a national government, economic processes, etc. [50]. Complex systems are often counterintuitive, may be insentitive to some parameters while being very sensitive to others. They may resist policy changes, compensate for corrective efforts, react differently in the short term and long term to a policy, or even tend toward lower performance. System Dynamics models are needed to capture and understand these types of behaviors.

2.3.3.1 History of SD

System Dynamics has been used for integrated assessments and policy decisions. It appeared in the 1960s as an application of control system theory to complex systems, specifically industrial production and distribution system [49], which includes Forrester's first system dynamics publication on the role of advertising in industrial dynamics [51]. These industrial dynamics models have four main foundations listed by Pfaender [133] and summarized here:

- Information feedback control theory, which was applied to real systems such as electrical systems, hydraulic systems, and was extended to industrial systems which represent virtual elements.

- Modeling of decision-making processes: Forrester explores the effect of supply

chain decision. Oscillations are observed because the system reacts to purchasing decisions with material shortages or surpluses.

- Experimental approach to system analysis: by representing elements and relationships visually, the understanding of the model is more accessible.

- Use of computer simulation: Forrester initiated the use of simulations with differential equations describing the main processes and parameters.

Forrester later applied this theory to model social systems such as urban systems [50]. He then expanded the scope of his research to create the aforementioned World Dynamics model. This model captures a number of non-technical variables such as capital investment, natural resources, quality of life and pollution [133]. The model was used in a book titled "The Limits to Growth" [109] which explores a number of scenarios for human welfare and human ecological footprint from 1972 to 2100. In this book, Forrester concluded that trends in human footprint could be altered to avoid reaching global limits and obtain economic stability and sustainable future, and that the sooner steps are taken, the better it is in terms of sustainability. He also points out that there are particular challenges with emissions of species such as CO_2, which have an unknown upper limit and natural delay in ecological processes. Finally, he argues that the combination of technological developments with checks on growth is the key to better futures. This motivates the use of models to try to predict and quantify the effects of different scenarios.

2.3.3.2 Steps in creating SD model

The developement of a System Dynamics model follows the steps summarized in Figure 7. First, the modeler identifies the main variables, starting with what can be represented as a stock. A stock is traditionally used to model the accumulation of something. A parallel may be drawn with a tank of water with incoming and outgoing flow. A stock represents a state variable as defined in Equation 2:

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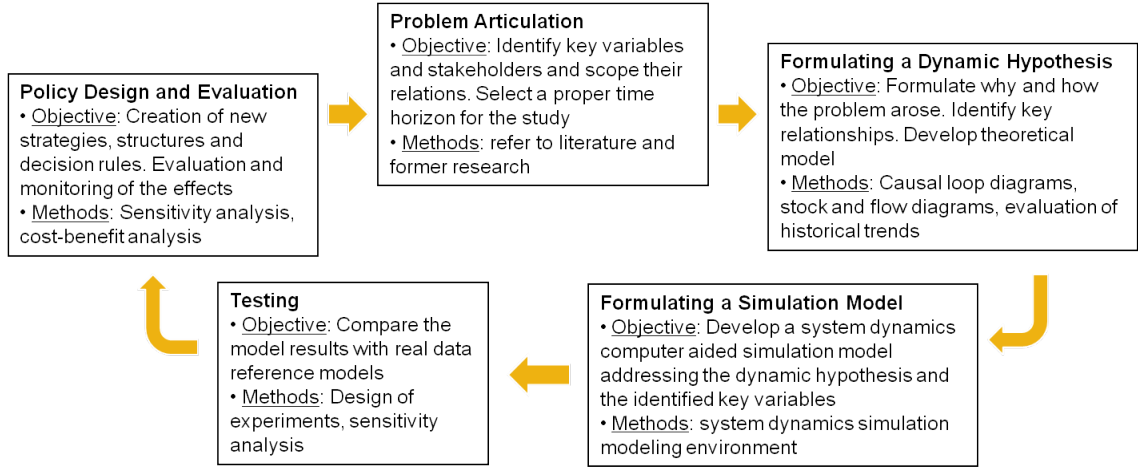
Figure 7: Developing an SD model (adapted from [18])

$$S_t = \int_t^{t_0} (F_i - F_o)dt + S_{t-1} \tag{2}$$

where

S_t is the value of the stock at time t

F_i is the sum of the inflow rates

F_o is the sum of the outflow rates

dt is the time step

Causal relationships between variables are then identified and quantified if possible. This is a challenging step conducted through literature and/or results from other models. The model then needs to be properly calibrated and validated against existing data before being used for policy analysis. As described in Forrester, 1969 [50], a model is a theory describing the structure and interrelationships of a system. The main challenges often lie with validation against the real system. Validation may be done through available experience and data.

2.3.3.3 Relevant applications of SD

System Dynamics has been applied to a wide variety of problems such as decision-making under uncertainty [105], evaluating the impact of decisions and alternatives

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on a system [32], identifying scenarios of interest for policy/strategy evaluation [101], and this across many domains such as socio-economic sciences [52], energy [118], public health [71]. System Dynamics is a suitable technique for IAMs as showed by Fiddaman [45] and the Feedback-Rich Energy-Economy (FREE) model. System Dynamics has been encouraged for transportation applications [5]. It has been used for aerospace application: Lyneis [101] modeled the aircraft market, as shown in Figure 8. This model is built around four main stocks, which are the demand, the operating aircraft fleet, the order backlog, and the fare. Many feedback loops are represented, such as traffic congestion effect on demand.
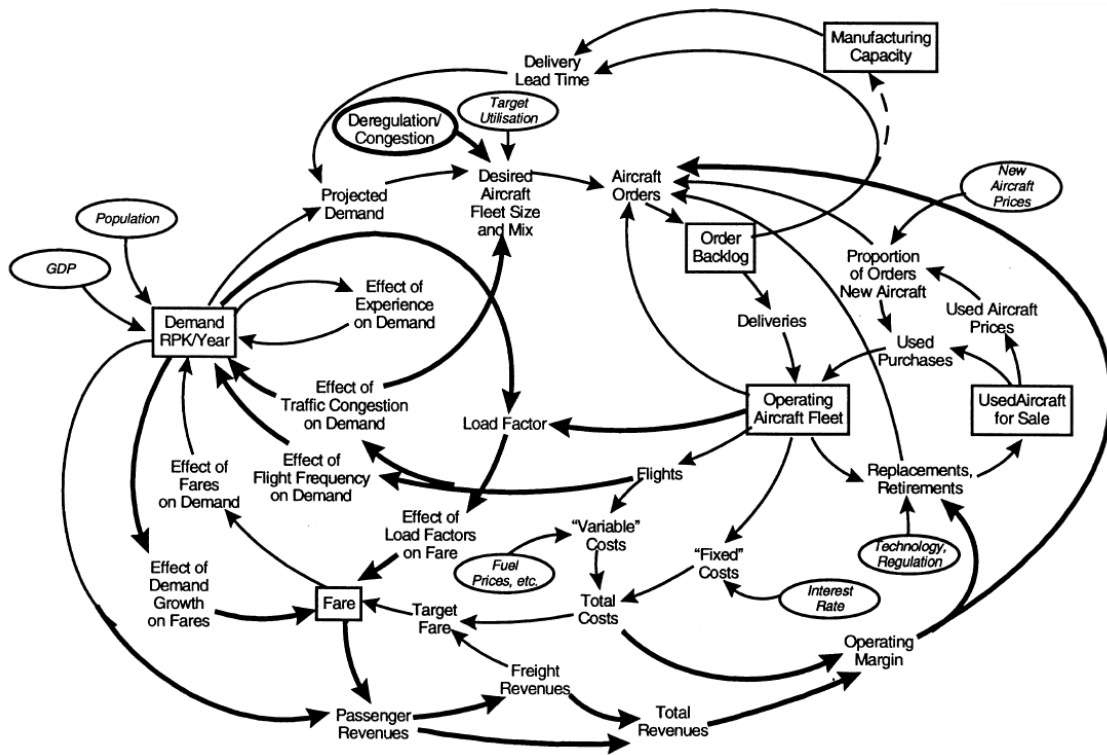
Figure 8: System Dynamics model of aircraft market [101]

Galvin [57] created a system dynamics model to investigate the impact of a Small Aircraft Transportation System on the behavior of future Air Traffic Control system. Bonnefoy and Hansman [19] developed a System Dynamics model that captures airport performance and its impact on other regional airports. Suryani et al. [162]

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created a System Dynamics model to evaluate the future need for additional capacity at Taiwan Toyuan International Airport. Abad and Clarke [4] modeled different portfolios of airspace infrastructure investments for National Airspace System (NAS) modernization.

SD has been adopted for various policy assessment studies aiding policy-makers in reaching an optimum design policy [5]: CO_2 emission mitigation policy for inter-city passenger transport [63], vehicle ownership intervention policy in an urban area [175], congestion pricing policy for a transportation socio-economic system [100], runway and terminal capacity expansion policy [162]. Most SD efforts take transportation demand as an explanatory variable. Different forms exist to serve their own study purposes and scopes: a projection of volume growth rate [63], a simple function of parameters such as GDP and population [62], or more sophisticated sub-models using SD [100, 175, 162]. Because the goal is in general to understand the dynamics of policy impacts rather than obtaining exact values, demand models are not required to be precisely calibrated. Suryani et al. [162], however, calibrated the demand model with historical data but the scope of the model is aviation, at a particular airport. To the author's knowledge, no SD model of the intercity transportation system demand in the continental U.S. is available.

Observation 4: System Dynamics is a well suited approach for modeling complex systems such as the Transportation System-of-Systems.

2.3.4 ABM and SD Summary and Comparison

ABM is an inductive, bottom-up modeling approach, based on a set of agents and interaction rules in a given environment. Due to its flexible nature, it can be used to model a large variety of systems. It enables sophisticated interactions between agents with heterogeneous state space, which often leads to discovery of emergent behaviors. As described in Lattila et al. [87], ABM is the preferred modeling method when actors

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are not homogenous, structure is flexible and complex events exist. The advantages of ABM may be overshadowed by a number of difficulties. The parameterization and validation can be demanding [165], and computational cost is usually very high [124, 135, 136]. Consequently the assessment of a large number of scenarios with ABM is not practical and time progressive simulation is challenging.

In contrast, SD is a top-down modeling approach that focuses on dynamic complexity which arises from the system's structure, feedbacks and time lags [152]. It enables easier model construction and validation but makes assumptions about the homogeneity of modeling entities [165]. As mentioned in Lattila et al [87], SD works particularly well with systems following a policy. Lyneis [101] and Randers and Goluke [137] advocate the use of system dynamics models for forecasting in situations where there is a significant deterministic backbone in the system or dominant structural momentum, which presupposes that the structure of the system determines future behavior with little uncertainty due to noise and complexity. SD is essentially equation-based and needs quantified metrics and relationships between variables, often difficult to obtain for complex systems with unknown structure. On the other hand, in situations with incomplete knowledge of the system's structure, ABM may still reasonably represent the system based on a limited number of relatively simple rules through emergent behavior. The main differences between the two modeling paradigms are summarized in Table 2 (adapted from [145, 146, 87, 124, 134]).

These modeling and simulation methods have been widely accepted and applied to a myriad of topics. In the field of transportation, Agent-Based modeling has been used for travel demand modeling [61] and System Dynamics has been encouraged for policy analysis and decision-making [5]. There has been a growing recognition of using both ABM and SD as a potential approach to model complex systems [147], especially for cases where statistics are not available to feed into the SD model. It is apparent that the complexity of the transportation SoS calls for a hybrid ABM/SD modeling and

Table 2: ABM and SD comparison

Paradigm	System Dynamics	Agent-Based Modeling
Perspective	Top-down	Bottom-up
Level of aggregation	Aggregates (homogeneity)	Individual agents (heterogeneity)
Unit of analysis	System's structure	Agents' rules
Main building block	Feedback loop	Individual agent
Major mechanism	Feedback between different parts of the system	Emergent behavior due to interactions
System structure	Fixed	Flexible
Origin of dynamics	Levels	Events
Handling of time	Continuous	Discrete
Simulation time	Relatively low	Relatively high
Calibration and validation time	Relatively low	Relatively high

simulation framework. This research thus explores the multi-paradigm methodologies through a literature review, and applies a new approach to the transportation system.

2.3.5 Hybrid ABM/SD

As introduced in the above sections, both ABM and SD are suitable techniques for transportation SoS demand modeling (Observation 3 and 4). This leads to

Assertion 1: A hybrid ABM/SD modeling and simulation framework is the most suitable approach to model the transportation SoS demand.

The resulting research question is

Research Question 1.1: How is a hybrid model created?

The first hybrid simulation models combining both ABM and SD appeared in the late 1990s (e.g. Kim and Juhn [82] created a SD model with array variables representing agents). This pioneering work faced a lack of integrated environments and toolsets, especially for ABM, making hybrid models a challenge to build. Integration tools have been developed to facilitate this process and discussed notably

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by Borshchev and Filippov [21], Osgood [124] and Grossler et al. [59] among others. Meanwhile, an interest for multi-paradigm techniques has been building up, demonstrated by the increasing number of discussions, tools, applications and literature reviews for hybrid modeling.

ABM and SD have been used together in a variety of applications: Akkermans [7] developed a model of supply networks in a system dynamics environment using concepts from ABM. Scholl [148] compared ABM and SD results and used the example of the bullwhip phenomenon. Pourdehnad et al. [134] compared ABM and SD in the context of learning and concluded that both are powerful tools. Shieritz and Grossler [145] developed another hybrid model for supply chains and used system dynamics to model agents' schemata. Other applications include cellular receptor dynamics [174], long term firm performance [149], food web evolution [123], the dynamics of diffusion [136], strategy decisions in the automotive industry [81], energy systems [69]. In Teose et al. [165], an Agent-Based Model with an embedded System Dynamics model was used to simulate complex adaptive systems and was applied to epidemiology and ecology.

Some literature reviews have appeared: Schieritz and Milling [146] contrasted SD (modeling the forest) and ABM (modeling the trees), and discussed potential integration of these two fundamentally different approaches. Lattila et al. [87] offered a literature review of hybrid models using ABM and SD and their use in the context of expert systems. Swinerd and McNaught [163] organized various hybrid simulation approaches into a classification that includes the interfaced, the integrated and the sequential hybrid designs. These publications illustrate the recent shift from stitching codes together and simple comparisons to a simultaneous development of hybrid techniques that benefit from the best of both paradigms. As can be seen in the citation graph in Figure 9, the field initially built around a small set of publications and is quickly expanding.

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Figure 9: Hybrid ABM-SD citation graph

In this research, the ABM model Mi is readily available, which leads to the following hypothesis:

Hypothesis 1.1: With proper analysis, derivations, and aggregation, a SD model can be derived from an ABM.

Thus ABM can be used as a supporting tool in the first steps of the SD development that can be challenging. With this approach the shortcomings of both ABM (long computation time, some macro-level behavior hard to capture) and SD (key variable and relationship identification can be difficult to identify) are addressed.

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2.3.6 Model Calibration and Databases

Models used in this research need to be calibrated in order to generate meaningful results. As mentioned above the calibration of an SD model is often the challenging part of the modeling process. This leads to the following research question:

Research Question 1.2: How is rigorous calibration achieved?

This section summarizes databases available for calibration of transportation demand. The most suitable resource for multimodal demand analysis is the 1995 American Travel Survey (ATS). This survey based database provides information on long distance travel patterns of American residents and covers all transportation modes: automobile, commercial air transport, general aviation, train, buses, etc. The 1995 ATS offers a solid reference for calibration of demand models, however it was conducted for 1995 only. Consequently, in order to carry out multiyear calibration of the multimodal transportation model, other databases need to be investigated.

The Bureau of Transportation Statistics (BTS) provides a large amount of data on air transportation. The T-100D is a complete enumeration of the airline domestic operations. This database is crucial to this study as it provides important metrics such as the total Revenue Passenger Miles (RPM). The Airline Origin and Destination Survey (DB1B) database provides a 10-percent sample of airline ticket information from reporting carriers and is the only publicly available database of passenger itineraries. T-100D presents data from the market standpoint, whereas DB1B presents data from the passengers' standpoint.

For ground transportation, it is a lot more challenging to find sets of data on long distance travel behavior. The publicly available databases include the 1995 ATS, the 1995 National Personal Transportation Survey (NPTS), the 2001 National Household Transportation Survey (NHTS) and the 2009 NHTS. NPTS and NHTS provide trip-related data such as mode of transportation, duration, distance and purpose of trip. They also gather demographic, geographic, and economic data for analysis purposes.

The above databases provide transportation demand for different modes, and can be used as calibration data for demand models. In order to generate demand forecasts, the environment in which the consumers live and make decisions needs to be defined. In particular socio-economic variables, such as Gross Domestic Product (GDP), Consumer Price Index (CPI), population, household size, and consumer sentiment using the Michigan Consumer Sentiment Index (MCSI), which define the amount of money a person is willing to spend on travel, need to be quantified. Databases used for these variables are listed in Lewe et al. [92] and may be found in Appendix A of this document.

These databases have been used to calibrate the ABM $\boldsymbol{Mi}$. As a result, $\boldsymbol{Mi}$ can be used as a data generator for calibration purposes, and thus help with the calibration of SD. This is particularly important since the goal is to have a standalone SD model that captures the behavior of $\boldsymbol{Mi}$ with a faster computation time and more macro-level view of the system. Hence the following hypothesis:

Hypothesis 1.2: Through a cross-calibration process, SD can produce results similar to ABM within given ranges.

If this hypothesis is true, then SD can be used as a surrogate of the ABM.

In order to explore the impact of different policies and technologies on transportation sustainability (mobility and climate impact) the output from demand models is used to quantify emissions and climate impact. This leads to the following research question:

Research Question 2: How is the transportation system's impact on the atmosphere quantified?

As introduced in Section 1.1, sustainability is defined as finding the proper balance between current and future environmental, social and economic qualities. In the context of this research, it was narrowed down to mobility and climate impact

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of transportation. In order to quantify the climate impact of the U.S. transportation system, actual fuel burn and life cycle emissions from the different modes of transportation need to be obtained. Fleet models are needed to account for different scenarios in terms of technology implementation, adoption rates and resulting fleet fuel efficiencies. The following section discusses these aspects in more detail.

2.4 Transportation Fuel burn and Emissions Modeling

2.4.1 Transportation Emissions

2.4.1.1 Emissions from Air Transportation

Current commercial aircraft engines burn Jet A-1 fuel, which is a mixture of hydrocarbons (C_nH_m). Combustion of this fuel results in carbon dioxide, water vapor (H_2O) and sulfur oxides (SO_x) for ideal combustion. It also releases unburned hydrocarbons (UHC), carbon monoxide (CO), soot and nitrogen oxides (NO_x). The Jet Fuel Combustion equation is:

$$C_nH_m + S + N_2 + O_2 \longrightarrow CO_2 + H_2O + N_2 + O_2 + NO_x + CO + SO_x + Soot + UHC$$
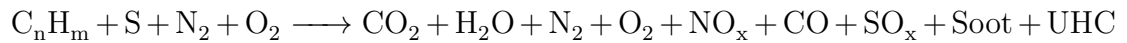
Because the exact quantities of CO_2, H_2O and SO_x are a function of the fuel composition, emission rates for each fuel type can be used to obtain emissions from fuel burn. NO_x emissions can be obtained using empirically derived correlations based on the P3T3 method (which utilizes temperature and pressure information to estimate NO_x emission indexes) and the current inventory combustor data found in the ICAO Engine Emissions Databank (EEDB). More details on NO_x modeling can be found in Reference [131]. Emission rates for other species can be estimated using the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model, developed by the Argonne national laboratory, which provides a life cycle analysis of different modes of transportation. Then the only remaining building block is a fleet forecasting tool to predict fuel burn.

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2.4.1.2 Emissions from Ground Transportation

Similar to aircraft engine combustion, most ground vehicles use hydrocarbons and air and produce carbon dioxide and water vapor under perfect conditions. A typical engine emits unburned hydrocarbons, nitrogen oxides and carbon monoxide. Hydrocarbon is emitted when fuel molecules are only partially burned. Nitrogen oxides are formed from nitrogen and oxygen under high pressure and high temperature conditions in the engine. Carbon monoxide comes from partial oxidation of the carbon in the fuel.

Catalytic converters were introduced in 1975 to decrease hydrocarbon and carbon monoxide emissions. At the same time, unleaded gasoline was introduced because lead was proven toxic and it inactivates the catalysts used in converters [56]. This introduction came with large health benefits. Second generation emission control systems were introduced in 1980 to convert carbon monoxide and hydrocarbons to carbon dioxide and water, and reduce nitrogen oxides to nitrogen and oxygen.

In order to monitor ground vehicles' emissions, tools were developed by the EPA and the Argonne National Laboratory. The MOtor Vehicle Emission Simulator (MOVES), developed by the EPA, estimates emissions from highway vehicles. Simulations can be run to obtain emissions from different vehicle types, road types, weather conditions, etc. MOVES currently estimates emissions for mobile sources (cars, trucks and motorcycles). It covers a broad range of pollutants and enables multiple scale analysis.

With the introduction of the electric car, often advertised as zero-emission car in terms of operating emissions, further considerations are needed to account for the higher relative effect of upstream emissions. The whole life cycle emissions including well to pump emissions need to be accounted for. A new type of vehicle will only reduce emissions if the emission saving during operation is higher than the additional energy consumed in other stages of the life cyle [58]. Life cycle emissions are described

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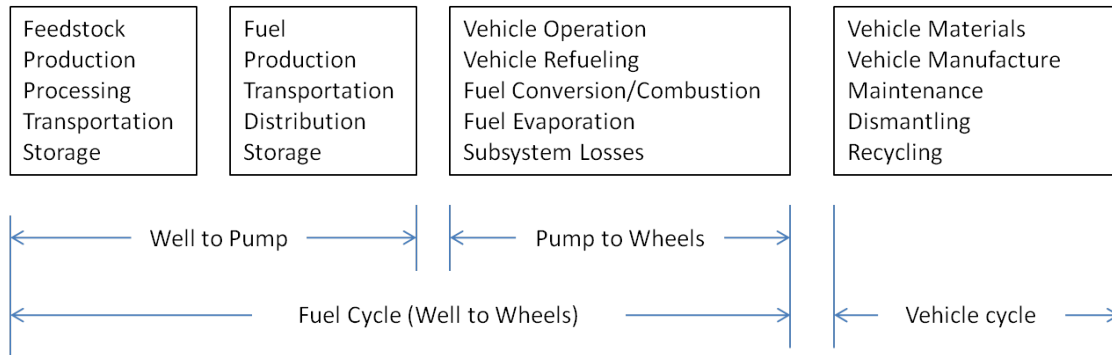
in Figure 10.

Figure 10: Life cycle emissions

The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model, provides a life cycle analysis of the transportation, computing emissions from vehicle usage (pump to wheel) as well as upstream emissions (well to pump). It can simulate passenger cars and light duty trucks for many different fuel systems such as conventional engines, hybrids, plug-in hybrids, electric and fuel cell vehicles.

For each mode of transportation, different vehicle types, and fuel types, will result in different fuel efficiencies and emission factors, which leads to the following observation, research question and hypothesis:

Observation 5: Existing modes of transportation emit a number of gaseous and aerosol species whose quantities vary based on fleet composition.

Research Question 2.1: How can fuel burn and emissions from different modes of transportation be quantified?

Hypothesis 2.1: The integration of parametric demand and fleet replacement models, and the use of life cycle emission factors enables scenario-based environmental analysis.

Fleet forecasting models are thus needed for each mode of transportation. With the fleet composition, fuel burn and resulting emissions, it is then possible to assess

the impact on climate.

2.4.2   Fleet Replacement Modeling

2.4.2.1   Air transportation Fleet Modeling

More fuel efficient aircraft are currently being designed that will be available in a given number of years. When they become available, airlines will start purchasing them based on financial considerations and compliance to noise and emissions regulations. Therefore, in order to quantify future emissions, a fleet replacement tool is needed. The Integrated Dynamics Environmental Analysis (IDEA) model is a SD model that is capable of modeling this fleet replacement. In IDEA, the Net Present Value of aircraft is used and airlines decide to replace an aging aircraft with a new aircraft when it is no longer economically valuable to operate with an aging aircraft. Older, less efficient aircraft with higher maintenance requirements are potentially retired and replaced with newly available aircraft based on financial consideration focused on the acquisition cost and improvements in operating cost amortized over a time period [95]. The outputs from IDEA include fuel burn, CO_2 and NO_x [132]. For more information on the retirement and replacement algorithms, see Reference [77].

IDEA uses results from the vehicle analysis tool Environmental Design Space (EDS), which is a physics based tool that estimates aircraft emissions. EDS uses an engine multi-point design loop with a solver that parametrically design fan and compressor maps, sizes the specified engine cycle, and performs flow-path analysis to estimate the weight of the engine. Once the engine converges on a solution, Numerical Propulsion System Simulation (NPSS) creates an engine deck and the aircraft is flown on a design mission using the Flight Optimization System (FLOPS). Another fleet assessment tool that produces results similar to IDEA is the Aviation Environmental Design Tool (AEDT). AEDT models aircraft performance in 4-dimensional space and time to produce fuel burn, emissions and noise [1]. The Aviation Environmental Portfolio Management Tool (APMT) can take results one step further by estimating

the environmental impact from aircraft operations through changes in health and welfare endpoints for climate, air quality and noise. It models airline and aviation market responses to environmental policy options [103]. For the purpose of this study, which is to quantify fuel burn from different fleet replacement scenarios, IDEA has the appropriate level of detail and is therefore the most suitable tool. It needs to be integrated with the demand model. Results from the demand model need to be inputted into the fleet model to generate fleet replacements. Once the fleet composition is obtained, an average fuel burn can be computed that may have an impact on the ticket price and therefore on the demand. If airlines change their ticket price with fuel burn improvement, a rebound effect on demand will be observed, and iterations between demand and fleet models are needed.

2.4.2.2   Fleet model for ground transportation

With improvements in technologies, emissions are reduced over time due to the replacement of older vehicles with new more fuel-efficient ones. Quantifying and forecasting the rate at which these changes occur is crucial and has been the subject of numerous studies [15, 9, 85]. The market share of different types vehicles, based on their size and fuel type, is an important variable to determine the fuel burn from ground transportation activities [15]. Consequently, a fleet replacement model for the ground transportation, similar to IDEA for the air transportation is needed. Market shares vary with a number of parameters resulting in different life cycle emissions.

Once fuel burn and emissions are quantified as introduced above, the climate impact can be determined. The following section discusses how the different species emitted impact the atmosphere.

2.5   Climate Impact Assessment

The emissions introduced in the previous section affect the atmosphere and may have non negligible impact on climate. A number of studies and tools exist to assess the

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impact of different species on the climate, but they rarely are sector specific. In the context of policy and technology scenario exploration, a sector specific approach is needed. In order to appropriately design the policies, the way the transportation system affects the energy balance of the Earth needs to be understood and modeled with an appropriate level of accuracy and computation time. It is important to choose the right metric for climate impact assessment. Hence the following research question:

Research Question 2.2: What metric is appropriate for transportation climate impact assessment?

The transportation sector impacts the Earth radiative balance through a variety of gaseous and aerosols emissions. These emissions result in Radiative Forcing (RF), a commonly used metric for climate impact assessment, that quantifies the difference between radiative energy received by the Earth and energy radiated back to space. As defined by the Intergouvernmental Panel on Climate Change (IPCC), RF is a change of radiative flux at the top of the atmosphere (TOA) due to an external perturbation.

$$\Delta F = F_{net,pertubed}(TOA) - F_{net,clean}(TOA) \tag{3}$$

where $F_{net,pertubed}(TOA)$ is net flux in perturbed atmospheric conditions at the TOA and $F_{net,clean}(TOA)$ is net flux in clean atmospheric conditions at the TOA.

Positive values of RF imply warming while negative values imply cooling of the Earth-atmosphere system [129]. High values of RF may result in significant changes in climate that would be associated with a number of consequences that are beyond the scope of this research but are discussed in the literature [108, 60]. RF has been used in previous studies on the climate impact of the transportation sector [54].

Observation 6: RF is a standard way of comparing the effects of the various emissions on climate and usually compare present day forcing with pre-industrial times [55].

Considering only CO_2 can lead to non optimum designs for immediate climate

impact [28]. An example is the altitude variation and the tradeoff between fuel consumption and contrail avoidance strategy [6]. As can be seen in Figures 11 and 12, many non-CO_2 emissions are significant and need to be taken into account to increase the accuracy of the climate impact assessment.

Radiative Forcing from Aircraft in 1992
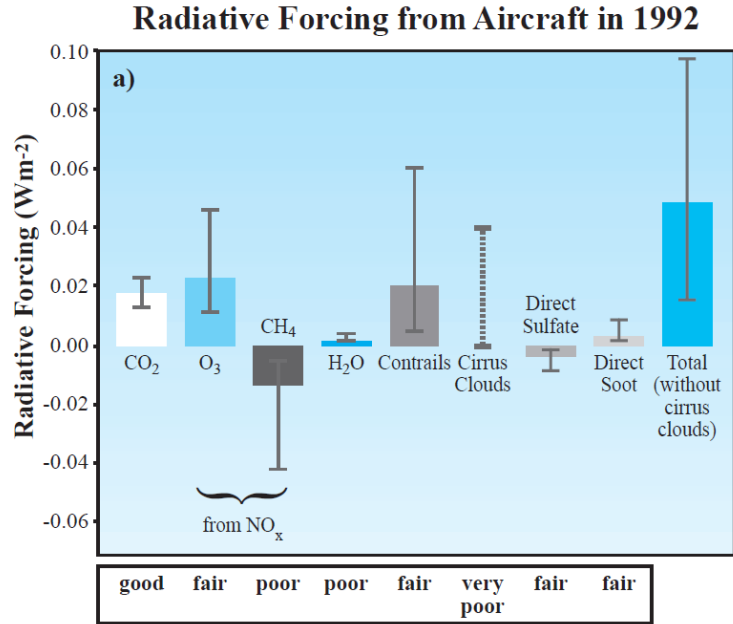
Figure 11: Radiative Forcing in 1992 [129]

2.5.1 Climate Impact of Transportation

The main gas emitted is carbon dioxide (CO_2). It is a long-lived gas in the atmosphere and the location of emission has no effect on its climate impact. At subsonic cruise altitudes, aircraft emitted nitrogen oxides (NO_x) cause the amount of ozone (O_3) to increase, and in turn, results in warming of the atmosphere. Supersonic aircraft flying at higher altitude result in ozone depletion. NO_x emissions also result in methane (CH_4) concentration decrease, which tends to balance the warming effect due to ozone. In addition aircraft have short lived effects such as condensation trails (contrails), which form behind the aircraft under ice-supersaturated atmospheric conditions. They reflect solar radiation and stop outgoing longwave radiation, with the
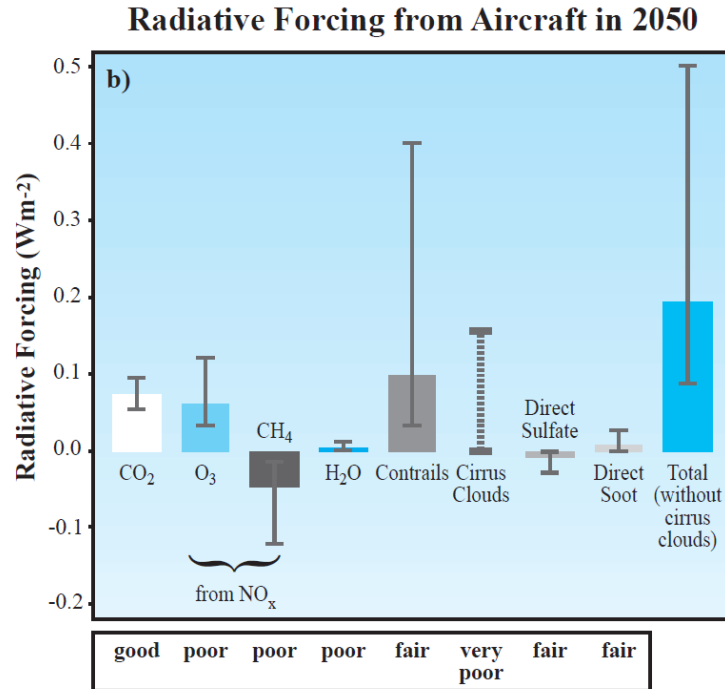
Figure 12: Radiative Forcing expected in 2050 [129]

second effect dominating. With increasing air traffic in the future, it is expected that the impact from contrails will increase. A linear relationship between the RF of contrails and flight distance or fuel burn is often assumed, based on the constant emission factor of water vapor per amount of fuel. However, this assumption may not always hold and many other factors need to be accounted for, such as ambient conditions (tropopause temperature [168], etc.). Another impact that is not well understood is the transition from contrails to cirrus clouds, which could significantly increase the impact from contrails alone if taken into account. Remote sensing techniques have been used to estimate contrail coverage and contrail characteristics, and will be discussed in more detail in subsection 2.5.4. Knowing the coverage and the optical properties (optical depth and effective particle radius), the RF can be computed using the mean fractional contrail coverage per distance traveled or per fuel burned.

Ground transportation also emits both long lived and short lived species that

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affect the energy balance of the atmosphere. The main concern in terms of atmospheric composition is due to nitrogen oxides, non-methane hydrocarbones and carbon monoxides, which are precursors of ozone. In the presence of sunlight, nitrogen oxides result in ground-level ozone, which is a major component of smog [171], as depicted in Figure 13 [170]. Ground transportation emitted species impact air quality at the urban scale, but they also impact the global climate (which is the focus of this research). The major climate impact is through CO_2, similar to aviation, but in much larger quantities (ground transportation, as a whole, results in a much larger total emissions than air transportation). Ozone has a shorter lifetime and is non-homogeneously distributed. A mean impact can be calculated and is usually smaller than the impact from aviation because of the altitude of emission (aircraft emissions occur close to the tropopause) [170]. Due to NO_x emissions, a decrease in methane in the atmosphere is observed. Nitrous Oxide (N_2O) has a small impact on climate in spite of its large warming potential. Ground transportation also emits aerosols which interfere with radiation through reflexion, absorption and scattering. Black carbon is the main aerosol. Some indirect effects of aerosols on cloudiness are possible but much smaller than aviation cirrus induced clouds [170]. Regulating these emissions can result in non negligible climate and health impact as demonstrated by Shindell et al. [153].

Due to the large variety of sources of climate forcing from the transportation sector, emission based metrics (such as total CO_2 emitted) are less useful than RF and temperature based metrics [29]. Therefore quantifying CO_2 emissions is not sufficient and leads to the following assertion and research question:

Assertion 2.2: To fully address transportation climate impact, all gases and aerosols must be considered and Radiative Forcing is an appropriate metric.

Research Question 2.3: What is the RF of the species with the most
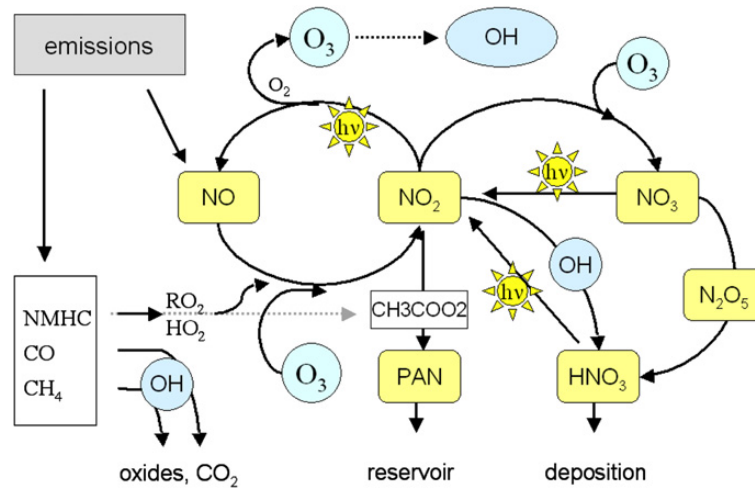
Figure 13: Basic processes in tropospheric chemistry [170]

impact?

In order to quantify RF, climate models are needed.

2.5.2 Climate Models

Climate models help simulate Earth's climate system and predict future climate. They solve the conservation of mass, momentum and energy and radiant exchange in each box of a three dimensional grid [103]. These models provide an increasingly high level of understanding of atmospheric processes, but are computationally expensive. They are located at the top of the climate modeling pyramid presented in Figure 14. They can be integrated with carbon cycle models to better simulate feedback effects. Earth system models of intermediate complexity are simplified models with lower spatial resolution. Some aim to capture a given process such as chemical transport models (CTMs) for atmospheric dynamics. One-dimensional radiative convective (RC) models are single column models which represent the temperature profile of the atmosphere with radiative transfer and convective energy transport. Energy balance models (EBM) are zero or one dimensional models, which perform energy balance calculations between incoming and outgoing radiation of the planet.
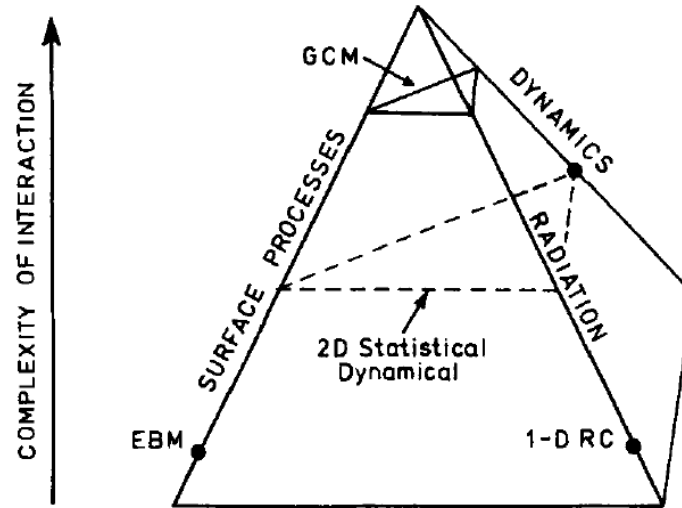
Figure 14: Climate modeling pyramid [154]

Reduced-order approaches used in integrated assessment models include the impulse response function (IRF) and system dynamics (SD) models. The IRF is an expression of the climate response due to a small perturbation [103] and is estimated using carbon cycle models. It has been used in previous studies [107, 143] to help reduce computational time. Other carbon cycle approaches can be envisioned in System Dynamics as done by Fiddaman with the DICE model [45]. Running a full blown climate model can be particularly computationally expensive. Hence, when building an IAM, it is crucial to take into account the uncertainties associated with a given approach as well as computational burden. To compute radiative forcing, radiative transfer codes are necessary. In order to gain a better understanding of how the different species emitted by the transportation modes impact the energy balance of the planet, a short background on Radiative Transfer (RT) theory is provided in the following section.

2.5.3 Principles of Radiative Transfer

The sources of radiations are the sun, which emits in the visible spectrum, and the Earth, which emits in the Infrared (IR) spectrum. When going through the atmosphere, radiation is absorbed and scattered. The energy decreases due to absorption by molecules and deviation of the beam due to scattering. However energy also increases due to emission by these same molecules. The energy flows through the system are represented in Figure 15. A common approximation is the plane parallel atmosphere, which depicts the atmosphere as one-dimensional and bounded at the top and bottom by horizontal plane surfaces.
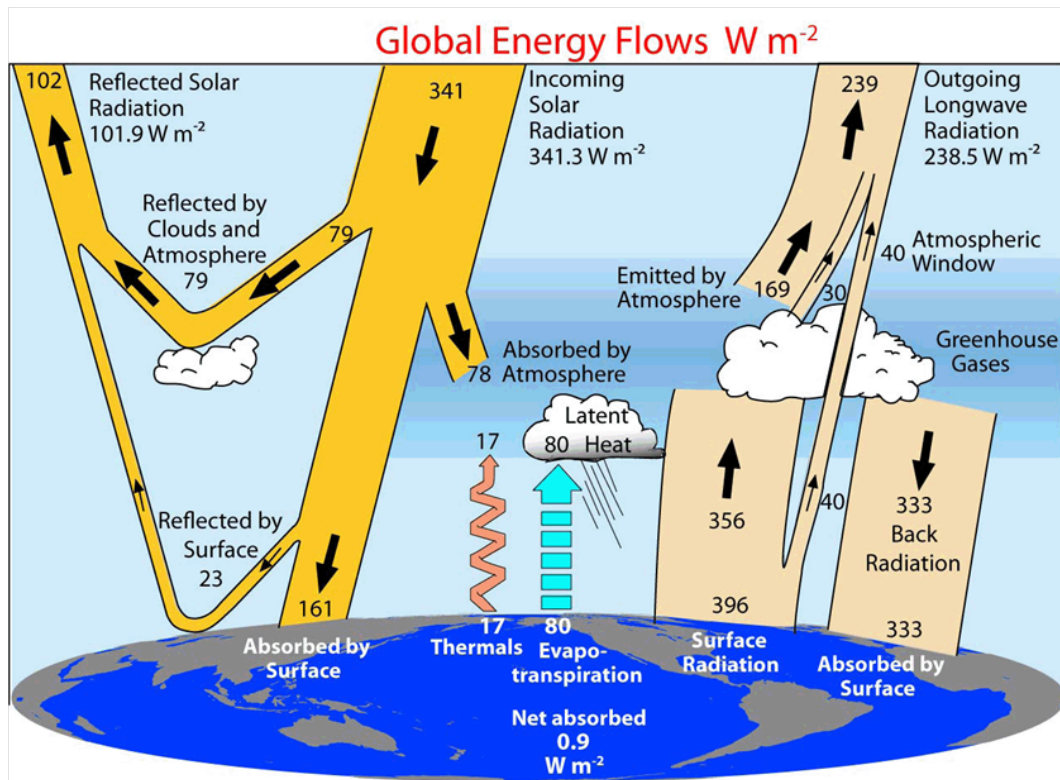
Figure 15: Global annual mean Earth's energy budget for the 2000-2004 period (W.m-2) [169]

Climate is defined as the average state of the atmosphere observed as weather in terms of the mean and its statistical deviations that measure the variability over a period of time [99]. Natural changes may occur due to the solar constant, atmospheric

composition after volcanic eruptions, causing external forcing. Changes due to human activity also cause forcing. Gaseous species that absorb radiation result in forcing. Aerosols interact with radiation by reflecting and absorbing sunlight, and absorbing and scattering IR radiation. They also have indirect effects through their interactions with clouds.

Radiative Transfer (RT) codes are used to quantify Radiative Forcing from these species. The Santa Barbara DISORT Atmospheric Radiative Transfer (SBDART) radiative transfer code uses the discrete ordinate method, a commonly used approach that reduces the full radiative transfer equation to a set of coupled linear first-order differential equations, to solve the equations of plane-parallel radiative transfer in a vertically inhomogeneous atmosphere [139]. It accounts for absorption and scattering from gaseous and aerosol species. Important parameters in the RT calculations include aerosol characteristics, different species concentrations, vertical profiles, surface albedo (which measures the reflecting power of a surface). From the fluxes given by the simulations, the radiative forcing may be obtained.

2.5.4   Remote Sensing

In order to quantify the necessary inputs to the RT calculations, some remote sensing data is used. Remote sensing of the Earth-Atmosphere system with the increasing number of satellites specifically designed for this purpose has tremendously improved the capability to accurately quantify radiative forcing from aerosols. Using remote sensing techniques, better characterization of aerosol physical properties and distribution is possible. Remote sensing is useful for proper setting of the Radiative Transfer codes, such as surface albedo, and aerosol profile. It has been used in previous studies on the Radiative Impact of aerosol: Young et al. [182] studied the regional impact of a volcanic eruption and used data from multiple satellites to properly constrain the radiative transfer calculations. As discussed in [182], the type of surface, solar

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zenith angle and the altitude of aerosols are significant parameters hence the following hypothesis:

Hypothesis 2.3: Radiative Forcing efficiencies vary based on the mode of transportation, location and season of emission.

Radiative Forcing efficiencies are defined as radiative forcing per unit of emitted species.

Some examples of satellites that may be useful include but are not limited to:

- The CALIOP lidar onboard the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) that operates at 532 nm and 1064 nm wavelengths. CALIPSO was developed by NASA and CNES and is on a sun-synchronous orbit at 705 km of height with 15 orbits per day [24]. The analysis from the CALIOP instrument focuses on desert aerosols and smoke (soot and organic carbon mostly). The CALIPSO vertical feature mask is used to determine the location of aerosols in the atmosphere.

- The MODIS instrument onboard the Terra and Aqua satellites may be used to determine aerosol optical depth and horizontal distribution of aerosols.

Both of these are part of the NASA A-Train satellite constellation shown in Figure 16. It gathers some of the most powerful instruments for the better understanding of the climate.

Contrails are visible on satellite imagery as captured in Figure 17 by the Terra satellite over western Europe in April 2010. Based on this image, conditions over the UK and Ireland appeared to have been favorable to the formation of contrails. The National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) split-window pattern recognition technique has been used by Mannstein et al. [106] for detection of line-shaped contrails. The

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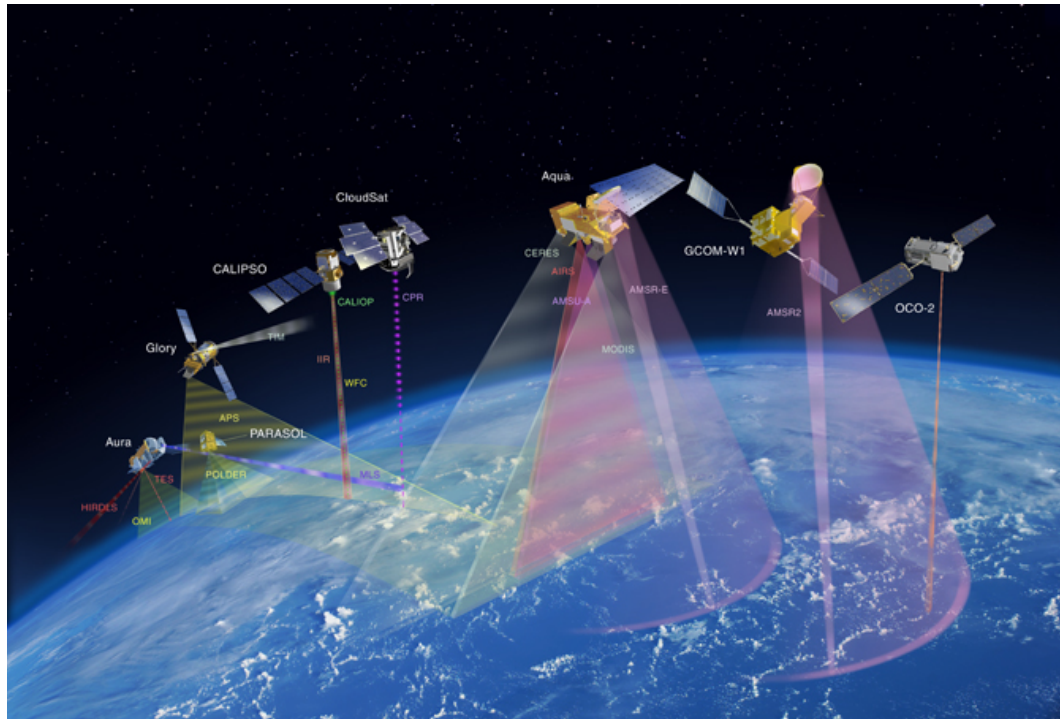
Figure 16: A-Train constellation of satellites (credit:NASA)

Geostationary Operational Environmental Satellite (GOES) Imager Detection Technique was used by Minnis et al. [114] for the detection of persistent contrails and cirrus. Some similar work using NOAA/AVHRR has been accomplished by DeGrand et al. [34] for the 1977-1979 time period and by Travis et al. [168] for 2000-2002. Minnis et al. [113] used an automated contrail detection algorithm (CDA) using the Moderate Resolution Imaging Spectroradiometer (MODIS) data taken by Terra and Aqua over the United States during 2006-2008. Other regions have been studied as well, southern and eastern Asia by Meyer et al. [111], and Western Europe by Meyer et al. [112].

With each one of the previously introduced building blocks (demand, fleet and climate models), it is possible to build an IAM for the U.S. intercity transportation system. The resulting model development will be presented in the following chapters. Once the IAM is completed, it can be used for policy and technology scenario exploration, and answer the following research question:

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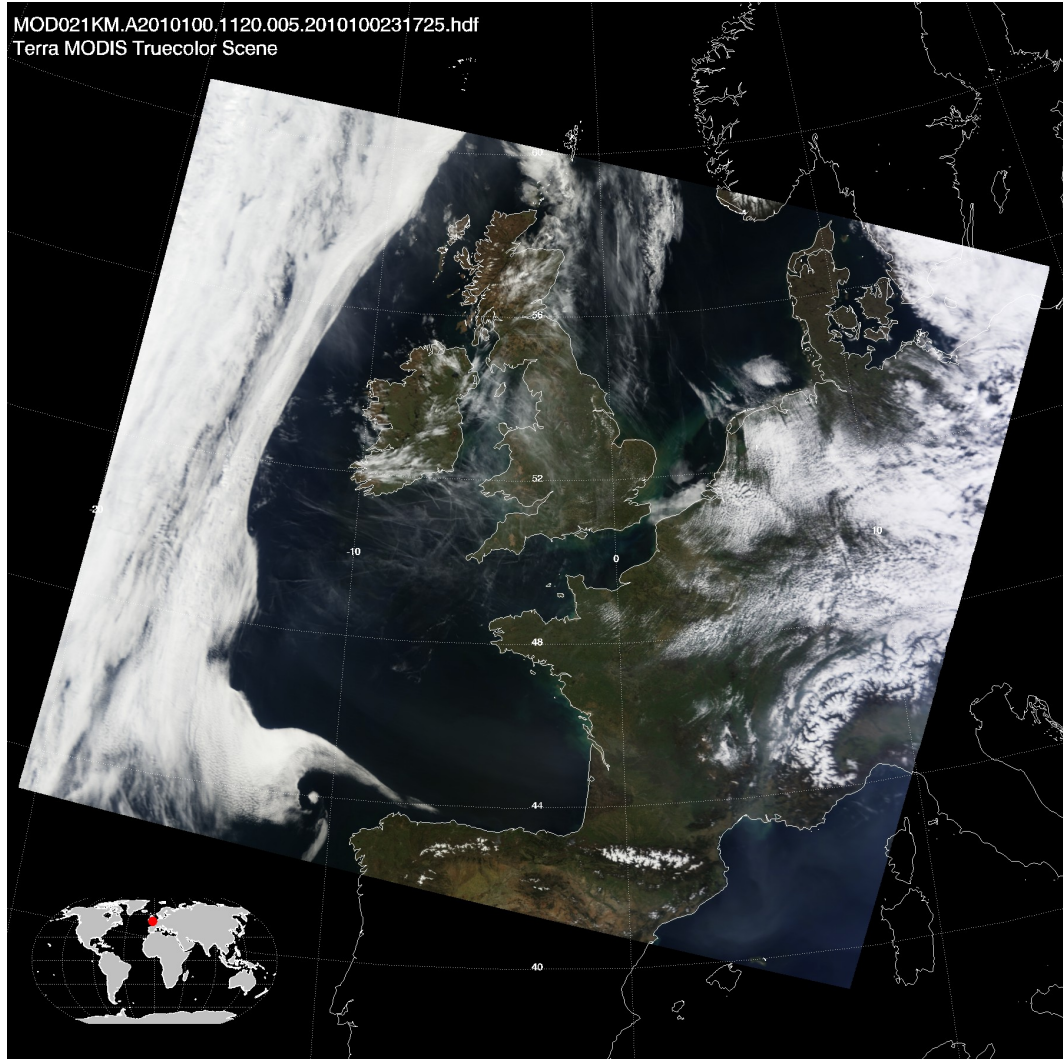
Figure 17: Contrails visible on MODIS image from April 10, 2010

Research Question 3: What are the impacts of policies and technologies on the demand and fleet of different modes of transportation?

A subquestion arises:

Research Question 3.1: Can transportation emissions and climate impact stabilization goals be achieved through market measures alone?

The impact of an increased cost of travel will be explored using different fleet scenarios and the following hypothesis is made:

Hypothesis 3.1: Climate impact goals may be achieved through a combination of technologies and policies.

The stabilization and reduction of emissions and climate impact is one of the multiple attributes to take into account when looking at policies and technologies for the sustainability of the transportation system. It is indeed also important to maintain a certain level of mobility for social and economic welfare of the society. Hence the following observation:

Observation 7: The evaluation of policy and technology scenarios in terms of transportation sustainability involves tradeoffs between climate impact and mobility.

Once the demand and fleet models are integrated and the radiative forcing quantified for multiple policy and technology scenarios, some Multi-Attribute Decision Making (MADM) techniques are needed to help identify the best scenario. More details on MADM are provided in the following section.

2.6 Multi-Attribute Decision Making

Different policy and technology scenarios can be envisioned. Policies may include fuel taxes, or cap and trade systems, which would result in an increased cost of travel, at a given time and with a given value. Depending on socio-economic parameters and fleet fuel efficiencies, the demand for transportation modes and the market share of different vehicles would change. Evaluating and ranking scenarios in terms of climate impacts is necessary to support decision making.

2.6.1 MADM for Policy and Technology Scenarios

Decision making is often associated with tradeoffs and competing objectives, especially in the case of sustainability and policy. There is not a single objective, but multiple, conflicting goals such as increasing mobility while decreasing climate impact. In order to identify the most suitable option based on multiple attributes, established methodologies may be used. Multi Attribute Decision Making (MADM)

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is used when multiple conflicting goals exist. The first step is to identify the objectives, for example reducing cost, increasing demand, reducing climate impact. Then available alternatives are identified. These alternatives may be different technologies or different policies. Finally, alternatives may be ranked based on a scoring system.

Climate policies aim to identify strategies to limit long-term environmental impact and highlight tradeoffs between the main areas involved in sustainability: environmental, economic and social criteria. While one option for policy making could be to aggregate performance indices into a single economic metric, doing so would require to assign a value on variables that are sometimes difficult to compare. MADM, on the other hand, motivates discussions between policy makers by explicitly showing multiple criteria [14].

Bell et al. [14] provide some insight into the need and challenges of MADM. In particular they identify the following considerations as having an impact on the decision being made:

- the choice of metric for decision making

- the granularity of the models

- the spatial and temporal scope

- the physical and socio-economic models and related assumptions

- the treatment of uncertainty

- the visualization of outputs

- the policy and technology alternatives considered

2.6.2 Pareto Frontier

The best alternative will lie along the pareto frontier which defines the set of non-dominated solutions. If the goal is to minimize $F(x) = [f_1(x), f_2(x), ..., f_n(x)]$, a

feasible solution is Pareto optimal if and only if there is no other feasible solution such that $f_i(X) \leq f_i(X^*)$ for all f_i and $f_i(X) < f_i(X^*)$ for at least one f_i. However, it is sometimes difficult to identify which solution on the pareto frontier is best, especially in multiple dimensions. Hence the use of ranking systems.

2.6.3 Ranking System

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a MADM technique developed in the 1980s by Yoon and Hwang [72]. It ranks alternatives based on their Euclidean distance from the positive and negative ideal solutions, as depicted in Figure 18. The positive ideal represents an imaginary design, which combines the best performance attributes of the entire set of designs considered [86]. Similarly, the negative ideal is an imaginary design representing the worst attributes of the set of designs. It is a powerful technique and is widely used. However, it requires to sometimes arbitrarily define the relative weights of each objective, which may have a non negligible impact on the final ranking.

Figure 18: TOPSIS

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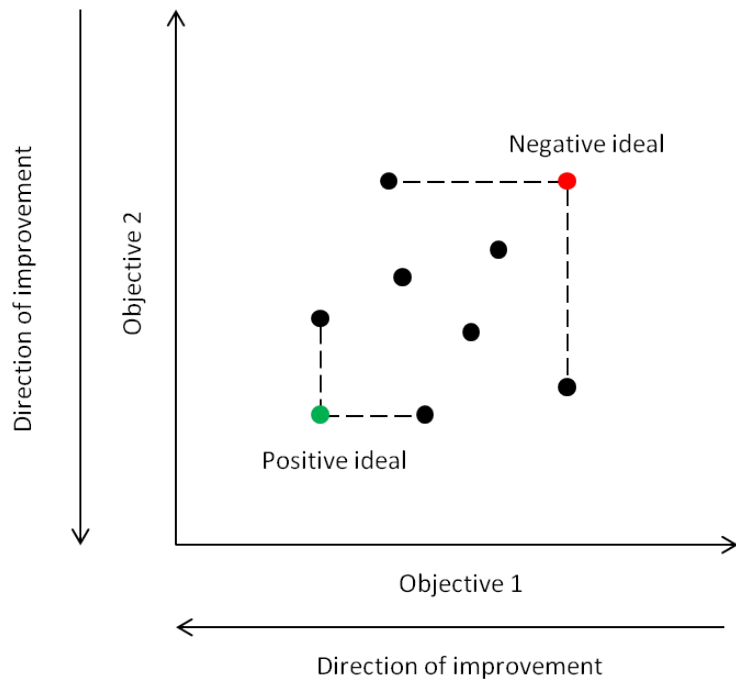
The Analytic Hierarchy Process (AHP) was developed in the 1970s by Saaty. It ranks alternatives based on pairwise comparisons. It can be used for alternatives ranking or objective prioritization and can handle qualitative inputs. However, due to the potentially high number of pairwise comparisons, it can be time consuming [86].

Using MADM, different approaches exist to identify the best set of policy and technology alternative and address the following research question:

Research Question 3.2: How can different policies and technologies be assessed?

Since sustainability is associated with multiple attributes and many interdependencies, the following hypothesis is made:

Hypothesis 3.2: Due to the many interdependencies involved in transportation sustainability, a scenario-based approach is best to assess different policies and technologies.

This will be verified through modeling and simulation as discussed in the following chapters.

2.7 *Summary of Observations, Research Questions and Hypotheses*

The literature review resulted in a number of observations, which led to research questions and hypotheses that will be verified using the modeling and simulation environment developed in this research. A summary of these observations, research questions and hypotheses and how they relate to each other is provided in Figures 19, 20 and 21.
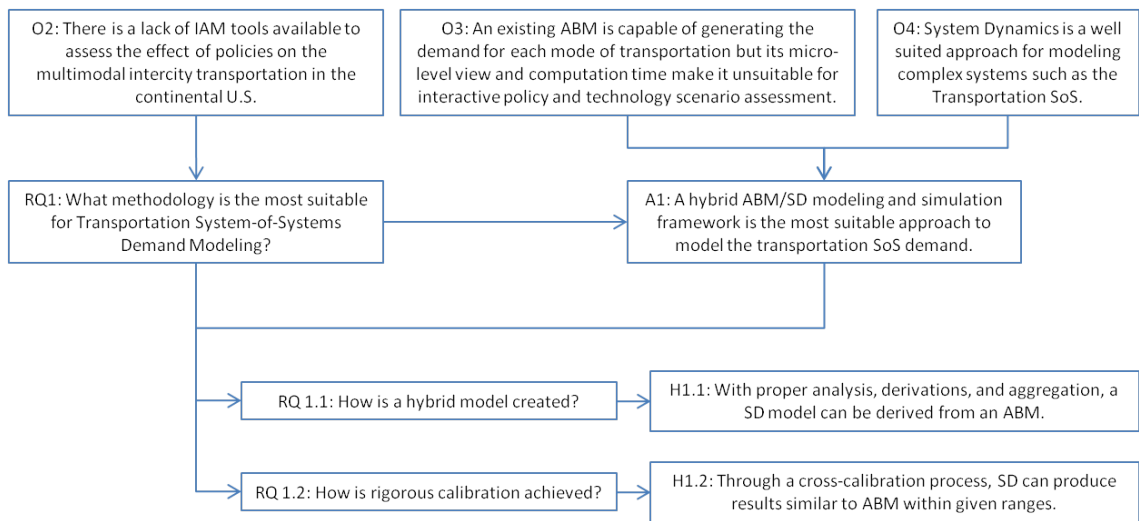
Figure 19: Observations, Research Questions and Hypotheses part 1
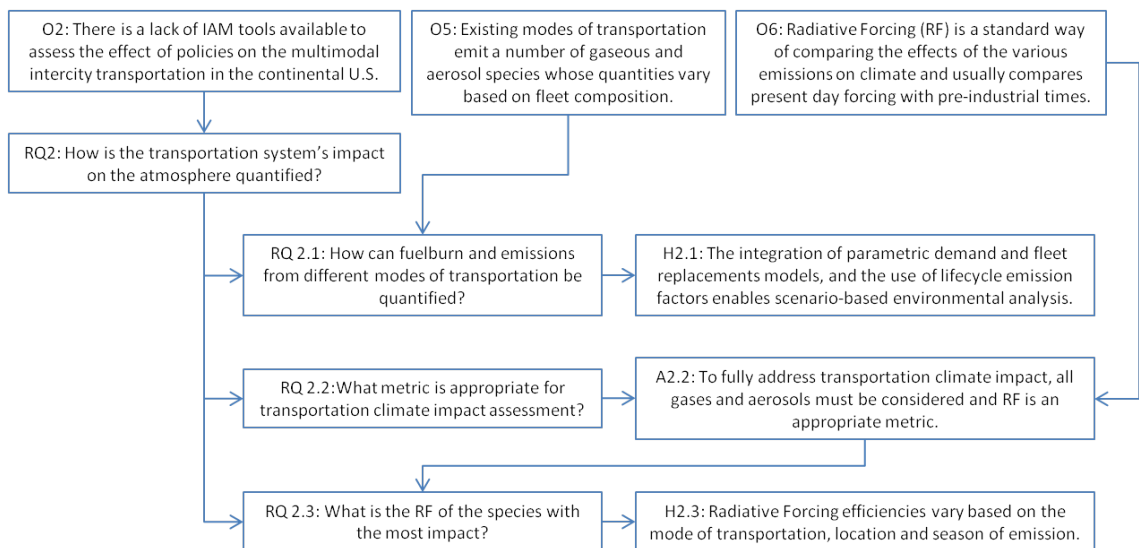
Figure 20: Observations, Research Questions and Hypotheses part 2
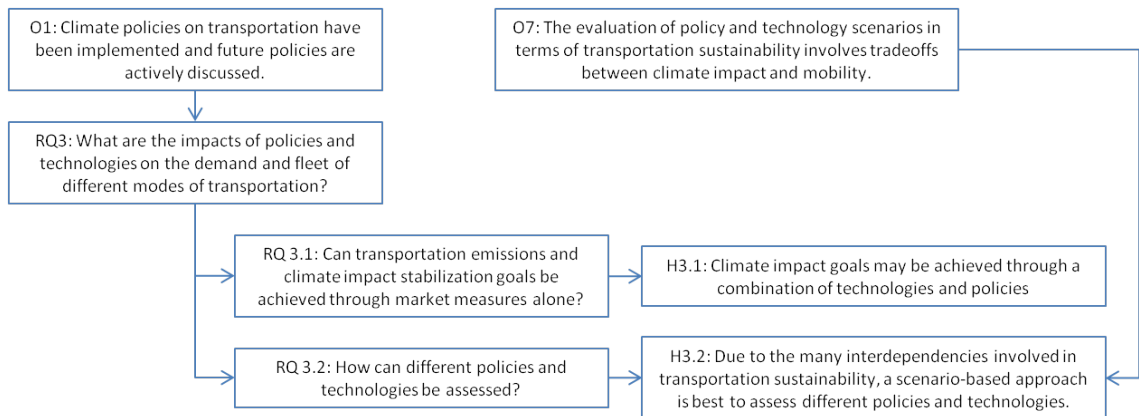
Figure 21: Observations, Research Questions and Hypotheses part 3

CHAPTER III

PROPOSED APPROACH

As introduced in the previous chapter, growing concern about the environmental impact of anthropogenic activity, and more specifically the climate, results in increasing discussions and implementations of policies and technologies. The climate impact and the effect of policies and technologies come with significant uncertainty. In an attempt to gain knowledge and explore interdependencies and potential effects of policies and technologies, modeling and simulation is needed. With an appropriate modeling and simulation environment, multiple scenarios may be explored and thus help address the overarching goal of this research which is to **create a framework for scenario based assessment of transportation demand and climate impact.** A number of models called integrated assessment models aim to quantify climate impact under different scenarios. However their scope and level of details are not always suitable for specific studies. In this research, the focus is on long distance transportation, as this is a significant segment of the economy in terms of emissions and an engine for social and economic welfare of the society.

Research Objectives:

- Generate Transportation Mode Demand for given scenarios.

- Quantify the resulting climate impact.

- Explore a variety of policy and technology scenarios to assess the sustainability of the transportation system.

The methodology proposed in this research aims to support the aforementioned

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research goal and objectives and address the research questions and hypotheses presented in the previous chapter. First, it is necessary to gain insight into the demand for energy in different sectors. In this research, the sector is transportation, and includes different modes of transportation. Then the energy efficiency must be determined. In this research, the changes that airlines may apply to their fleet, as well as ground mode fleet composition are explored. From the demand and the energy efficiency, the climate impact can be quantified. This is the purpose of the proposed framework called environmental Ground and Air Mode Explorer (eGAME), which includes a set of modules necessary to perform this integrated assessment as illustrated in Figure 22. The first step is to generate forecasts of demand for the different modes of transportation under different scenarios including socio-economic variables as well as vehicle design variables. Fuel burn is obtained using fleet models for each mode of transportation and the feedback to demand is explored. Finally the climate impact of emissions resulting from transportation activities is assessed. Based on the observed impact, different policies and technologies scenarios can be implemented and fed back into the demand models to recreate the new demand, emissions and climate impact.

The different steps presented in Figure 22 are described in more detail in the following chapters. The first part of this research will focus on the best available techniques for transportation System-of-Systems demand modeling using a hybrid ABM and SD as introduced in section 2.3. Then the climate impact will be quantified, using a two step process: first, fleet efficiency and emissions will be determined using fleet models as described in section 2.4, then radiative forcing will be quantified using a radiative transfer code as introduced in section 2.5.3. Finally, policy and technology scenarios will be explored in order to show how decision making can be performed using eGAME. An overview of these steps is provided in the following sections.
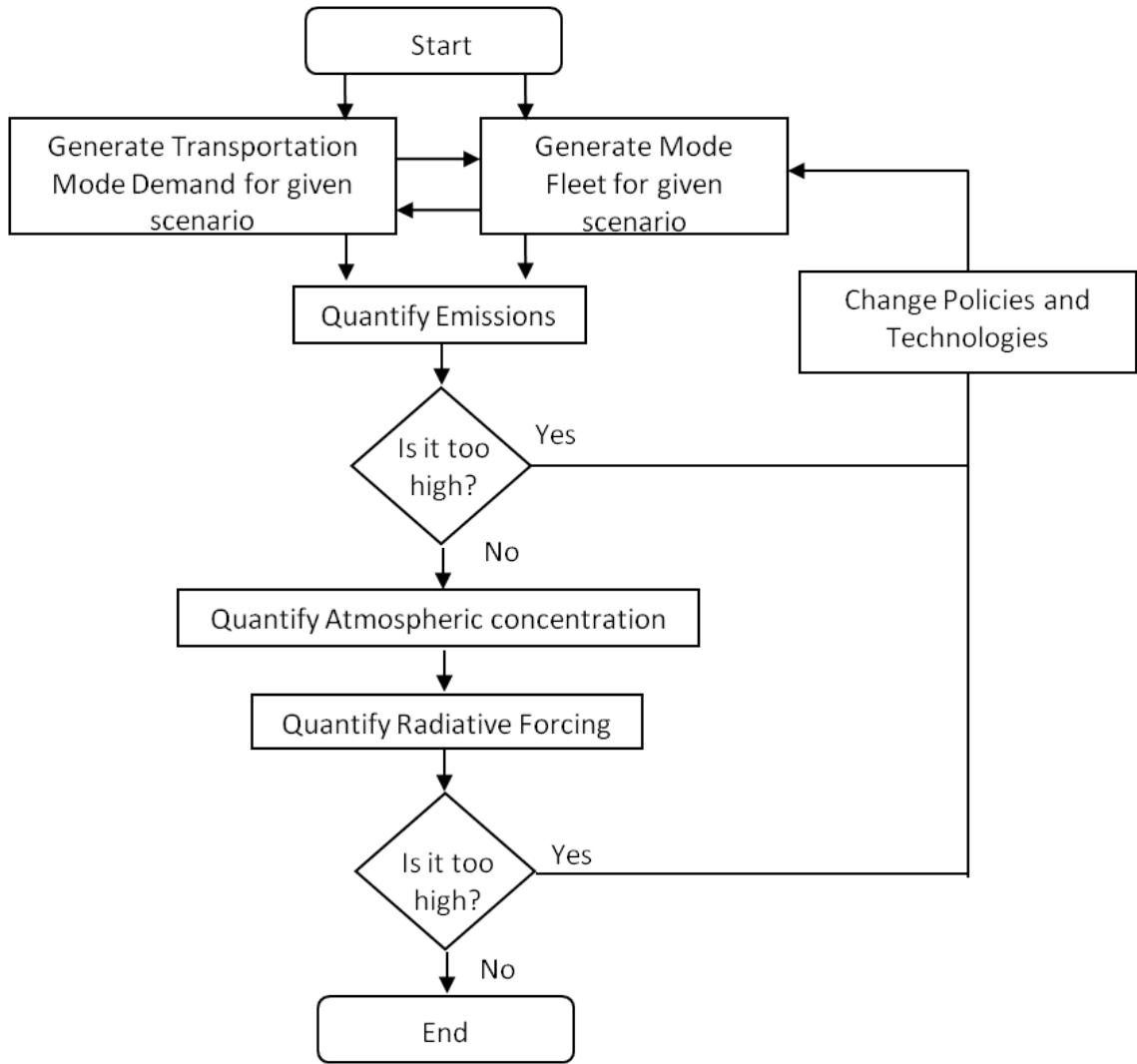
Figure 22: U.S. Transportation SoS integrated assessment framework

3.1 Hybrid Agent-Based and System Dynamics Demand Modeling

The Transportation System is a complex System-of-System composed of many inter-acting systems and stakeholders, which calls for specific modeling techniques. The stakeholders in the transportation system are adaptive autonomous agents. They are entities that try to fulfill a set of goals in a complex, dynamic environment, they have internal information processing and decision-making capabilities [90]. Therefore ABM

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is a well-suited modeling approach for transportation demand modeling. This micro-level, agent-based formulation captures consumer behavior in a versatile way which is not easily accomodated with an equation based modeling approach [94]. However, the advantages of ABM come with high computational cost that makes quick interactive assessments difficult. Furthermore, some macro-level characteristics, feedbacks and dynamic behaviors may not be captured. To address these challenges, an aggregated, System Dynamics modeling approach is most suitable. As discussed in Section 2.3, both ABM and SD have advantages and a hybrid model is best for the multimodal intercity transportation demand. Through this "multiscale modeling" approach, important features of the system are captured at both the micro and macro scales, and microscale models may be used to build the macroscale model. In this research, an ABM model is already developed and validated. Therefore, a System Dynamics model is developed based on the validated ABM presented in section 2.3.2.3, following the steps listed below:

- Screening of variables is performed with the ABM to identify a set of input variables that have the most impact on the desired output.

- An aggregation strategy is created to find the proper balance between model simplicity and accuracy of results.

- The ABM is used to generate data when statistics are not available.

- The SD model is then calibrated using ABM in order to increase the credibility of the results. To perform this cross-calibration, a range is defined for each input, and a number of cases are run within these ranges. Results from both models are compared and the SD model is adjusted until results match.

More details are provided in Chapter 4.

3.2 Transportation System's Climate Impact

The hybrid model quantifies demand for different modes of transportation. With this demand, and using fleet models and a radiative transfer code, climate impact can be quantified. A number of tools are available to quantify fleets fuel efficiencies and assess the transportation system's impact on the atmosphere. The first set of tools, fleet models, are used to quantify fuel burn. The second step uses existing radiative transfer theory to quantify climate impact.

3.2.1 Fuel burn and Emissions

To quantify fuel burn and emissions, an energy efficiency of each system needs to be quantified. For transportation systems, the following two steps are used:

- First, the composition of the fleet for each mode of transportation is determined using fleet models for each mode of transportation, thus providing fuel burn.

- Then life cyle emission factors are used to determine the life cycle emissions of different species based on the fuel burn.

The fleet replacement tools must be parametric to enable scenario-based exploration, and give market shares of different vehicles under different scenarios. Fleet replacement tools need to be properly integrated with the demand models in order to best capture the system's behavior. This is further described in section 5.1.1. The tool IDEA presented in section 2.4 is used in this research for its capability to model fleet replacements under different environments. As previously discussed, no tool is readily available for long distance ground transportation. Therefore data from existing models is used to create a ground module in eGAME. The fleet model determines an attractiveness of different vehicle types based on a number of characteristics related to the cost of transportation and keeps track of vehicle replacements. A detailed description of the ground module is provided in section 5.1.2. Once the fleet is known,

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fuel burn can be quantified. Based on the fuel burn and life cycle emission factors, emissions of different species are determined. Life cycle emissions include upstream emissions, that become more significant when alternative fuels such as Electric Vehicles are introduced in the modeling framework. The emitted species from transportation activities impact the radiative transfer through the atmosphere, and these effects can be quantified.

3.2.2 Climate Impact Assessment

In order to find the best scenario for climate impact reduction, the first step is to find the proper metric to assess this climate impact. As discussed in section 2.5.1, Radiative Forcing is a widely used metric. It is chosen and quantified for each mode, taking into account uncertainties associated with location and time of emission. Multiple simulations are run using radiative transfer codes to assess the different radiative forcing under different conditions (different regions, seasons and modes of transportation). The following steps are implemented:

- Define a grid that represents different regional and seasonal characteristics.

- Define each region/season characteristics (solar zenith angle, surface albedo, aerosol vertical profile, atmospheric conditions, etc.)

- Define each aerosol characteristics.

- Run a Radiative Transfer code with different weather conditions (cloud cover).

- Derive an average Radiative Forcing efficiency for each mode of transportation.

This approach is presented in section 5.2. The observations resulting from this section enable better quantification of the relative climate impact of different modes of transportation.

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3.3 Policy and Technology Scenario Exploration

With the modeling and simulation environment (eGAME) developed in the steps introduced above, it is then possible to implement policy scenarios and assess their impact on demand and fleets. These policies may be associated with technology scenarios to capture potential interaction effects. Therefore a number of technology and policy scenarios are defined and evaluated using eGAME, as further discussed in Chapter 6.

CHAPTER IV

HYBRID AGENT-BASED AND SYSTEM DYNAMICS DEMAND MODELING

4.1 Modeling Paradigms for the Transportation System-of-System Demand

As depicted in Figure 23, the first step in the framework is to quantify demand from different modes of transportation using demand forecasting tools. Transportation demand is the foundation of any transportation system design effort. Forecasting demand is, however, a challenging task due to the complexity of the transportation system, which has increased with the level of mobility. People have a need to travel, and they choose from all existing modes, routes and infrastructure. Moreover, a wide variety of stakeholders are involved in the transportation systems: travelers themselves, suppliers (such as airlines), manufacturers and government. This variety of interacting systems and stakeholders constitutes a transportation System-of-Systems (SoS), which exhibits typical characteristics of a complex system: autonomous agents (travelers and other stakeholders), adaptability (competition between suppliers), self-organization, emergent and dynamic behaviors, feedbacks, nonlinearity (congestion and delays) and phase transitions (e.g. new mode introduction as demonstrated by significant shifts in demand for different modes in history). A holistic approach is critical for proper representation in capturing the complexity of the system. As introduced in Section 2.3, well established paradigms such as Agent Based Modeling (ABM) and System Dynamics (SD) are suitable modeling techniques [21, 180]. Each has its advantages and limitations in terms of representation of the system behavior.

Research Question 1: What methodology is the most suitable for transportation System-of-Systems demand modeling? was answered through literature and led to the following assertion:

Assertion 1: A hybrid ABM/SD modeling and simulation framework is the most suitable approach to model the transportation SoS demand.

More details on hybrid approaches are provided in the following section.
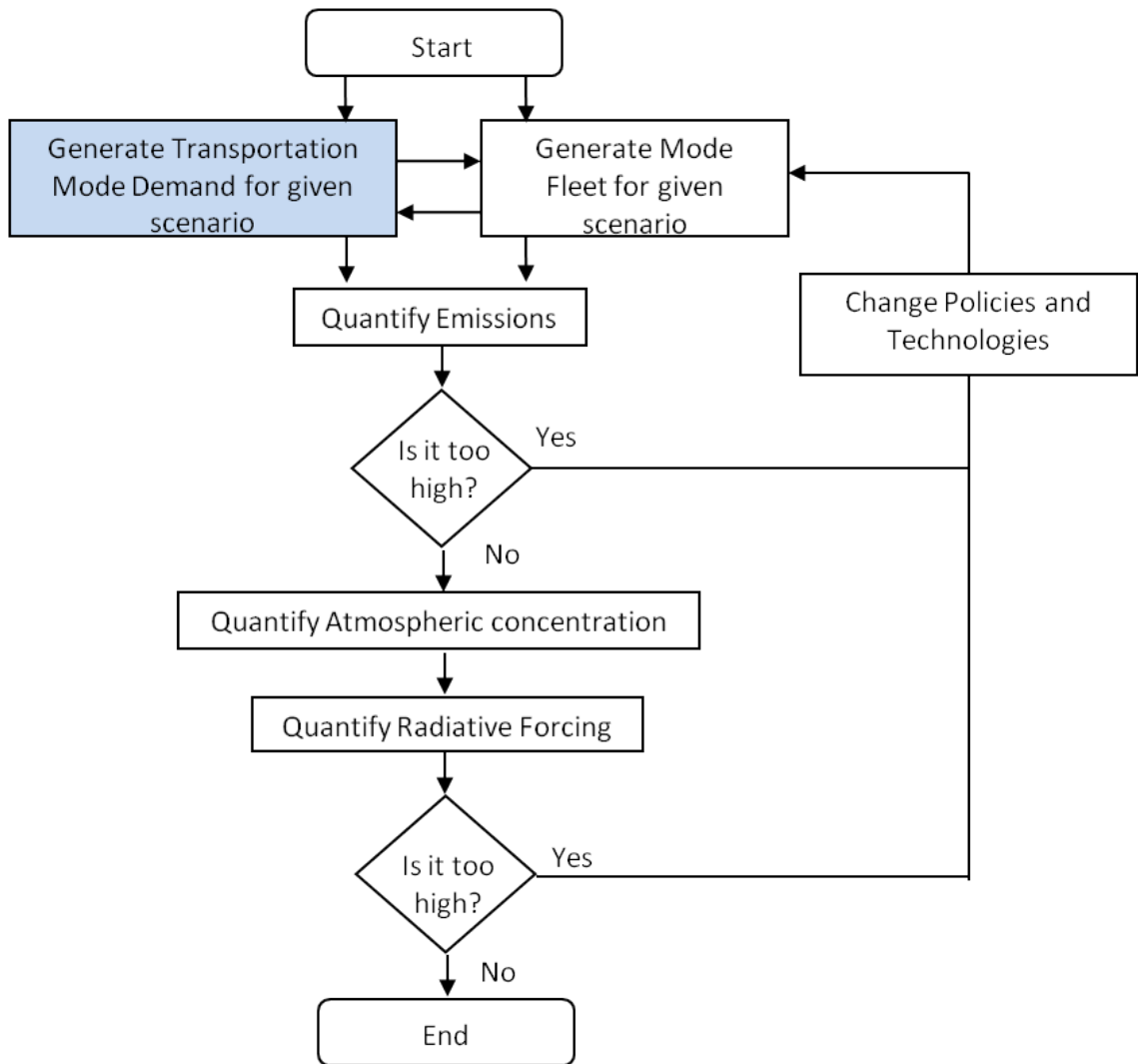
Figure 23: Step 1: Demand modeling

4.2 Hybrid Methodologies

Multiple approaches can be envisioned to combine ABM and SD, with different perspectives and levels of integration. This variety of possible hybrids may create some confusion in the initial phases of the modeling effort. In order to help modelers in their modeling architecture choice, a generic classification of hybrid techniques is proposed [94]. It can be used as a guide and gathers concepts from an extended literature review. Two main categories are identified. The first set of models are distinct standalone ABM and SD models, with their specific capabilities. The second set of models represents fully integrated models, where the two models are tightly linked.

4.2.1 Standalone Models

The first group of models mixes two submodels of different paradigms. These submodels can be separated and retain their capability, identity and characteristics. Two subcategories are identified: cross-validation (class 1A) and sequential models (class 1B). In the cross-validation (Figure 24) category, modelers from each school develop their own model with their respective methodology and calibrate them with available data. Results from both models are then compared to further validate the results. This approach was used by Rahmnandad [135] for the model of contagion. Upon comparison, models may be modified in order to converge to similar results.
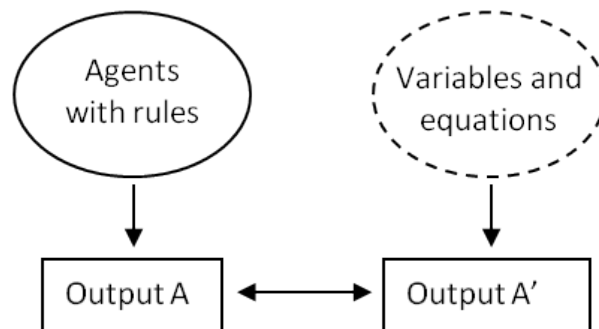
Figure 24: Cross validation

With the sequential approach (Figure 25), a model is used to obtain sufficient

knowledge or data to build a new model with a different paradigm. With this scheme multiple consecutive connections are also possible, where a unit simulation begins once it has received necessary information from the other model. An instance of this process is given by Schieritz and Milling [144], who suggest that ABM be used to quantify macro structures in SD. Conversely, SD can be used to provide some necessary information to a bottom-up approach that cannot capture macro-level behavior, as illustrated in He et al. [65].
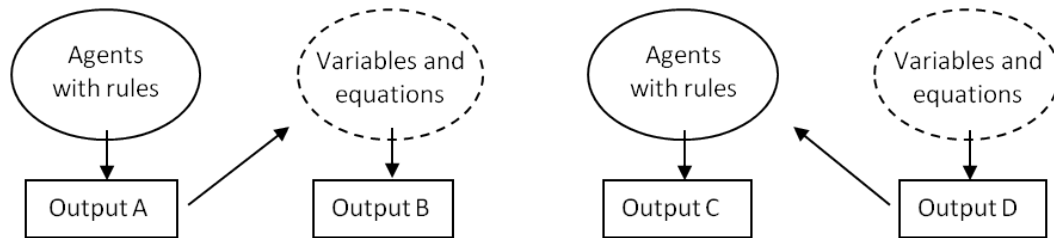
Figure 25: Sequential approach

These standalone models suggest that hypothesis 1.1 is true. It will be further verified through the creation of a SD demand based on the existing ABM **Mi**.

4.2.2   Fully Integrated Models

In this second category, models are integrated more fully and their separation requires some treatment and induces a loss of capability. At each simulation the models run together and at each time step data is needed from both models. Models can be embedded (Figure 26). These schemes can be traced back to as early as the 1990s. For instance, Parunak et al. [127] discussed two approaches for combining ABM and SD models: agents can exist in a System Dynamics model or System Dynamics can be used to model each agent. Multiple options are available depending on the embedded and the primary models. ABM can be embedded in SD (class 2A), in which case the ABM model can be used to influence a stock or a parameter in the SD model. An example is given in Kieckhafer et al. [81] for automotive manufacturers under CO_2 emission regulations. SD can be embedded in ABM (class 2B) to model agents

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internal structure. An example is given by Duggan [37]. These embedded designs can be directly mapped to the integrated design in Swinerd and McNaught [163].

Figure 26: Embedded systems

Another fully integrated option is a model where both ABM and SD are equally important (class 2C) (Figure 27). There is no primary/overarching paradigm. Both ABM and SD are equally balanced in terms of role and treatment. SD is used to model the environment in the ABM model [173]. In this scheme, SD can model dynamics of the agents' environment which are beyond agents' limited rules [147]. Both paradigm interact closely, coordinate, but their domain of application remain separate.
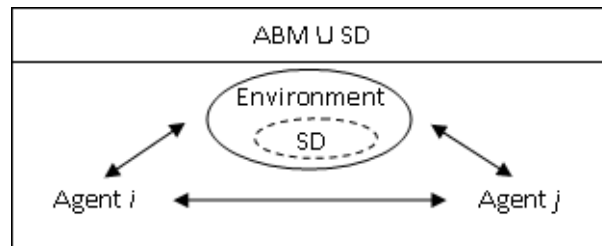
Figure 27: ABM with SD environment

The main characteristics of these hybrid models are summarized in Table 3. Even though a wide spectrum of diverse approaches can be created, the suggested classification scheme offers a parsimonious and primal way to group most cases and applications, as illustrated by Table 4. This limited and comprehensive list of classes enhances the readability of the different hybrid approaches. In some instances, a combination of classes may be used. For example, the research from Sterman [157]

Table 3: Hybrid Models Characteristics

Hybrid	Cross-validation	Sequential	Fully integrated
Time Progression	Independent	Asynchronous	Synchronous
Integration Level	Totally separate	Information transfer	Fully integrated
Purpose	Mutual learning	Partial learning	Problem solving

Table 4: Hybrid Models Examples

Hybrid	1A	1B	2A	2B	2C
[135]	X				
[65]		X			
[81]			X		
[37]				X	
[173]					X
[157]			X	X	
[158]			X	X	

and Sterman and Wittenberg [158] can be classified as derivative subclasses using a combination of embedded systems (classes 2A and 2B). As described in Swinerd and McNaught [163], in these examples, scientific paradigms can be seen as "agents with rich internal structure" and the behavior of the model is driven by a number of interacting feedback loops.

Other derivatives are possible using a combination of the different hybrid categories. The above classification organizes a wide spectrum of different methods. Depending on what the modeler is trying to achieve, standalone models or fully integrated models may be preferred. Generally speaking, standalone models are used to get a better understanding of the complexity of the system so that a single or multi paradigm model can be created with good fidelity. Standalone models can thus be used as a step toward a fully integrated model. Through the cross-validation process, models mutually learn about the system as a whole, and each model can then be used

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independently with enough confidence. In the sequential approach, the final model partially learns from the initial model to derive the necessary information. It can be trained to eventually function on its own or it may call the other model for input at every simulation. Fully integrated models are used when the problem structure is understood, in order to answer a specific question quantitatively. Each paradigm requires data from the other paradigm at every step of the simulation. In this case, each paradigm achieves a different task and is fully connected to the other.

In this research, the modeling target is the transportation SoS with an emphasis on demand. The ultimate purpose is to develop an interactive tool that helps decision-makers explore and compare different policy and technology scenarios. Due to the complexity of the transportation SoS, both learning and problem solving strategies are needed. An existing agent-based model has been validated as discussed in section 2.3.2.3. It has, however, some limitations which motivated the use of a SD model, that is described in Section 4.3. The SD model complements the ABM and introduces a novel hybrid approach using classes 1A and 1B.

4.3   Hybrid Methodology for Transportation System-of-Systems Demand

ABM is a bottom-up approach capable of capturing micro-level types of behaviors, whereas SD is a top-down approach better suited for macro-level types of behaviors. As introduced in Sections 2.3 and 3.1, both types of behaviors are expected and a hybrid approach is justified. The tool **Mi** is a good ABM candidate and is used as a starting point for this research. It is however not well suited for some macro-level views necessary for climate policy and it is too computationally expensive for an integrated assessment.

Two questions arose, with their associated hypotheses. The first question relates to the classification established in Section 4.2:

Research Question 1.1: How is a hybrid model created?

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The literature suggests that an ABM can be used for SD model development. Hence the following hypothesis:

Hypothesis 1.1: With proper analysis, derivations, and aggregation, a SD model can be derived from an ABM.

An ABM is available but has limitations. Therefore a SD model is developed. In the process presented in Figure 7, the ABM can help at different steps, such as the identification of significant variables, the quantification of some relationships, as well as the validation. The latter relates to the following research question:

Research Question 1.2: How is rigorous calibration achieved?

Hypothesis 1.2: Through a cross-calibration process, SD can produce results similar to ABM within given ranges.

These research questions will be discussed in more details in the following sections.

4.3.1   Ground and Air Mode Explorer (GAME) System Dynamics Model

In the beginning stages of the development of a System Dynamics model, little is known about the system. The ABM model can help identify the main parameters and their impact on the behavior of the system. Creating accurate forecast at this aggregated level can be challenging. Some behavior can be difficult to represent and model, which requires the use of an ABM to derive the necessary information and appropriately model the system. Therefore, the approach is to use a pre-validated ABM to teach and train the system dynamics model. The standalone model approach presented above is adopted to create a SD surrogate of the existing ABM model. Each model therefore remains independent. The ABM is used to build the SD model and derive aggregate numbers and relationships. The main parameters are identified and screening of variables is performed. Once the ABM model has been created and validated, it can be used as a data generator, particularly to initialize the SD model. However, as mentioned in Table 2, the two modeling paradigms have different

Table 5: Modes' Design Variables

Variable Type	Commercial Air Transportation	Ground Transportation
Exogenous	GDP, MCSI, jet fuel price	GDP, MCSI, gasoline price
Design	Block speed, Range, Aircraft size, Operating Cost	Fuel efficiency, Speed, Persons per vehicle
Operational	Airport operating hours, maximum operations, Delays	Speed limit, Congestion
Infrastructure	Number of runways and airports, Access distance, Transit time	Road type

aggregation levels, which requires some treatment of the data. Intelligently aggregated quantities are derived from the ABM and transferred to the SD model.

The approach is to derive some necessary knowledge from the ABM model to build and calibrate the SD model. First, the main output variables are identified. The variables tracked are number of passengers, Revenue Passenger Miles (RPM) for the commercial air transportation mode (ALN mode) and Vehicle Miles Traveled (VMT) for ground transportation mode (GND mode). Then, the main input parameters are screened: Gross Domestic Product (GDP), Michigan Consumer Sentiment Index (MCSI), fuel price, mode design variables. The main variables are listed in Table 5.

Exogenous variables such as GDP and MCSI have a direct impact on the number and types of trips people can afford. Gasoline price has a direct impact on the cost of traveling by car. However, for the commercial air transportation system, a supplier entity, the airline, makes it more difficult to predict the impact of fuel price increase on the cost of flying (ticket price). Market fuel prices increased by a factor of five between 2002 and 2008, and reached their highest values in the summer of 2008 (Figure 28), resulting in an increase in fuel cost and direct operating cost.
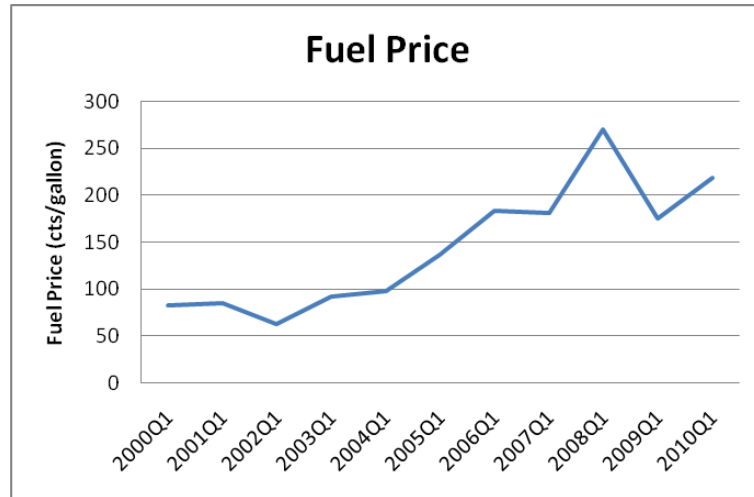
Figure 28: Fuel Price History

Brueckner and Zhang [23] found that an increase in fuel price, or an equivalent imposition of airline emissions charges, may lead to a higher fare, lower flight frequency, a higher load factor, more fuel-efficient aircraft, and an unchanged aircraft size. In an attempt to try to better capture the relationship between fuel price and ticket price, a study is performed using the Airline Origin and Destination Survey DB1B, which is a 10 percent sample of airline tickets from reporting carriers. The Ticket Fare varies significantly, even for a given origin, a given airline and a given distance. Therefore, a process is needed in order to try to identify some trends over time and potential correlations with fuel price. The methodology is as follow: for each airline, an average of the ticket fare is calculated for each distance group (from 0 to 3000 miles, with increments of 500 miles). Only domestic flights are considered and values that are not credible are removed. Correlations for the one coupon data (one way tickets), and the two coupons roundtrip data (which represent the 50-70 percent of the flights) are calculated. Two periods are identified due to the restructuration of the airline industry observed in the early 2000s. In order to try to better capture the fuel price effect, the period 2005-2010 is used. Results for the two coupons data are listed in Table 6, including two Network Legacy Carriers (NLC) and two Low Cost

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Table 6: R-squared values for ticket price 2 coupons round trip data

Airline	Average R-squared (all distances), 2000-2010	R-squared for 2005-2010
NLC 1	0.1934	0.3051
NLC 2	0.2702	0.3717
LCC 1	0.6650	0.3101
LCC 2	0.9058	0.8437

Carriers (LCC). As can be observed in Table 6, LCC 2 shows a higher correlation between ticket price and fuel price (R-squared value closer to 1). Other carriers may not have passed the extra cost on to the customer, or may have used fuel hedging strategies.

A rapid and direct way for airlines to increase revenue in order to account for the operating cost increase is to increase air fares. It can be observed that airlines increased their fares when fuel price went up, and that long distance flights were more sensitive to fuel price than short distance flights. However, the correlation between air fare and fuel price is relatively low for most airlines. A lot of other parameters can have an impact on air fare, such as lower competitor's fare, changing demand, etc. Moreover, data includes the ticket price, taxes and airport fees, but does not include extra fees charged by airlines such as baggage fees, internet in-flight and select coach fee. More details on the impact of fuel price increase on airlines' strategies are provided in Appendix B.

Although some small correlation may be observed for specific airlines at a given time, system wide variations may be non significant. A system wide average ticket price is obtained by weighing each distance group average ticket price with the number of tickets sold. This analysis shows little correlation between ticket price and fuel price, as can be observed in Figure 29. Ticket price historically had small correlation with fuel price. Due to the low correlations observed, an average ticket price is used
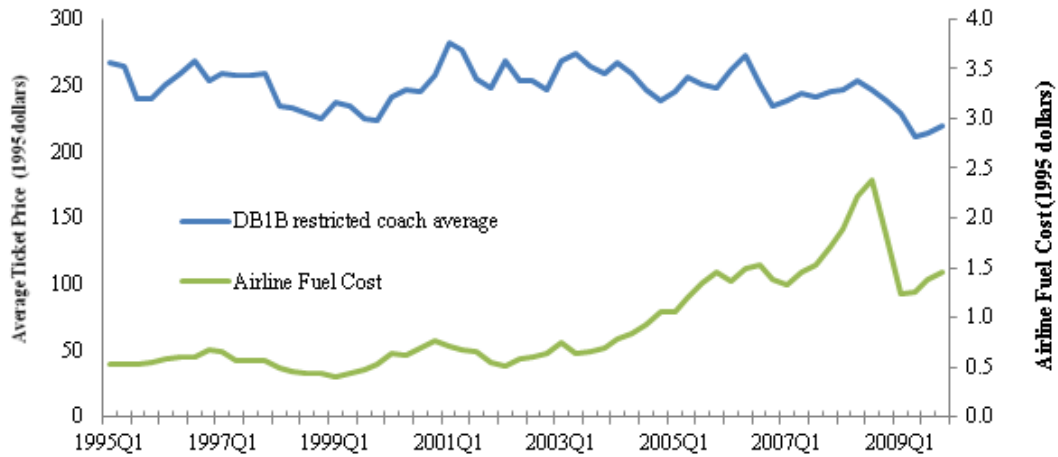
Figure 29: Ticket Price and Fuel Cost

for past data, with no relationship to fuel price. In the future, if jet fuel price increases more significantly and for a longer period of time, it is very likely that airlines will pass the fuel price increase on to the passengers. Therefore, fuel cost will need to be considered.

Other variables also have an impact on the demand for each mode of transportation. They relate to the time and cost it takes to travel using the given mode. For the ground mode, it is straightforward that the average driving speed and the fuel efficiency of the vehicle will determine the time and cost respectively. For the commercial air transportation, other parameters are important such as the distance to the closest airport, the transit time, potential delays, etc.

The Ground and Air Modes Explorer is created using the following concept: the System Dynamics model GAME provides the demand for each transportation mode, which is represented as a stock of passengers as shown in the conceptual sketch in Figure 30 [93]. This stock of passengers varies with modes' characteristics (endogenous variables such as vehicle speed) that define an attractiveness of each mode (which will be discussed in section 4.3.3 in more details), based on time and cost it takes to travel using different modes of transportation. Demand also varies with exogenous variables

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such as population, income, consumer sentiment index and fuel price. The fuel price variations result in changes in ticket price based on the pass through model described in section 5.1. An aggregated capacity module introduces a negative feedback loop on air transportation demand and enables forecast in a capacity constrained environment. The stocks are initialized using Mi results listed in Appendix C. The results from Mi may be used as actual data since Mi has previously been validated. A more detailed view of GAME is provided in Figures 31, 32 and 33, which represent the modules for time of travel with the air transportation mode, the cost of travel with the air transportation mode, and the time and cost of travel using the ground mode, respectively. As can be observed in Figure 31, time of travel increases due to delays when the system approaches saturation, which result in a decrease in attractiveness. Demand is adjusted based on GDP, MCSI, and population growth. Figure 32 shows the ticket price adjustment with fuel price and fuel consumption. More details on the effect of fuel consumption on demand is provided in Section 5.1.1.
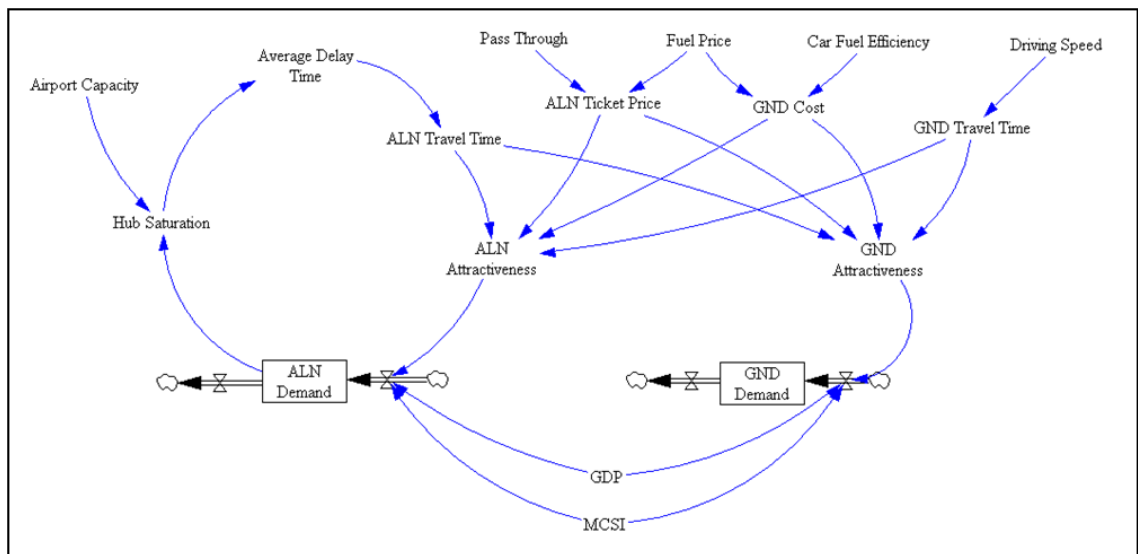
Figure 30: GAME concept
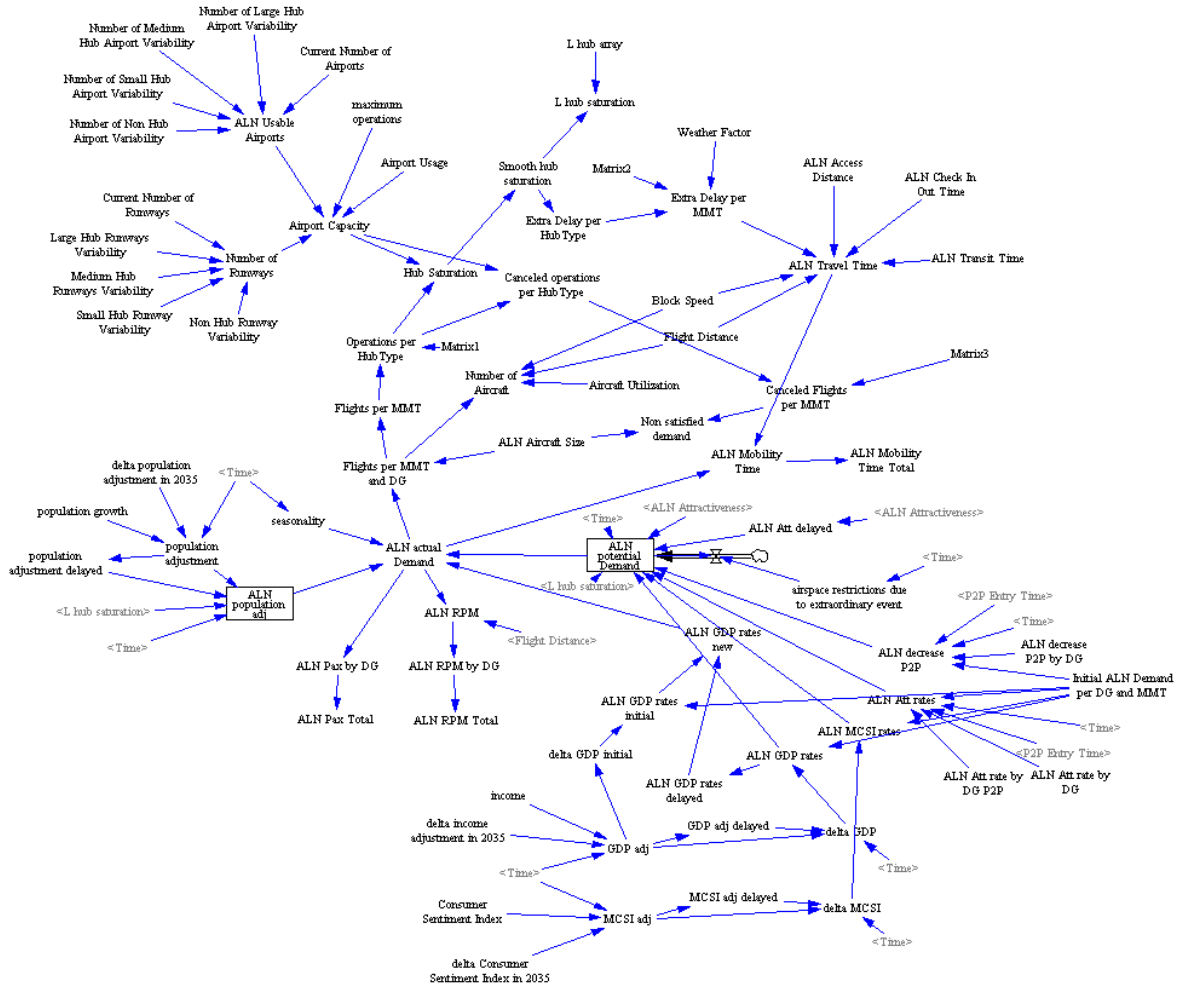
Figure 31: GAME Airline mode time module

4.3.2 Aggregation

As introduced in Table 2, the aggregation levels of ABM and SD are notably different. Therefore, an aggregation strategy needs to be created to aggregate data from the ABM to feed into the SD model. It is necessary to aggregate without losing correct representation of some fundamental system behavior. In terms of transportation mode choice, the time and cost are the main factors. Therefore, distance is a key parameter. As can be seen in Figure 34, significant changes in mode choice occur when distance increases, with more variations in the shorter distances, requiring smaller distance groups as distance decreases. The data in Figure 34 is from the

75
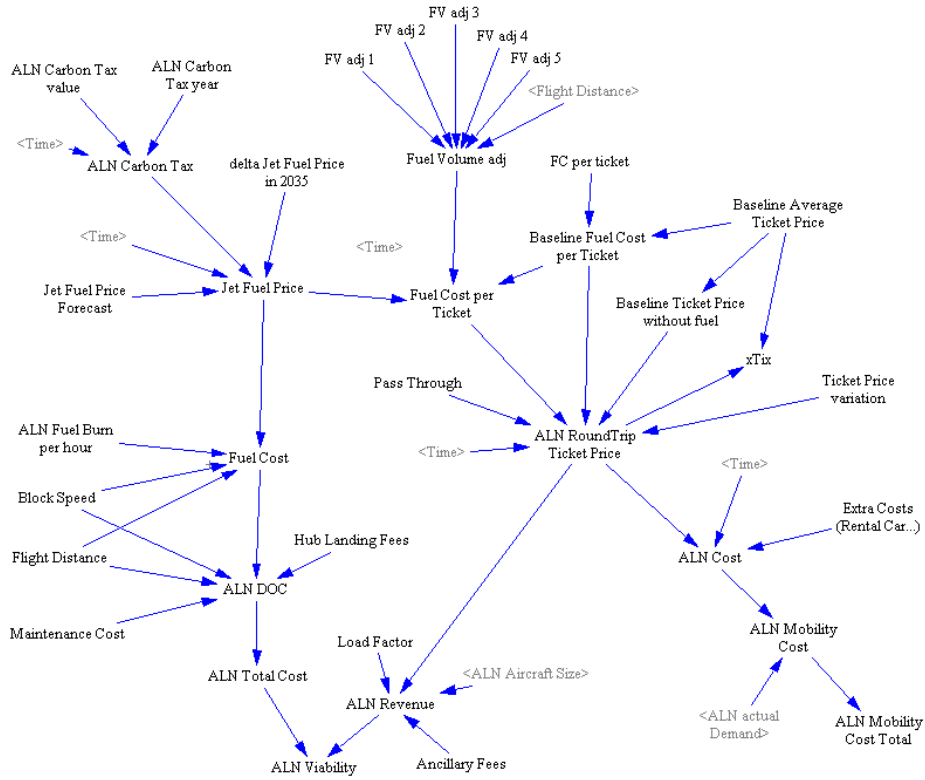
Figure 32: GAME Airline mode cost module

U.S. Department of Transportation, Research and Innovative Technology Administration, Bureau of Transportation Statistics, Federal Highway Administration, National Household Travel Survey, long-distance file, 2001 (Washington, DC). The Distance Groups (DG) listed in Table 7 were defined to capture mode share and travel behavior as precisely as possible with five categories. Since the region of study is the continental United States (CONUS), these DGs cover all great circle distances between any two cities.

Another important factor is the metro market type: the flight between two large metropolitan areas is likely to be direct, whereas a flight between two remote locations might have so many connections and long airport access distances that driving may become preferable. The access distance (distance to the closest airport) mentioned in the list of variables in Table 5 depends on metro market group. Therefore, four
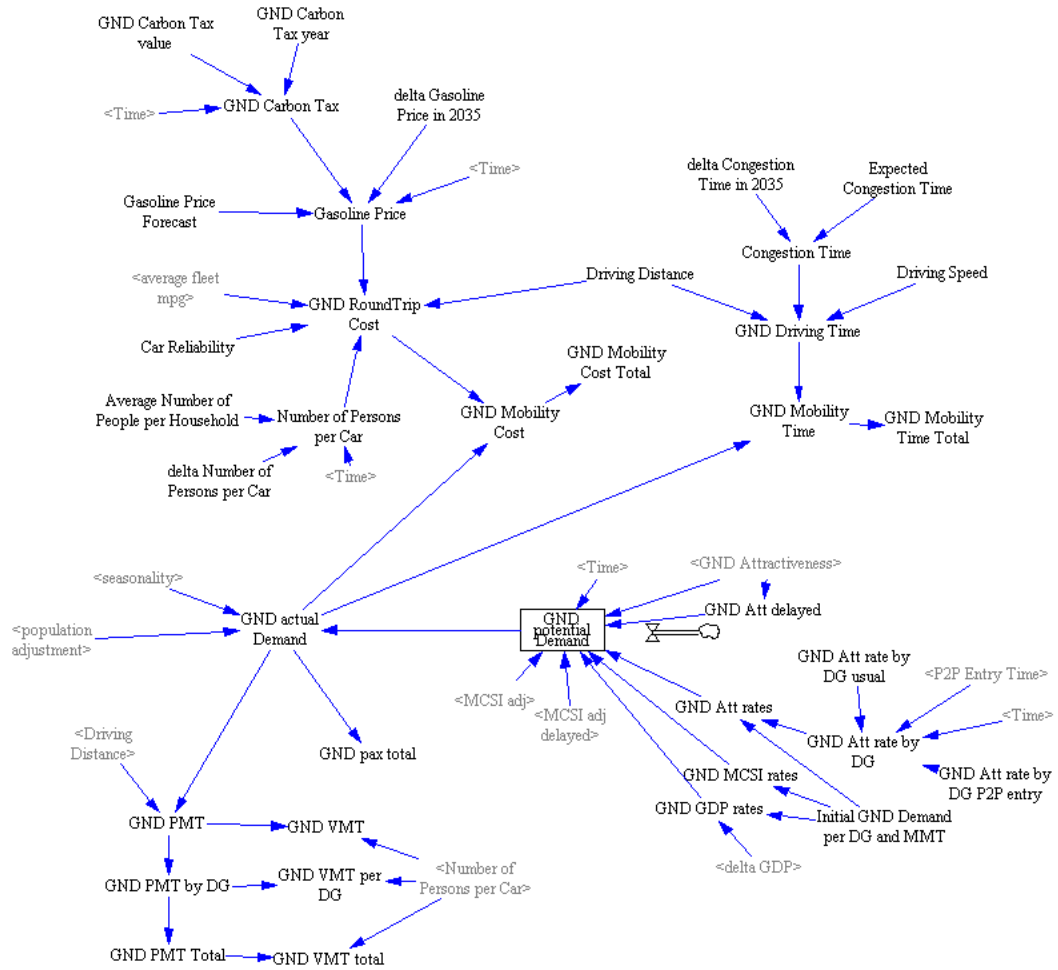
Figure 33: GAME Ground module

metropolitan areas, resulting in 16 Metro Market Groups (MMG) are considered (Figure 35). The number is reduced to 10 MMG when considering the symmetry due to roundtrip travels. In terms of total demand, it is indeed the same to go from a medium metropolitan statistical area to a large, and then from a large to a medium, as to go from a large to a medium, and then from a medium to a large. These MMGs are listed in Table 8.

To go from the 204 by 204 OD matrix obtained from the ABM to the data aggregated by DG and MMG in SD, a matlab code is used (as described in Appendix C), that goes through each cell of the OD matrix and counts the number of passengers

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Table 7: Distance Groups

DG1	100 to 200 miles
DG2	200 to 400 miles
DG3	400 to 800 miles
DG4	800 to 1600 miles
DG5	1600 to 3200 miles

Table 8: Metro Market Groups

MMG1	Large to Large
MMG2	Large to Medium
MMG3	Large to Small
MMG4	Large to Non-metro
MMG5	Medium to Medium
MMG6	Medium to Small
MMG7	Medium to Non-metro
MMG8	Small to Small
MMG9	Small to Non-metro
MMG10	Non-metro to Non-metro
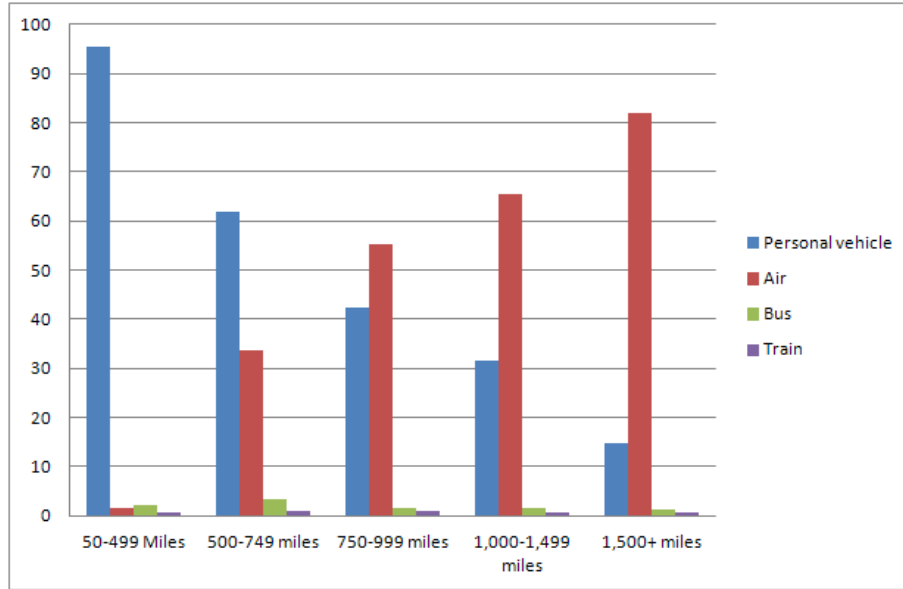
Figure 34: Percent trips by mode for one way distance
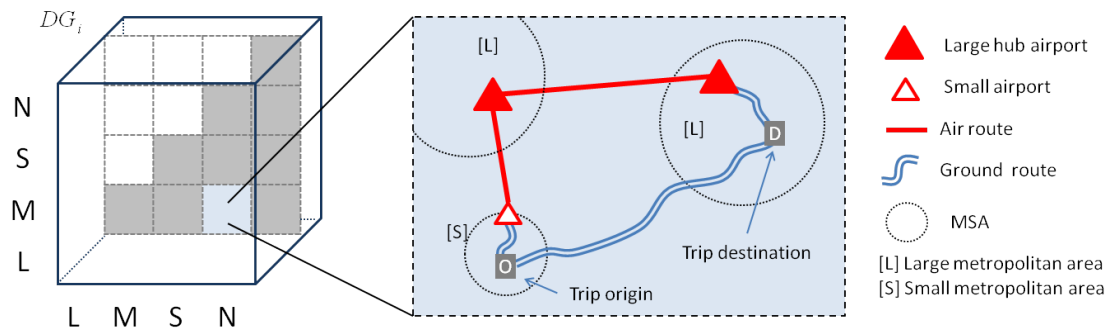
Figure 35: Geographic aggregation

or the passenger miles traveled based on the DG and MMG that the OD matrix cell falls into. Initialization data for GAME is provided. The DG and MMG subscripts represent the granularity of the GAME SD model and the calculations are performed for each one of the 50 DG-MMG combinations.

4.3.3 Model Equations: Demand and Mode Attractiveness

Mi's main output is the transportation volume of passengers and is a function of time, exogenous variables such as income, and transportation mode's characteristics such as vehicle speed and range. The abstract concept of attractiveness of a mode is

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introduced to account for its measurable (such as time and cost) and non-measurable characteristics (such as comfort, flexibility, or perception of safety). Due to the challenging task of quantifying non-measurable characteristics, and assuming that their effect can be considered as negligible compared to measurable characteristics, attractiveness is based on measurables only. For these reasons the attractiveness is chosen to be limited to time and cost of travel. The volume of demand for a given mode is a function of time, attractiveness and exogenous variables.

$$V_m = V_m(t, A_m, \underline{X}) \tag{4}$$

where V_m, t, X and A_m denote the volume of mode m, time, a set of exogenous variables, and attractiveness of mode m, respectively. The attractiveness can be expressed as followed:

$$A_m = \frac{e^{U_m}}{\sum_{i=1}^{M} e^{U_i}} \left(1 + \gamma \frac{U_m - U_m(refyear)}{U_m(refyear)} \right) \tag{5}$$

where τ_m is the time of travel with mode m, μ_m the cost of travel with mode m, U_m the disutility of mode m, and γ a parameter that adjusts the impact of demand increase from mobility improvements. The definition of attractiveness was found to be a critical step toward a correct representation of the SoS behavior. It is indeed challenging to find the right formulation to replicate the ABM behavior. As defined above, variations in demand depend on variations in attractiveness, which depends on the endogenous variables of the system that affect time and cost of travel. A multinomial logit model was considered to define the attractiveness of each mode, similar to what was done in the ABM model. However, the logit model has some limitations when it comes to forecasting future changes in demand, since the total demand for transportation is expected to increase. In the ABM, a smaller cost of transportation or a shorter time will result in more trips being taken due to the budget space concept described in section 2.3.2.3. An increase in total trips, including all modes of transportation is possible. However, in the SD model, this agent's budget

space is not represented. Mode choice is based on attractiveness, and demand is scaled up with population, and other exogenous variables, such as consumer sentiment index. With a standard logit model, the probabilities sum up to one, therefore only mode shift can be captured. Induced demand due to global improvements in mobility throughout the years is not accounted for. Therefore, a modified logit model is used to account for both mode redistribution and demand increase. Adjusting the parameter γ in Equation 5 changes the sensitivity to global improvements in mobility.

The disutility U_m is defined as

$$U_m = \alpha \left(w_t . VOT . \tau_m + w_c . \mu_m \right) \tag{6}$$

with α the scale parameter, w_t and w_c the weights that define the importance of the time and cost attributes on the disutility of mode m, and VOT the value of time.

The ABM approach is most suitable to represent agents' heterogeneity. In an attempt to facilitate the development of GAME, a single agent type is used, thus the value of time VOT is estimated as an average income per household per working hour. This value of time can change with income growth. The model could be refined by adding an agent group and a trip purpose subscript in the discussion about aggregation in Section 4.3.2. This would be necessary if the calibration exercise described in Section 4.4 shows that output similarity between ABM and SD is unreachable.

Based on the behavior of **Mi** and the above formulation of attractiveness, the attractiveness of a mode can change with changes in any mode of transportation, as demonstrated in the equations below. This, in turn, justifies the use of a multimodal approach. Unlike the ABM formulation where demand emerges from agents' rules, the rate of change of demand stock variables is one of the main parameters that needs to be quantified in System Dynamics. The change in demand for each mode is a function of the change in exogenous variables and the change in attractiveness of this mode:

$$\frac{dV_m}{dt} = \frac{\partial V_m}{\partial t} + \frac{\partial V_m}{\partial A_m}\frac{dA_m}{dt} + \sum_{i=1}^{N}\left(\frac{\partial V_m}{\partial X_i}\frac{dX_i}{dt}\right) \tag{7}$$

The change in attractiveness depends on the change in time and cost it takes to travel using each mode:

$$\frac{dA_m}{dt} = \sum_{i=1}^{M}\frac{\partial A_m}{\partial \tau_i}\frac{d\tau_i}{dt} + \frac{\partial A_m}{\partial \mu_i}\frac{d\mu_i}{dt} \tag{8}$$

with τ the time of travel, function of the mode design variables x_k, and μ the cost of travel, function of the mode design variable and some exogenous variables such as fuel price. Thus changes in the mode's design variables will result in a change in time of travel

$$\frac{d\tau_m}{dt} = \sum_{k=1}^{n}\frac{\partial \tau_m}{\partial x_k}\frac{dx_k}{dt} \tag{9}$$

And changes in mode design variables and/or exogenous variables result in changes in cost of travel:

$$\frac{d\mu_m}{dt} = \sum_{k=1}^{n}\frac{\partial \mu_m}{\partial x_k}\frac{dx_k}{dt} + \sum_{i=1}^{N}\frac{\partial \mu_m}{\partial X_i}\frac{dX_i}{dt} \tag{10}$$

These equations show how ABM can be used to obtain necessary information for the SD model. The sensitivities $\frac{\partial V_m}{\partial A_m}$ and $\frac{\partial V_m}{\partial X_i}$ in Equation 7 are originally unknown and experiments need to be run with the existing ABM to observe the system's behavior and adjust these parameters to replicate this behavior. These experiments aim to derive expressions for the unknown parameters above. A variation in exogenous variable dX_i is applied and the change in volume V_m is obtained through ABM simulation. Then, the sensitivity parameters in the SD model are adjusted so that, for the same variation in exogenous variable, a similar change in volume V_m is measured. These sensitivities are initially assumed to be constant but a non-linear relationship can be found based on ABM simulations. In this case, a polynomial equation is fitted to ABM data using the least squares fit and used in the SD model. An example is given in Figure 36, where a change in GDP results in a change in RPM. The extent

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of this change decreases with higher values of GDP due to the fact that agents run into their time constraint (as depicted in the budget space concept in Figure 5).
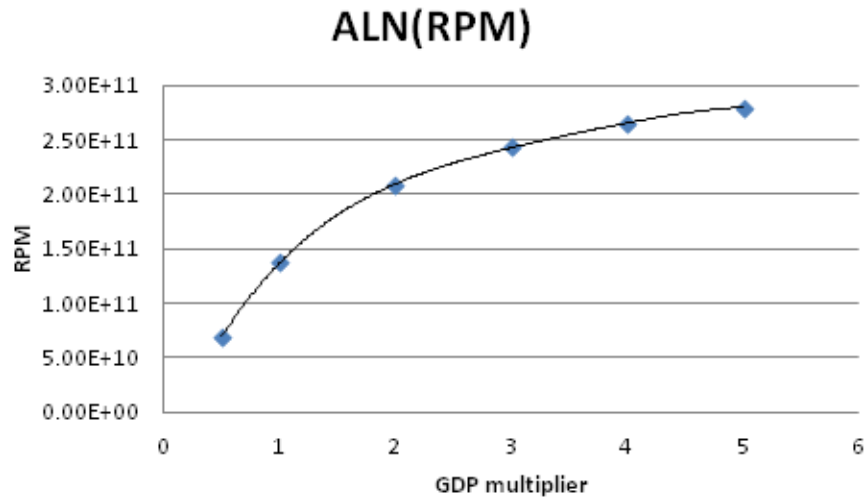
Figure 36: Change in RPM due to change in GDP from *Mi* simulations

Through this process, some information is obtained from the analysis of the ABM model, mathematical formulation and relationships are derived and an aggregation strategy is developed. Therefore the following hypothesis is verified:

Hypothesis 1.1: With proper analysis, derivations, and aggregation, a SD model can be derived from an ABM.

In order to gain confidence in this SD model, the next step is to validate the model.

4.4   Validation

To validate the SD model, the pre-validated ABM is used to generate data. The results from the ABM and the SD models are compared. The parameters in SD are then adjusted. Sensitivities to each input within given ranges are checked, and further validation is obtained through the comparison of more data points generated using a Design of Experiments. GAME was cross-calibrated using the two basic modes of transportation (ALN and GND). GAME was originally developed with a time step

of a quarter due to the fact that most databases are available quarterly. It can be changed to a yearly time step if yearly RPM, VMT, and emissions are needed in the forecast. It is relatively easy to switch from one time step to the other depending on the purpose of the study. The time span can also be changed depending on whether we need past data or not. In order to calibrate the model, past data is included, starting in 1995, and the quarterly version of GAME is used. To validate the model, GAME results are compared to databases and results from the ABM. Results need to be checked for past values and potential future values. The equivalency box concept is used to calibrate the results. The rates of change of stock variables are adjusted until results from GAME are close enough to Mi.

4.4.1   Equivalency Box

In order to ensure equivalency of the SD and ABM models, the SD model GAME is developed parametrically and the parameters are adjusted until results from the SD model are close enough to the results obtained from the ABM. This means an error that remains below a few percent, and an R-squared value close to 1. For this exercise, an equivalency box is introduced that defines the ranges of input variables within which SD must replicate the ABM's results. These ranges are defined based on potential future values of the input variables. Data points are generated within the equivalency box and cases are run using both models. Then, results are compared, as done in the cross validation scheme described in section 4.2.

4.4.2   Sensitivity Analysis

Sensitivities within the equivalency box are adjusted until GAME is able to replicate the behavior of Mi. As can be seen in Figure 38, an increase in GDP results in a nonlinear increase in RPM and VMT, with a stronger impact on RPM. The nonlinearity is due to the time constraint imposed on the agents and is introduced in GAME. GDP has the biggest impact: a better economy increases total volume and

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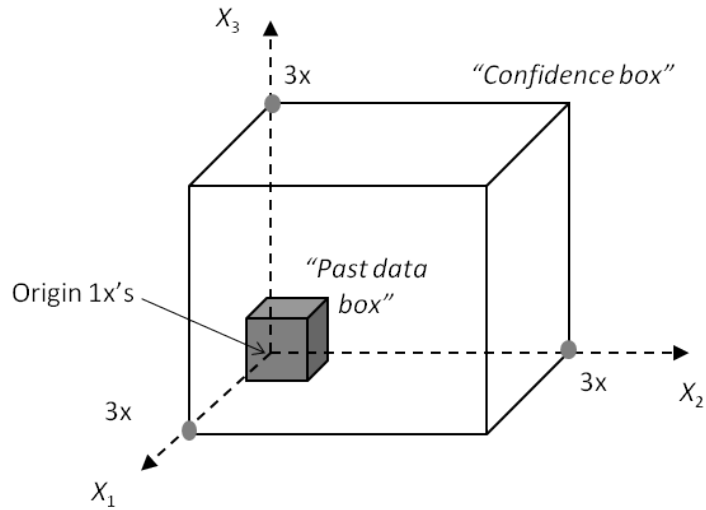
Figure 37: Equivalency box

commercial air transportation market share. The sensitivity to MCSI is relatively low (Figure 39). It is interesting to see that almost no variation is observed for the ground mode with MCSI, which captures how people feel about the economy. This may be explained by the fact that, as MCSI increases, total volume may grow but people use air transportation more. Similarly, as MCSI decreases, total volume may shrink but people use ground transportation more, so overall ground transportation demand variations with MCSI are negligible. As observed in Figure 40, an increase in gasoline price results in an increased market share of air transportation. The ticket prices remain the same, while gasoline price and thus cost of driving increases which puts the air transportation at an advantage. Finally, the sensitivity to ticket price is high for both modes, demonstrating a significant modal shift effect (Figure 41).

4.4.3   SD as a Surrogate of ABM

Overall, sensitivities of both models are very similar which suggests that results should match for any point within the equivalency box. A system dynamics model that would replicate the behavior of the ABM Mi would essentially be a surrogate model of Mi. A short background on surrogate models and Design of Experiments is provided in
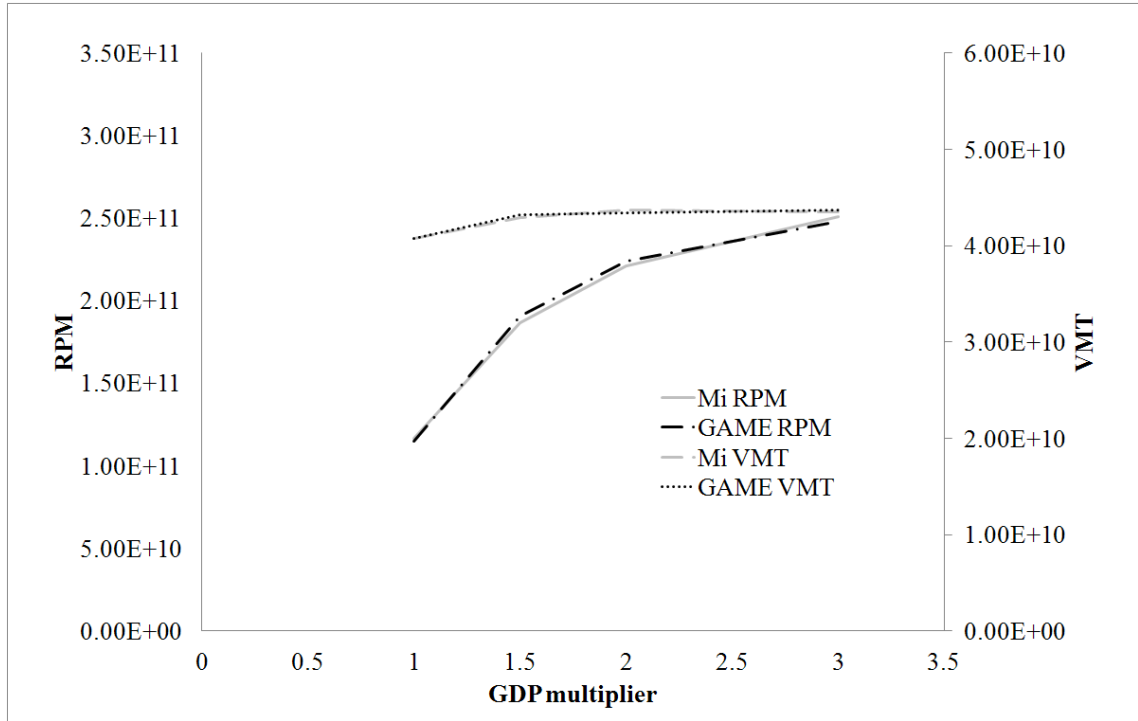
Figure 38: Sensitivity of RPM and VMT to GDP

the following paragraphs.

4.4.3.1 Surrogate model definition

A surrogate model is a model of a more complex and computationally expensive model. To create a surrogate model, first, the most important input variables in terms of output variability are identified, and the behavior is captured through a set of equations. Common techniques include but are not limited to Response Surface Methodology (RSM), neural networks and Kriging. RSM consists in developing linear regression models. Non-linear systems are usually not well represented with RSM, and methods such as neural networks and Kriging models are prefered. Neural Networks are inspired by nervous systems capable of machine learning. They approximate complex functions with a combination of simple elementary functions to automatically build models describing complex relations between inputs and outputs with a low computational cost [80]. Kriging uses a combination of a polynomial model and a
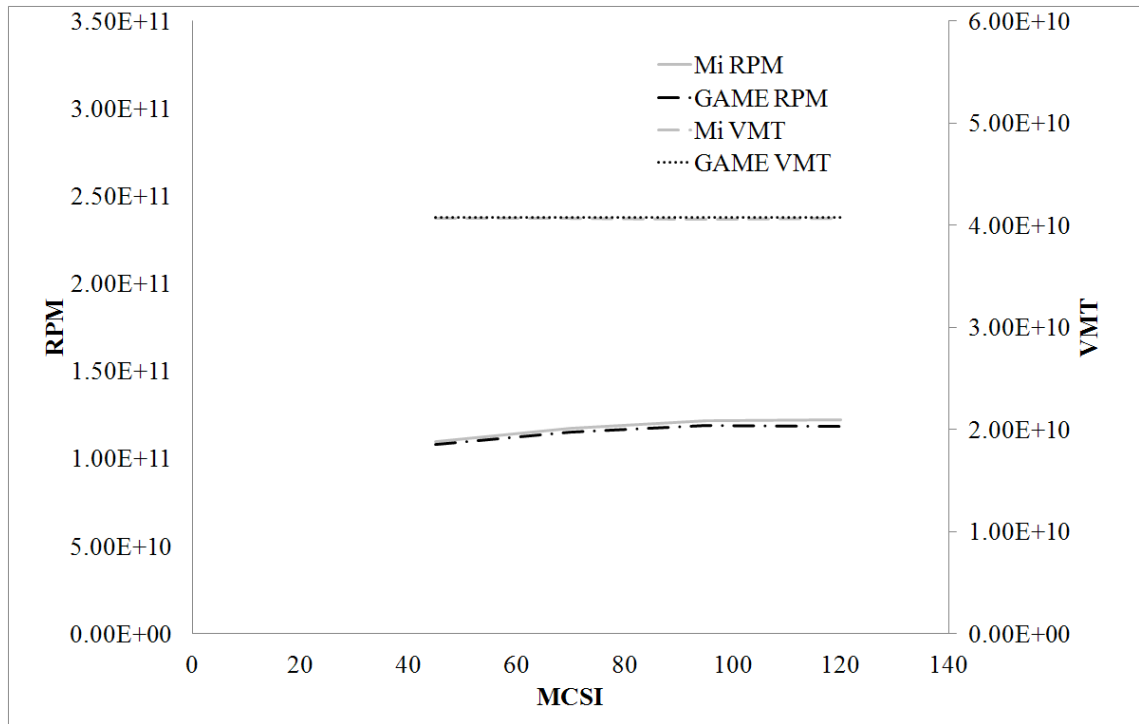
Figure 39: Sensitivity of RPM and VMT to MCSI

localized deviation using a normally distributed Gaussian random process [155]. In order to generate the sampling data that is used to fit the chosen mathematical model, design of experiments are used.

4.4.3.2 Design of Experiments

Through surrogate modeling, the simulation time can be reduced and enable faster scenario exploration and tradeoff analysis, a requirement for an interactive decision-making tool. Design of Experiments are used to generate points for simulation results. A Design of Experiments (DOE) is an approach that is an efficient means to obtain information about the interactions of factors and the system's behavior. DOEs provide a maximum amount of knowledge with minimal time and compuational expenditures. The simplest design is obtained by simulating every high, low and mid-point setting for each variable, and is referred to as a full factorial design. More efficient designs exist, such as the Box-Behnken design (represented in Figure 42), which requires fewer
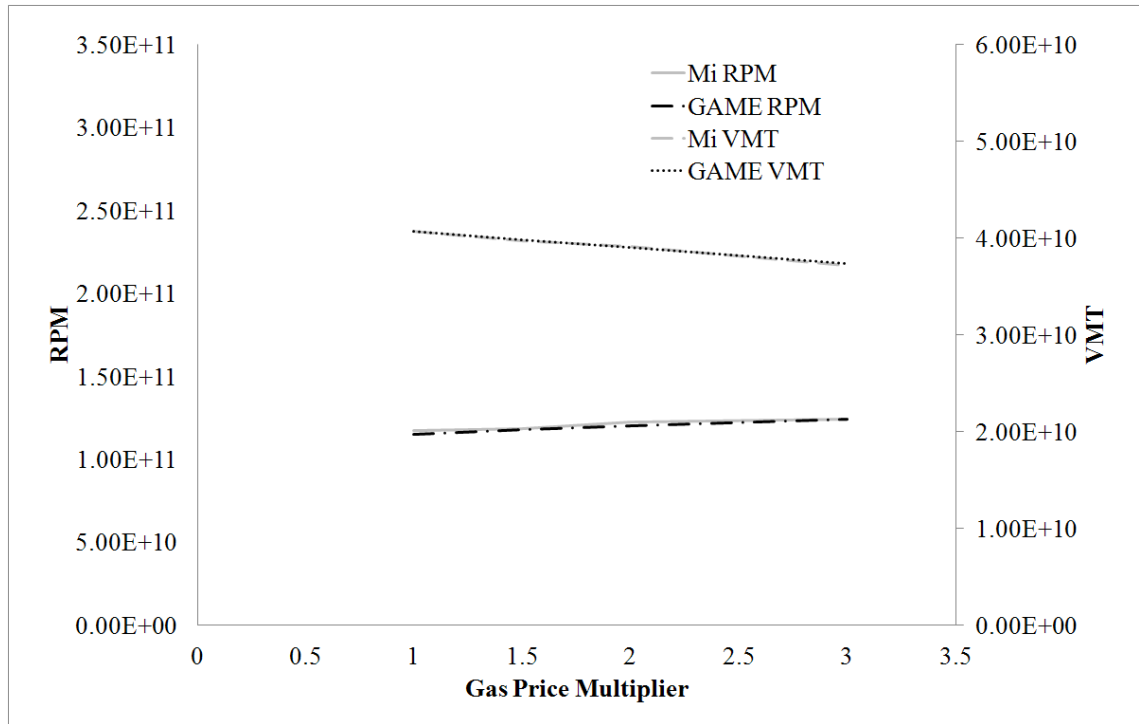
Figure 40: Sensitivity of RPM and VMT to gas price

executions.

In order to ensure that GAME can indeed be used as a surrogate of **Mi** within the equivalency box, the results must be compared for various, representative intermediate points in the equivalency box. A DOE is used to generate data points within this equivalency box. Specifically, a Box-Behnken design is selected since it requires fewer runs and explores the midpoints where the behavior needs to be checked. It is a three-factor case with respect to Gas price multiplier (X1), GDP multiplier (X2) and Ticket price multiplier (X3). MCSI (X4) is kept fixed at 1x to reduce the number of simulations but also because MCSI has negligible impact on both VMT and RPM, and little interactions with other factors. The results of the 13 DOE points are presented in Table 9 for VMT and Table 10 for RPM. An error between the SD and the ABM results is also computed. The error for RPM is slightly higher due to the higher sensitivity of RPM to changes in input variables. R^2 values are shown in Figure 43 for RPM and Figure 44 for VMT.

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Table 9: DOE results for VMT [94]

X1	X2	X3	Mi VMT	GAME VMT	VMT error
1	1	1.5	4.55E+10	4.54E+10	-0.15%
2	1	1.5	4.39E+10	4.37E+10	-0.43%
1	2	1.5	4.71E+10	4.81E+10	2.23%
2	2	1.5	4.53E+10	4.64E+10	2.45%
1	1.5	1	4.30E+10	4.32E+10	0.62%
2	1.5	1	4.20E+10	4.15E+10	-1.15%
1	1.5	2	5.09E+10	5.12E+10	0.55%
2	1.5	2	4.96E+10	4.96E+10	0.05%
1.5	1	1	3.97E+10	3.99E+10	0.37%
1.5	2	1	4.31E+10	4.26E+10	-1.09%
1.5	1	2	4.80E+10	4.79E+10	-0.20%
1.5	2	2	4.95E+10	5.06E+10	2.35%
1.5	1.5	1.5	4.67E+10	4.70E+10	0.63%

Table 10: DOE results for RPM [94]

X1	X2	X3	Mi RPM	GAME RPM	RPM error
1	1	1.5	8.56E+10	8.27E+10	-3.35%
2	1	1.5	8.91E+10	8.95E+10	0.47%
1	2	1.5	1.95E+11	1.92E+11	-1.42%
2	2	1.5	1.93E+11	1.99E+11	2.81%
1	1.5	1	1.87E+11	1.91E+11	1.84%
2	1.5	1	1.92E+11	1.96E+11	1.88%
1	1.5	2	1.25E+11	1.32E+11	5.42%
2	1.5	2	1.30E+11	1.40E+11	7.82%
1.5	1	1	1.18E+11	1.18E+11	-0.10%
1.5	2	1	2.23E+11	2.27E+11	1.89%
1.5	1	2	6.27E+10	6.10E+10	-2.72%
1.5	2	2	1.73E+11	1.70E+11	-1.93%
1.5	1.5	1.5	1.56E+11	1.62E+11	3.51%
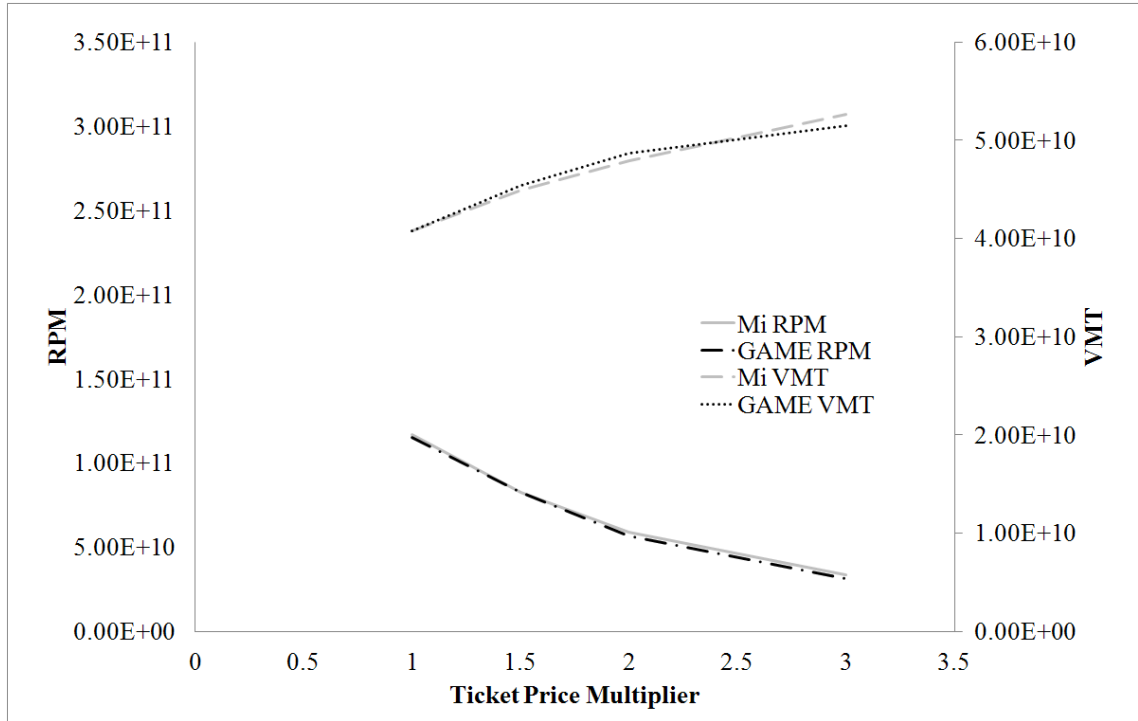
Figure 41: Sensitivity of RPM and VMT to ticket price

The results in Figures 43 and 44 show that, through the cross-calibration presented, SD is able to replicate ABM results with good accuracy within the given ranges, and thus the following hypothesis is verified:

Hypothesis 1.2: Through a cross-calibration process, SD can produce results similar to ABM within given ranges.

This cross-calibration process using the equivalency box concept may be replicated for any study using a hybrid ABM/SD approach.

4.4.4 Forecasting Capabilities

The results in Figures 43 and 44 justify the use of GAME as a surrogate of $\boldsymbol{Mi}$ as long as inputs remain in the equivalency box, which was designed to include both past data and expected future variations. Consequently, GAME is expected to replicate the past historical trend of RPM, which is confirmed in Figure 45. Over a time span of 17 years, results from GAME match $\boldsymbol{Mi}$'s and historical data (retrieved from T-100

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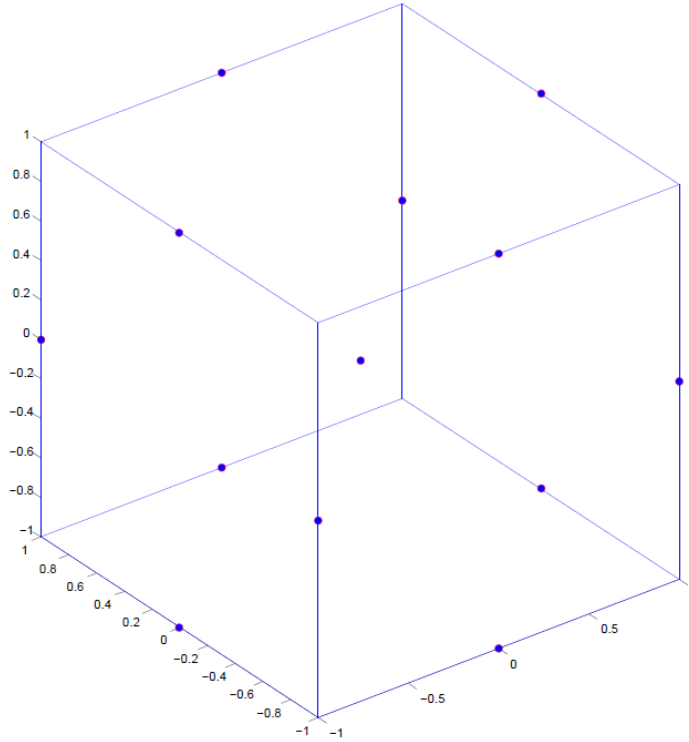
Figure 42: Box-Behnken Design

domestic data limited to continental US), with limited and acceptable discrepancy. A better match of historical could potentially be achieved, but it may result in a worse representation of other data points in the equivalency box. When adjusting the parameters in the SD model, it is important to remember its purpose which is to be able to accurately predict the behavior throughout the equivalency box. From the approach used in this validation process, it can be inferred that Mi's forecasting capability within the equivalency box is carried over to GAME.

The forecasting capability of GAME proved to be good: as seen in Figure 46 it gives results similar to the 2012 FAA forecast, slightly higher than predicted by Mi, and slightly lower than the 2011 FAA forecast.
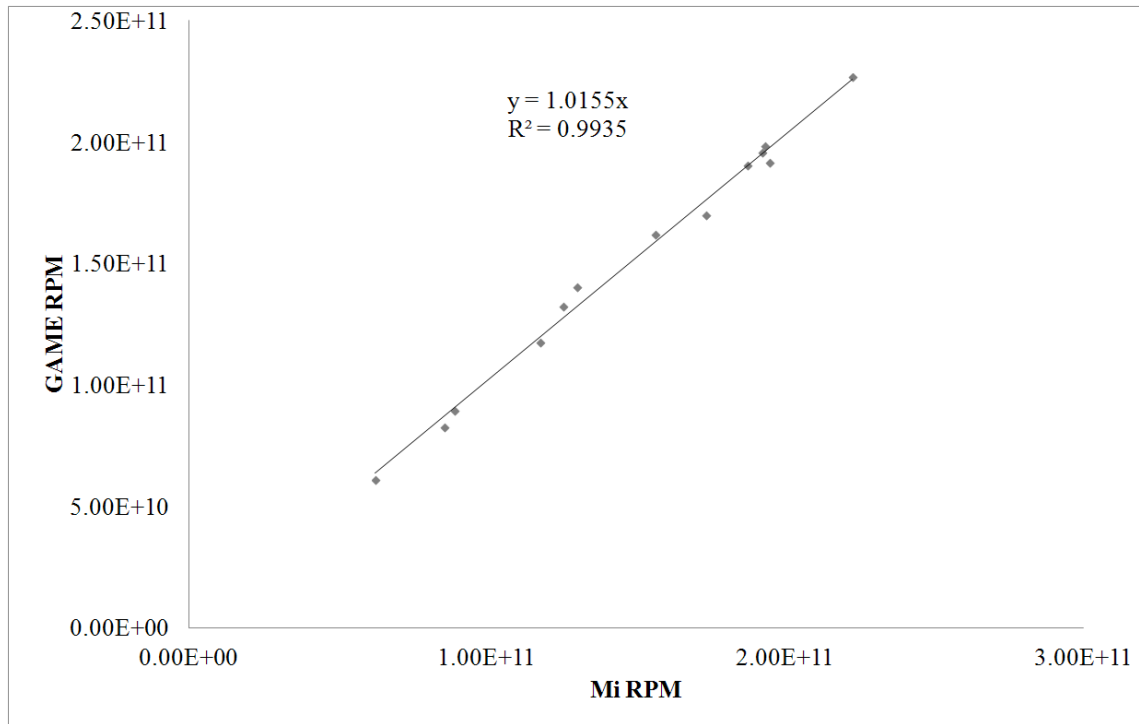
Figure 43: R^2 values **_Mi_** versus GAME for RPM

4.5 Demand Scenarios

With the model calibrated, it is then possible to quantify the effects of socio-economic variables, as well as technologies and policies, as will be discussed in the following sections.

4.5.1 Socio-economic Effects on Demand

Different scenarios are run with different sets of socio-economic exogenous variables. Optimistic and pessimistic forecasts are used for population growth, GDP growth, MCSI, and fuel price. These socio-economic scenarios are defined in Table 11. They result in different demand for each mode. Generally speaking, a high economic growth is favorable to the more expensive air transportation mode as can be seen in Figures 47 and 48. Indeed, a strong economy results in an increase in RPM and decrease in VMT, while a slow economy results in an increase in VMT and a decrease in RPM. In a strong economy, households have a higher income and they spend a higher portion
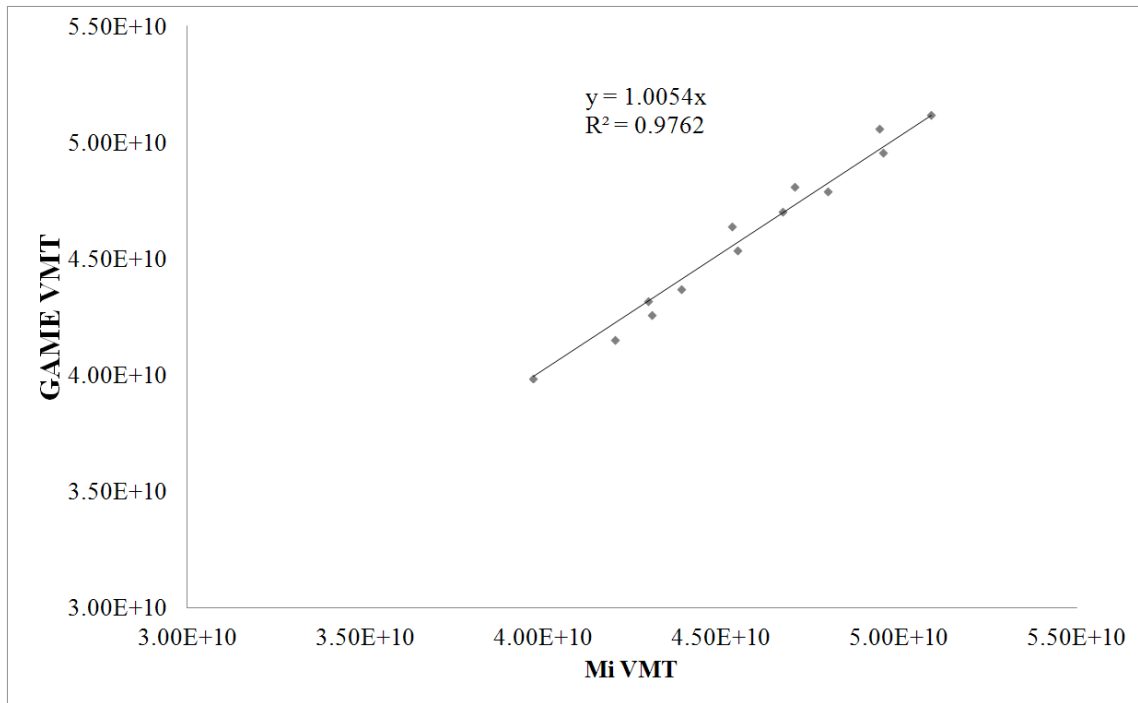
Figure 44: R^2 values **Mi** versus GAME for VMT

of their income on traveling, which allows them to travel more and use the more expensive ALN mode. In a slow economy, they will reduce their number of trips and prefer the less expensive GND mode.

The commercial air transportation system with its current operational capacity may reach maximum capacity some time in the future and it may be impossible to satisfy the forecasted demand. The capacity module implemented in GAME approximates saturation by assuming uniform flight distribution accross airports and time of

Table 11: Socio-economic scenarios settings

Scenario	Baseline	Strong economy	Slow economy
GDP adjustment in 2035 (1 in 1995)	2.40	2.89	1.92
MCSI adjustment in 2035 (1 in 1995)	0.77	1.000	0.69
Fuel price in 2035 (dollars per gallon)	2.287	3.287	2.287

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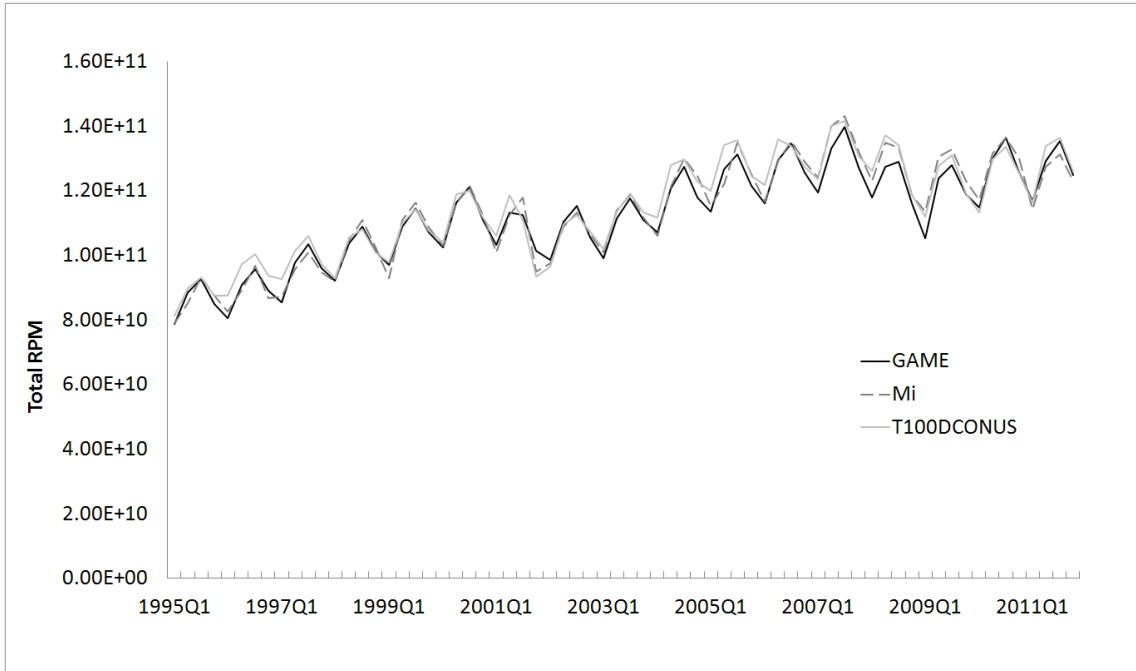
Figure 45: GAME validation with *Mi* and T-100 data
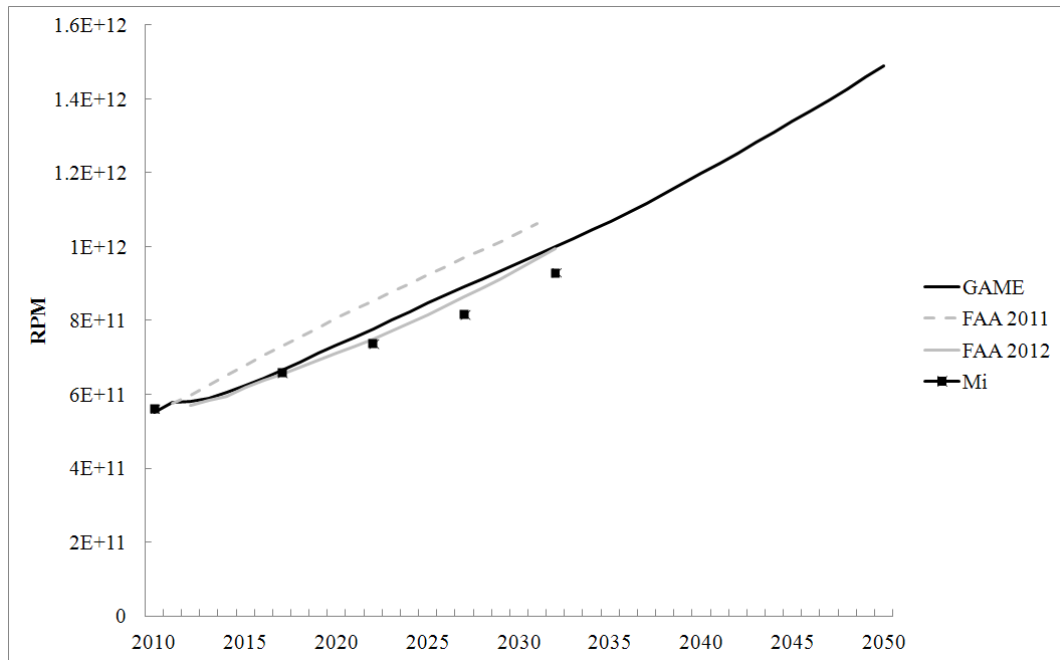
Figure 46: Future RPM

day. Delays would occur earlier at some specific airports but this type of local behavior is not captured at the aggregated level used in GAME. Therefore, GAME gives an approximate time when saturation might occur, knowing that local issues will emerge
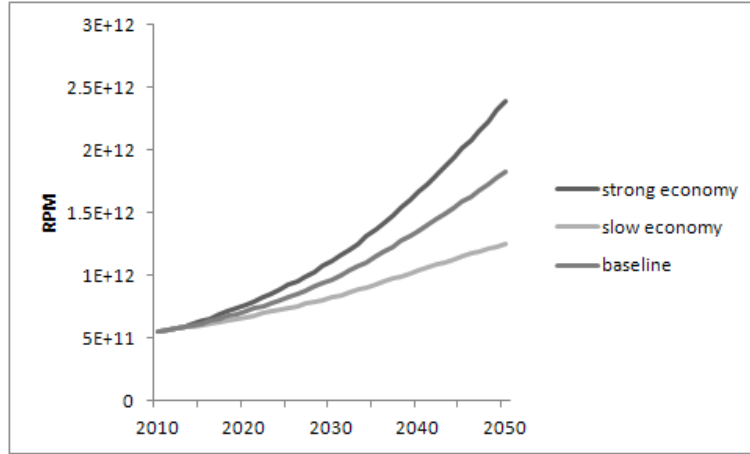
Figure 47: Socio-economic scenarios impact on ALN
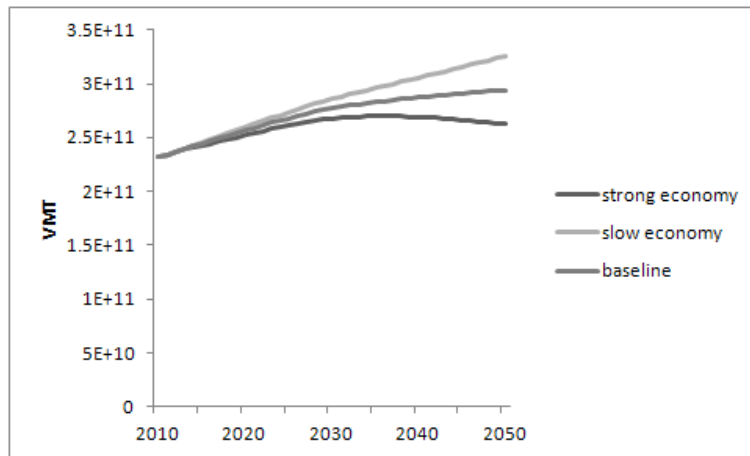
Figure 48: Socio-economic scenarios impact on GND

earlier. As can be seen in Figure 49, the system would be saturated in 2038-2039 approximately. This results in a zero growth of this mode after 2039 (Figure 50) and a significant decrease in attractiveness compared to other modes (Figure 51) due to the extra delays and time of travel. At the same time, these extra delays trigger a mode shift towards ground transportation which becomes relatively more attractive.

4.5.2 New Mode Introduction

The equivalency box is used in the version of GAME with only two modes of transportation (commercial air transportation and ground transportation). As presented
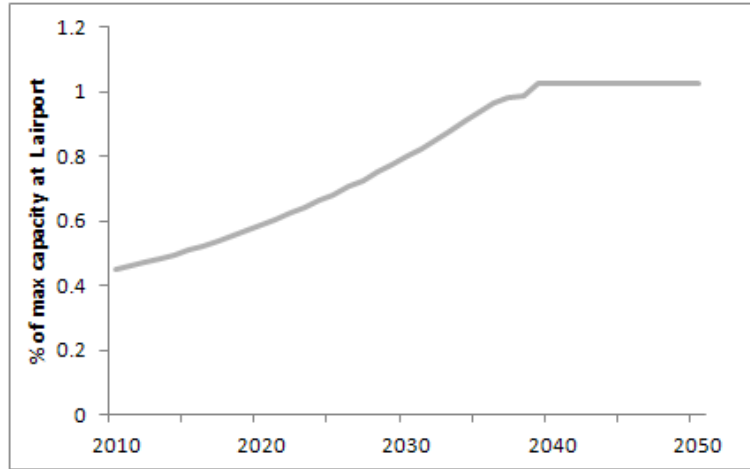
Figure 49: Percentage of maximum capacity at large airports
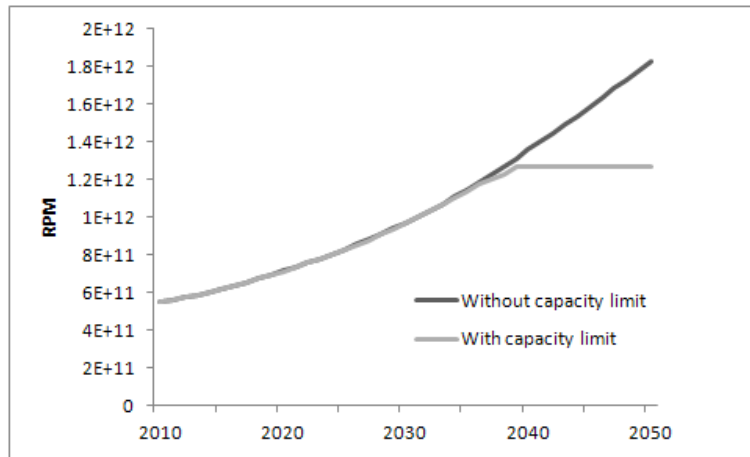
Figure 50: Capacity limit impact on ALN RPM
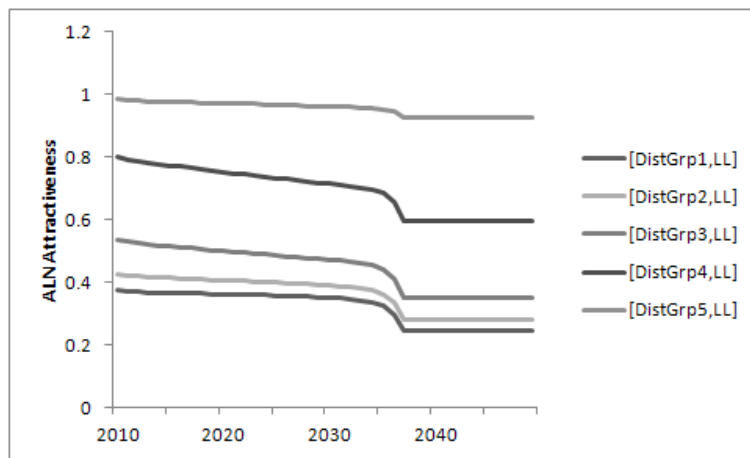
Figure 51: Capacity limit impact on ALN attractiveness

below, the introduction of a new mode creates a discontinuity in demand. To ensure that this discontinuity is properly quantified, the change in demand for existing modes, and the demand for the new mode are also calibrated against Mi's results. This process can be seen as an equivalency box on the new mode design variables. Different new mode characteristics will indeed result in different impacts on existing modes and different new mode demand.

The new mode example used here is a point to point mode using small aircraft (6 to 24 passengers) to utilize the existing community airport infrastructure and thus reduce congestion at major airports. Multiple scenarios can be run with different assumptions on the main modes characteristics, as well as on the new mode. These characteristics will define the relative advantage of each mode in terms of travel time and travel cost, and thus attractiveness.

The new, point to point air transportation (P2P) mode is introduced and calibrated based on different design characteristics, that include aircraft size, range and speed, as depicted in Figure 52. The main design parameters that impact the demand are the size of the aircraft, which defines the ticket price, the range of the aircraft, which defines the distance groups that can be served and the cruise speed. It appears that the introduction of P2P results in a small decrease in the demand for the ALN mode, as seen in Figure 53. As the size of the P2P aircraft increases, the ticket price decreases and the demand for P2P increases (Figure 54). Similarly, as the range increases, more routes can be served and the attractiveness increases for longer distances (Figure 55).

Mobility metrics were tracked. Mobility is quantified as an average time and cost spent traveling with each mode, which is then weighted with each mode's demand to obtain an aggregated time and cost. It can be considered as an average time and money spent per head for a typical trip. Variations in this metric may come from travel cost and time variations for a given trip, or from a shift towards longer trips.

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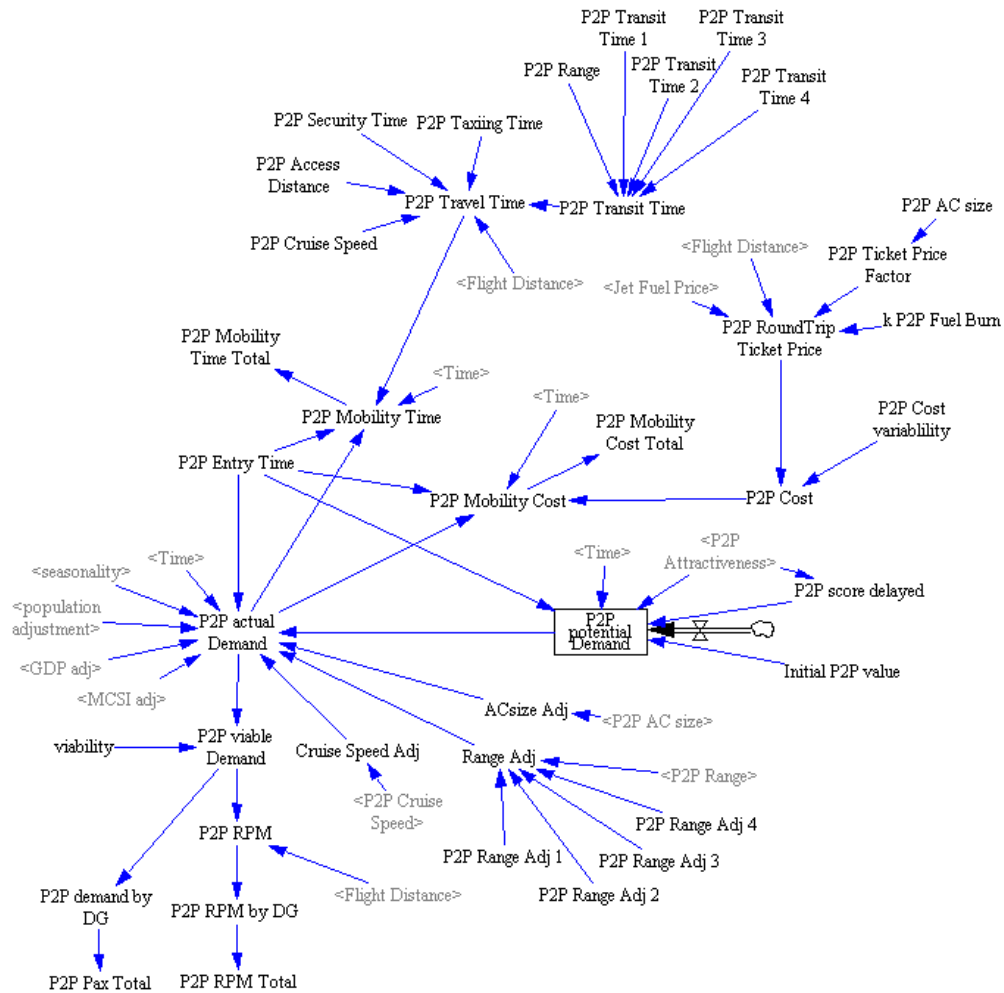
Figure 52: P2P module in GAME
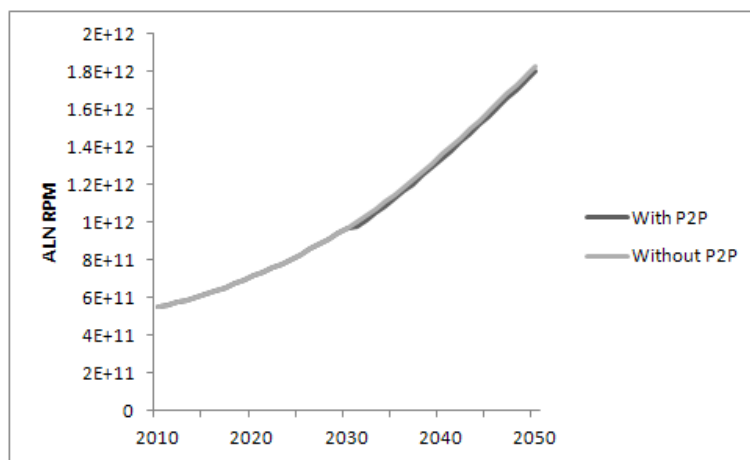
Figure 53: Introduction of P2P: impact on ALN
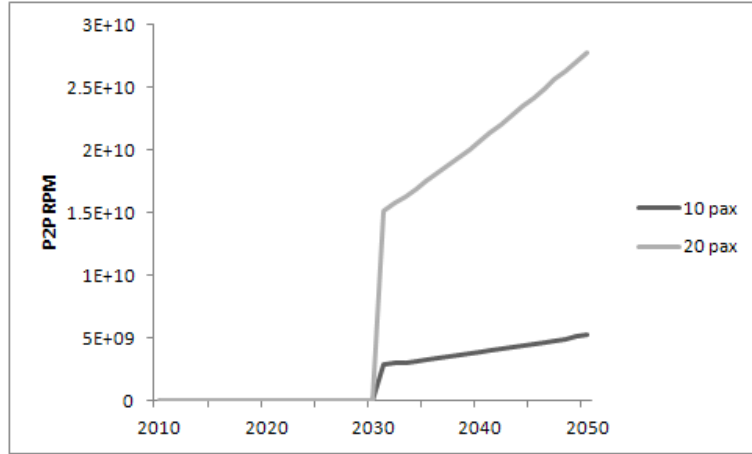
Figure 54: Introduction of P2P: impact of aircraft size on P2P demand
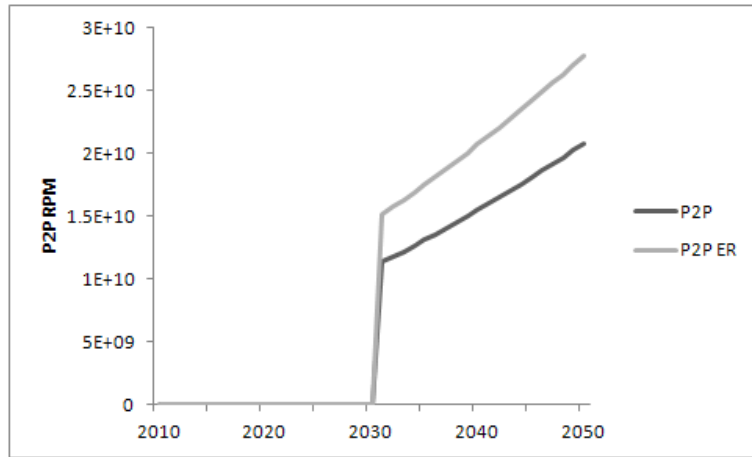
Figure 55: Introduction of P2P: impact of aircraft range on P2P demand

Multiple scenarios were compared: first it is observed in Figure 56 that capacity constraints result in a significant increase in average travel time. The introduction of P2P results in an increase in average cost and decrease in average time because the P2P mode introduced here, using small aircraft, is a more expensive mode. It can also be observed that P2P helps offload the large hub airports and slightly delays the saturation of the system.

Similarly, more simulations could be run that include a new high speed train system in some regions of the CONUS. The train system could be introduced between

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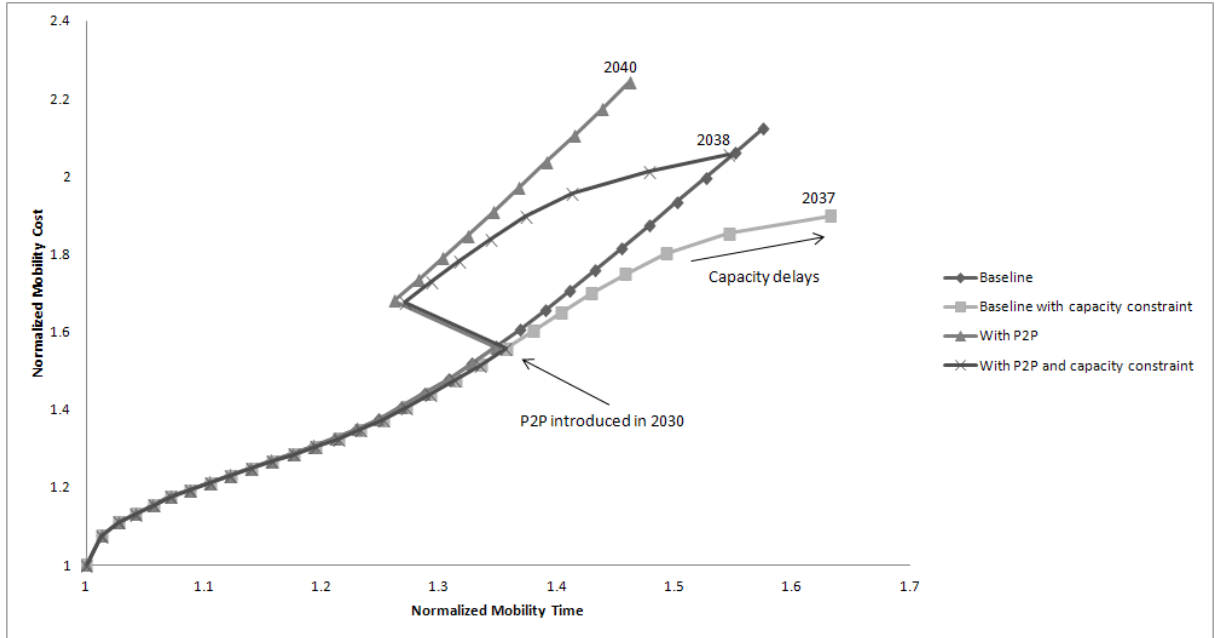
Figure 56: Mobility: Effect of capacity constraints and P2P introduction

large metropolitan areas when distance does not exceed a certain value. The introduction of the train mode would therefore only affect a subset of the DG-MMG pairs defined in GAME. Due to the flexibility of the hybrid ABM-SD approach, a wide variety of scenarios can be represented, with different levels of detail depending on the purpose of the study. The SD model can invoke the ABM whenever a finer granularity is needed, and the cross-calibration process then ensures that GAME captures the system's behavior. The hybrid methodology presented in this chapter may be used for other studies. In this research, the purpose is to assess climate impact and the effects of climate policies on transportation demand and fleets. With the demand generated with GAME, the climate impact can be quantified and the methodology will be described in the next chapter. The following research question will be addressed:

Research Question 2: How is the transportation system's impact on the atmosphere quantified?

The climate impact quantification in the environmental GAME (eGAME) will then enable the exploration of climate policy and technology scenarios.

CHAPTER V

TRANSPORTATION SYSTEM'S CLIMATE IMPACT

5.1 Fuel Burn and Emissions

This section adresses the following research question and hypothesis:

Research Question 2.1: How can fuel burn and emissions from different modes of transportation be quantified?

Hypothesis 2.1: The integration of parametric demand and fleet replacement models, and the use of life cycle emission factors enables scenario based environmental analysis.

Fleet models that integrate the demand generated by GAME are used to obtain fuel burn and emissions for the different modes of transportation and to eventually assess climate impact and policies as shown in Figure 57. Fundamental differences exist between modes and separate modules are used. In the commercial air transportation system, airlines make decisions for the replacement of their aircraft fleet based on a number of parameters, which include financial considerations, socio-economic variables, environmental impact, etc. Due to the long lifetime of aircraft, fleet replacements occur over many years, and future technologies may significantly change future fleet efficiency. On the other hand, the ground fleet is determined by individual decisions, and fleet turnover happens over a shorter period of time.

Going from transportation demand to fuel burn and emissions requires that assumptions be made on technologies and fleet composition. Technologies can be operational such as NextGen Air Transportation System technologies, Continuous Descent Approach, contrail avoidance trajectories, etc. They may also be technologies related to the vehicle, its performance, efficiency, etc. This type of technology is considered
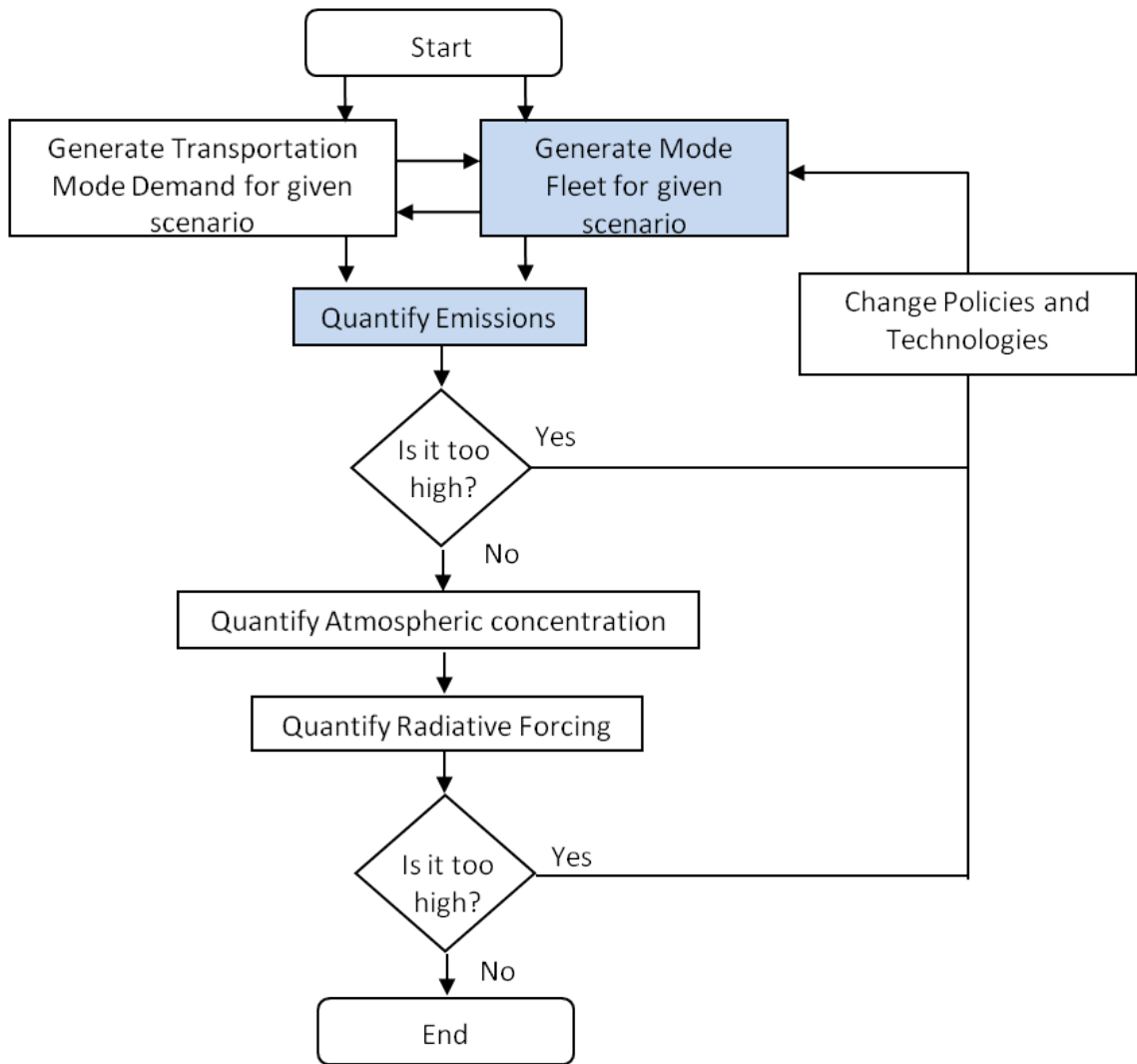
Figure 57: Step 2: Fuel burn and Emissions

in the IDEA fleet replacement model. Other types of technologies may focus on a new mode such as point to point, on demand aviation, high speed train. As presented by Argawal [6], a myriad of technologies are possible to reduce the environmental impact of both ground and air modes. The focus in this research is on mode and vehicle technologies to reduce fuel burn. Consequently, a subset of technologies is selected to study their impact on transportation demand and emissions. The focus is on technologies that might significantly affect these variables. Therefore, new technologies are considered with future fleet replacement scenarios that include aircraft

recently made available, future concepts such as NASA N+2 aircraft, automobiles with expected future fuel efficiencies, and electric vehicles. These new technologies will considerably reduce fuel burn, thus decreasing emissions, and potentially travel cost.

5.1.1   Air Transportation Emissions

As discussed in Section 2.4, the existing tool IDEA provides the necessary capability with sufficient flexibility and level of detail. It is therefore used for this research. It is important to properly integrate IDEA with GAME, and ensure that all necessary interactions between the models are taken into account and represented as accurately as possible.

IDEA takes the output from GAME as an input and run the fleet renewal code based on a given scenario. The integration of GAME and IDEA is further discussed in Reference [95]. IDEA takes the time series of RPM for each distance group. The RPM is then converted to operations. IDEA tracks the change in operations and determines the necessary changes in the airline fleet. Aircraft that are no longer economically valuable compared to new aircraft are retired. IDEA then gives the total fuel by distance group. The fleet system dynamics model computes fuel burn by fitting aircraft characteristics to a second order quadratic polynomial of flight distance [130]. IDEA provides outputs for fuel burn, CO_2 and NO_x. Using the fuel burn and emission factors provided in Table 12, all species of interest in terms of climate impact can be quantified.

5.1.1.1   Ticket Price Model

When GAME is run independently, assumptions on ticket price need to be made. Each distance group has a different average ticket price as shown in a study on past ticket price data using DB1B. It was also found that the ticket price changed very little due to the increase in fuel price. Further investigation led to the observation

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Table 12: Air Transportation Emissions Factors from GREET (g per pax/km)

Species	WTP	PTW	WTW
CO_2	12	57	70
CH_4	0.094	0	0.094
N_2O	0	0	0
VOC	0.006	0.010	0.016
CO	0.009	0.072	0.081
NOx	0.034	0.281	0.315
PM10	0.005	0.003	0.008
PM2.5	0.003	0.003	0.006
SOx	0.018	0.025	0.044

Table 13: Fuel Cost to Ticket Price Ratio

Distance Group	Fuel Cost to Ticket Price Ratio
DG 1	0.12
DG 2	0.15
DG 3	0.23
DG 4	0.30
DG 5	0.35

that airline did not noticeably change their fleet in response to the 2008 fuel price hike, as described in Appendix B. This lack of a strong correlation between fuel price and airlines' decisions is likely due to the short term increase in fuel price in 2008. Had this increase been stronger and had lasted longer, airlines would have been forced to adjust their fleet and pass the increase on to the customer by increasing their ticket price, to ensure their economic viability in the long term. Therefore, the model assumption in this research is that airline adjust their ticket price to account for fuel cost increase. A pass through model was created by quantifying the fuel cost portion of the ticket price for each distance group. Knowing the fuel burn by distance group from the fleet model, and the average ticket price from DB1B, the fuel cost to ticket price ratio can be determined as shown in Table 13.

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With these assumptions, any fuel burn improvement measured in IDEA needs to be fed back to GAME. The process is as follow: GAME is first run with a no fuel burn improvement assumption, then IDEA uses the demand from GAME to generate the fleet fuel burn and a fuel burn factor is computed and fed back into GAME to adjust the ticket price as depicted in Figure 58.
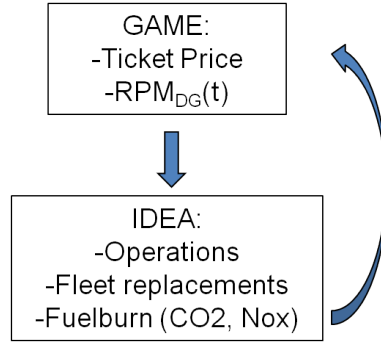
Figure 58: Link between GAME and IDEA

The fuel burn factor is obtained using the following equation:

$$FBF(t) = \frac{Fuelburn(t)/PAX(t)}{Fuelburn(t_0)/PAX(t_0)} \tag{11}$$

This fuel burn factor is combined with the fuel price factor defined as:

$$FPF(t) = \frac{Fuelprice(t)}{Fuelprice(t_0)} \tag{12}$$

With these fuel burn and fuel price adjustment factors, a new ticket price is computed.

$$TP(t) = TP(t_0) + PT.FC(t_0).(FBF(t).FPF(t) - 1) \tag{13}$$

PT is the pass through assumption (value between 0 and 1) which represents the amount of extra cost due to fuel price and fuel burn variation that the airlines pass on to the customer. Using the Airline Origin and Destination Survey (DB1B database, a 10 percent sample of airline ticket data), a baseline ticket price ($TP(t_0)$) is obtained.

A baseline fuel cost $(FC(t_0))$ per ticket is computed based on fuel burn data from IDEA.

This results in a new demand. This new demand is used to run IDEA and the process is repeated until convergence. Even with a low convergence threshold, results converge quickly after about 3 iterations.

5.1.1.2 Fleet scenarios

As explained above, different fleet scenarios result in different emissions and demand. A high efficiency fleet is more environmentally friendly and results in lower fuel burn, which in turn lowers the cost and creates more demand based on the pass through model previously described.

Different airline fleet scenarios may be used [68]:

- Business As Usual (BAU) scenario which only includes currently available aircraft types and technologies. Once out-of-production aircraft are retired, the fleet behaves as a fixed technology mix of current in-production types. As a result, after a transition period of less than 30 years, the fleet efficiency remains constant. This represents the worst-case scenario.

- Industry Response (IND) scenario which includes improved technology aircraft that have been announced (Figure 59).

- N+2 scenario in which future more efficient aircraft across all sizes become available for purchase in the 2025 time frame [120] (Figure 60). The underlying adoption rate is based on the airlines estimated NPV of continuing to operate an older less efficient aircraft with higher maintenance cost versus a new more efficient aircraft with lower maintenance costs.

The results from IDEA show that for a given demand, the total fuel burn varies dramatically between the different fleet scenarios. The Business As Usual (BAU)

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Aircraft	Entry into Service	Seats*	Range Capability**	Fuel Burn Improvement***	Reference Aircraft
Airbus 380-800 ****	October 2007	525		17% per seat (-22% per trip)	Boeing 747-400
Airbus 350-900	Late 2013	314	8,100	25%	Boeing 777
Airbus 350-800	2016	270	8,500	20%	Boeing 767
Airbus 350-1000	2017	350	8,400	25%	Boeing 777
Airbus 320NEO	2016	Comparable to reference with range or payload improvement		15%	Airbus 320
Airbus 319NEO	2017	Comparable to reference with range or payload improvement		15%	Airbus 319
Airbus 321NEO	2018	Comparable to reference with range or payload improvement		15%	Airbus 321
Boeing 787-8 ****	August 2011	210-250	7,650-8,200	20%	Boeing 767
Boeing 787-9	2014	250-290	8,000-8,500	20%	Boeing 777
Boeing 747-8I ****	2012	467	8,000	16% per seat (6% total trip)	Boeing 747-400
Boeing 737 MAX 7, 8, 9	2017	Comparable to reference with range or payload improvement		12%	Boeing 737-700, 800, 900
Bombardier CS100	2013	110	2,200	20%	Airbus 318,319 Boeing 737 G2
Bombardier CS300	2014	130	2,200	20%	Airbus 319,320 Boeing 737 G2

* Number of seats is representative, with a two- or three-class configuration as applicable
**Range capability indicated by manufacturer, corresponding payload and fuel load not specified
*** Fuel burn improvement is on a total trip basis unless otherwise stated
**** Considered In-Production for this analysis

Figure 59: IND scenario characteristics [131]

	Regional Jet (RJ)	Small Single Aisle (SSA)	Large Single Aisle (LSA)	Small Twin Aisle (STA)	Large Twin Aisle (LTA)	Very Large Aircraft (VLA)
Reference Airframe	CRJ900	737-700	737-800	767-300ER	777-200ER	747-400
Reference Engine	CF34-8	CFM56-7B27	CFM56-7B27	CF6-80C2	GE90-94B	PW4056
Number of Seats	86	128	174	210	301	416
Fuel Burn % Reduction (HWB)	33%	37%	36%	45%	40% 46%	44% 56%

Figure 60: N+2 scenario characteritics [77]

scenario results in a fuel burn that follows the increase in demand. This is due to the minor efficiency increase of this fleet. The industry only replacement scenario (IND) results in slightly better results. When N+2 aircraft are introduced, the gain in fuel burn is significant, as can be observed in Figure 61. Simulations were run with iterations between the demand and the fleet model in order to feed back the efficiency improvement and change the ticket price accordingly. Results are plotted in Figure 62. The rebound effect is observed: a more fuel efficient fleet result in a lower ticket price and thus a slightly higher demand for the ALN mode. With a pass through of 50 percent, there is about 10 percent increase in demand between the BAU

and N+2 scenario due to the rebound effect. This confirms that if airlines change their ticket price with fuel burn improvements, a non-negligible rebound effect on demand will be observed.
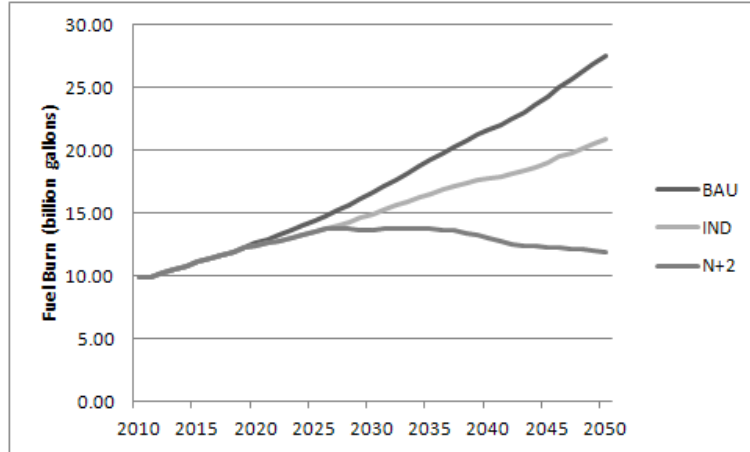
Figure 61: Impact of fleet on fuel burn
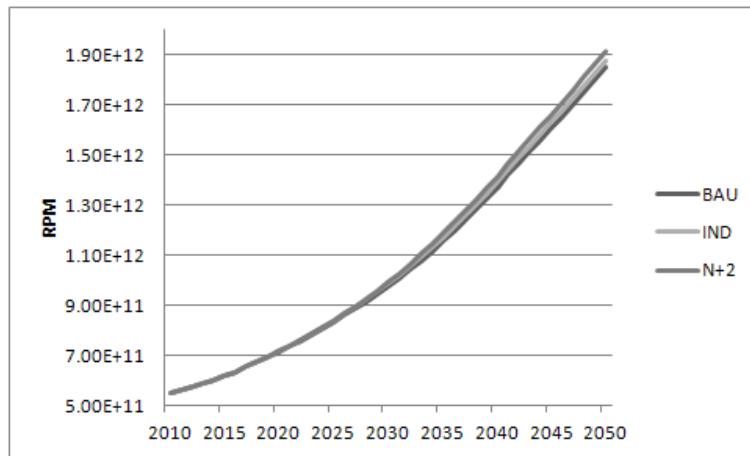
Figure 62: Impact of fleet on RPM

5.1.2 Ground Transportation Emissions

For the ground transportation, no existing model can directly be linked to GAME. Therefore a ground module is created using available data and tools. Two sets of variables are identified that determine emissions: the first one relates to the fleet composition, the market share of each vehicle type and fuel type, the second relates

to operating conditions. In order to quantify these effects, the research follows two paths:

- The development of a fleet replacement model to derive vehicle market shares.

- The quantification of fleet composition and operating conditions impact on fuel burn and emissions.

The fleet replacement model is created using a logit model and literature on the main characteristics that influence vehicles' attractiveness. Market shares vary based on a number of parameters resulting in different life cyle emissions. The impact of different variables on fuel burn is assessed through the use of the MOVES model, using CO_2 emissions as a proxy variable for fuel consumption. A set of variables that significantly impact emissions is identified. Emissions are obtained from the fuel consumption through emission factors that can be obtained from GREET. The fleet fuel efficiency has stagnated over the past few years and is expected to increase in the future due to higher expected miles per gallon (mpg) targets. The mpg targets cannot be directly used as an average fleet efficiency due to delays related to the time it takes for older vehicles in the fleet to be retired. With the demand from GAME and the fleet efficiency computed with the fleet module, the ground emissions are obtained and future climate impact can then be assessed.

5.1.2.1 Emission Factors

Emission factors are derived from MOVES for different vehicle types, and operating conditions. Experiments are run varying one variable at a time, and the most important variables are identified. For instance, it was observed that CO_2 emissions are highly dependent on vehicle age, driving speed, and outside temperature. Older designs indeed have lower fuel efficiency. Automobiles have an optimum operational speed where fuel consumption is minimum. Lower speeds with stop and go traffic result in higher fuel consumption, as well as high speeds. When outside temperature

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Table 14: Emissions Factors for gasoline vehicle from GREET (g per mile)

Species	Feedstock	fuel	operation
CO_2	20	60	377
CH_4	0.444	0.207	0.015
N_2O	0	0.005	0.012
VOC	0.018	0.117	0.180
CO	0.029	0.033	3.745
NOx	0.135	0.099	0.141
PM10	0.013	0.024	0.029
PM2.5	0.008	0.011	0.015
SOx	0.056	0.068	0.006

is above a certain threshold, fuel consumption increases due to the use of Air Conditioning. The process of identifying the main variables with an impact on emission is repeated for each species of interest. Functions of these variables are fitted to the data. More details are provided in Appendix D. These functions are derived using 2010 as the simulation year, which means that the emissions per mile correspond to the 2010 vehicle fleet mpg. Car fuel efficiency expected improvements are applied and future average fuel economy is obtained from the fleet replacement model. Emissions are then adjusted accordingly. Given the vehicle type distribution obtained from the fleet model, and emission factors for each fuel type, emissions of species of interest are quantified.

Upstream emissions can represent a significant part of total emissions, especially for Electric Vehicles. Simulations are run in GREET to determine life cycle emissions and emission factors. The following results are obtained from GREET and used in eGAME to generate life cycle CO_2 and NOx emissions for EVs. The well to pump CO_2 emissions for EVs is 352 g/mile (using the U.S. energy mix), as opposed to 80 g/mile for a conventional gasoline vehicle. NO_x emissions for EVs are 0.36 g/mile as opposed to 0.234 g/mile for conventional vehicles. A complete list of emission factors can be found in Tables 14, 15 and 16.

Table 15: Emissions Factors for diesel vehicles from GREET (g per mile)

Species	Feedstock	fuel	operation
CO_2	23	45	323
CH_4	0.370	0.156	0.003
N_2O	0	0.001	0.012
VOC	0.015	0.018	0.088
CO	0.024	0.025	0.539
NOx	0.113	0.074	0.141
PM10	0.011	0.017	0.030
PM2.5	0.007	0.009	0.016
SOx	0.047	0.051	0.002

Table 16: Emissions Factors for EV from GREET (g per mile)

Species	Feedstock	fuel	operation
CO_2	12	340	0
CH_4	0.889	0.007	0
N_2O	0	0.004	0
VOC	0.026	0.006	0
CO	0.016	0.076	0
NOx	0.061	0.299	0
PM10	0.440	0.021	0.021
PM2.5	0.110	0.011	0.007
SOx	0.034	0.741	0

5.1.2.2   Market Share

The market share of each vehicle type is determined using the ground fleet module (Figure 63), which uses a logit model for vehicle attractiveness. Vehicles are retired using a survival curve. People's decisions when it comes to buying a new vehicle is highly dependent on the economy, gas prices, the average cost of driving the vehicle, and tax incentives (such as those for EVs). It is therefore necessary to include a personal vehicle module that can account for different cost scenarios and result in different fleet forecasts. Depending on the cost of gasoline, and other cost related metrics, people will make decisions to keep their older vehicle or replace it, with a similar but more fuel-efficient or more comfortable vehicle. Different socio-economic and environmental scenarios will result in different decisions and therefore different ground vehicle fleets, which in turn will affect the emissions and climate impact. A utility can be defined based on the following list of parameters:

- purchase cost for each car category

- taxation cost for each car category

- maintenance cost

- fuel cost per car category

and a logit model may be implemented within the eGAME system dynamics framework. Car survival rates may be computed with the sigmoid equation:

$$survival(t) = 1 - \frac{1}{1 + exp(-\lambda(t - \tau))} \tag{14}$$

where λ defines the curvature of the survival curve, and τ is the age at which 50 percent of the vehicles have been removed from the fleet.

The retired vehicles are replaced by new vehicles based on the logit model that defines an attractiveness for each vehicle type. Six vehicle types are defined that
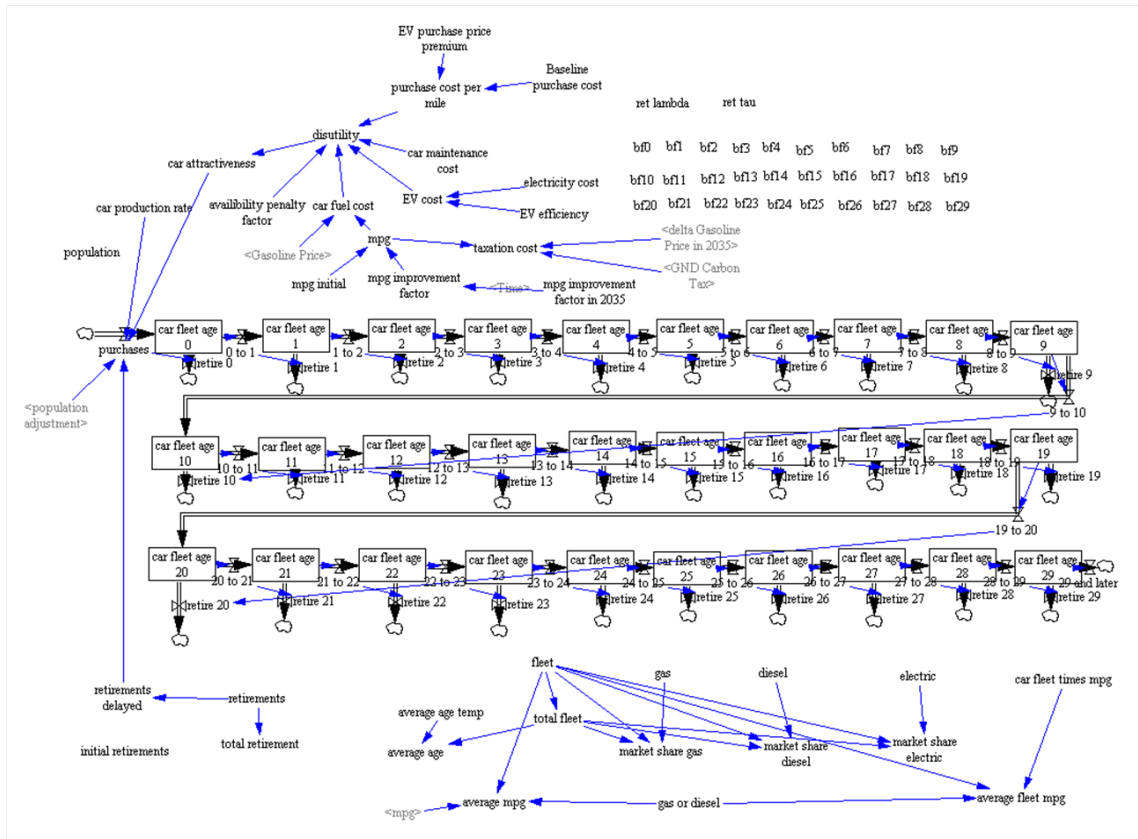
Figure 63: Ground fleet module

represent large and small vehicles using gasoline, diesel, or electricity. A utility of each vehicle is defined based on acquisition cost, maintenance cost, and operating cost. The model keeps track of the market share of each fuel type, in order to use the right emission factors. Depending on the price premium of EV, the market shares vary as seen in Figure 64. From the emission factors listed in Tables 14, 15 and 16, different life cycle emissions will be obtained.

5.1.3 Fleet Replacements in the Context of Climate Policy

The above discussion on fleet models and emission factors for each mode of transportation leads to the verification of the following hypothesis:

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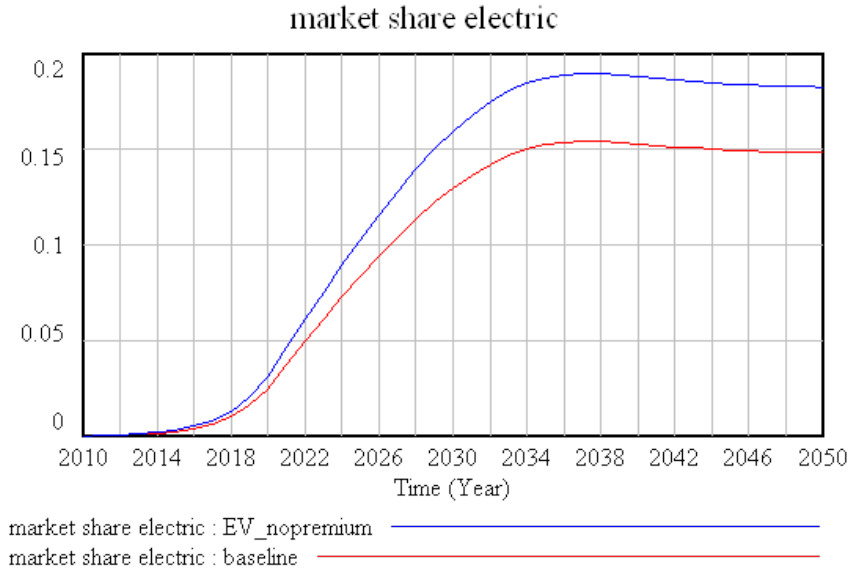
Figure 64: EV market share with and without purchase cost premium

Hypothesis 2.1: The integration of parametric demand and fleet replacement models, and the use of life cycle emission factors enables scenario based environmental analysis.

When fuel price increases due to policies such as a carbon tax, demand is expected to decrease and more efficient vehicles become more attractive and have an increased market share, which in turn result in a potential increase in demand. Responses may be faster for ground vehicles than aircraft due to the differences in acquisition cost and average retirement age. Other policies that encourage more fuel efficient vehicles include Corporate Average Fuel Economy (CAFE) standards, retirement programs, purchase/usage tax etc. Policies aiming at increasing the ground fleet efficiency are promising due to the quick turnover (rarely more than 20 years). In some cases, as discussed by Boucher and Reddy [22], some trade-off situations may exist when policies on BC aerosols result in higher fuel consumption and thus more long term CO_2. The focus of this research is on policies and technologies that would affect fuel burn, and emissions of different species are computed with emission factors that are assumed to remain constant. Therefore, this type of tradeoff between different species

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is not considered here.

In order to reduce overall transportation's climate impact, new modes of transportation may be envisioned. The approach presented in this research is flexible and can be repeated to include other modes. For example, if a high speed train mode is added, life cycle emissions will need to be quantified as well using assumptions on electricity consumption. Assuming a given energy mix, the emissions from this electricity consumption can then be quantified. A study has been performed on the high speed rail in California [25] and assumed a vehicle electricity consumption of 170 kWh per vehicle kilometer traveled.

Based on the technology level, the demand for each mode may vary significantly. The fuel consumption has indeed a direct effect on cost of traveling, which is one of the key parameter of mode choice. Increasing technology level will not only decrease emissions per mile traveled, it may also increase the demand. It is therefore important to assess fleet fuel efficiency, emissions and demand together as competing effects exist that might change total emissions. A given technology scenario is chosen, and is used to compute both the demand from GAME and the emissions from fleet models. eGAME provides a framework that captures these types of interactions and thus helps assess the effect of policies on both demand and fleet and capture rebound effects.

From demand and fleet models, a number of emissions are quantified, which can then be used to determine the impact on climate. The following section presents an approach to quantify the effect of emissions on the climate.

5.2   Climate Impact Assessment

In policy making, emissions may be used directly, and CO_2 is a widely accepted metric for certification requirements [20]. Some non-CO_2 metrics have been discussed in European Parliament though they are unlikely to be implemented in the near future [178]. As the transportation community becomes increasingly aware of the
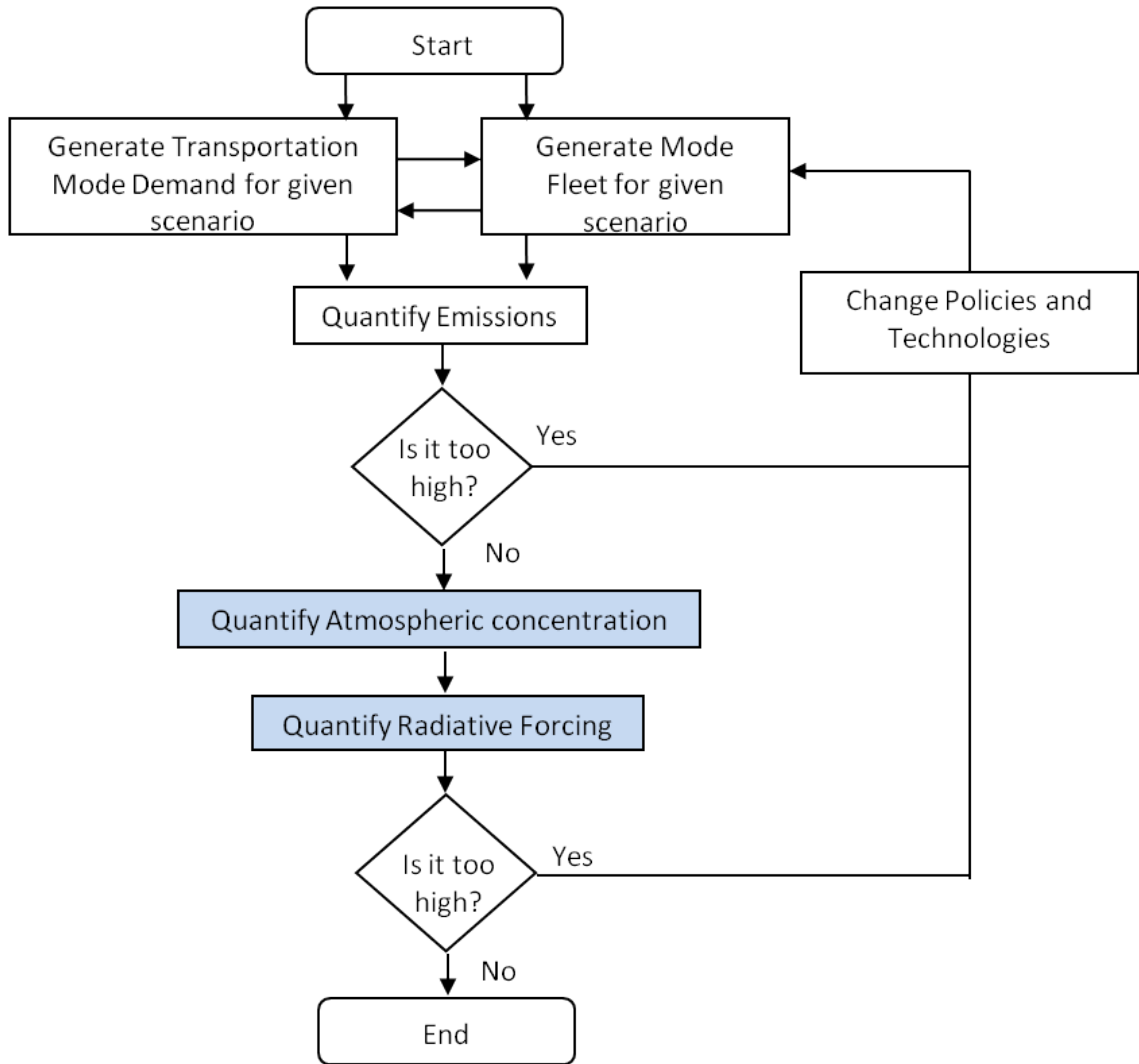
Figure 65: Step 3: Climate impact

impact of other gases and particles emitted by the transportation modes, and the climate modeling capabilities improve, other policies affecting these species might be envisioned and further climate impact quantification is needed in order to allow for all impact metrics and policies to be assessed. This step is depicted in Figure 65.

5.2.1 Climate Impact Metrics

As the scientific understanding of the impact of different species increases, the accuracy of the quantification of the climate impact of transportation modes improves and more appropriate and targeted policies can be envisioned. In order to enable for

this flexibility in policy making, it is necessary to allow for many different scenarios with different levels of complexity. With the fuel burn and emissions quantified using the methodology described in section 5.1, further atmospheric modeling is needed to assess the climate impact at different level of relevance and uncertainty, as described in Figure 66.
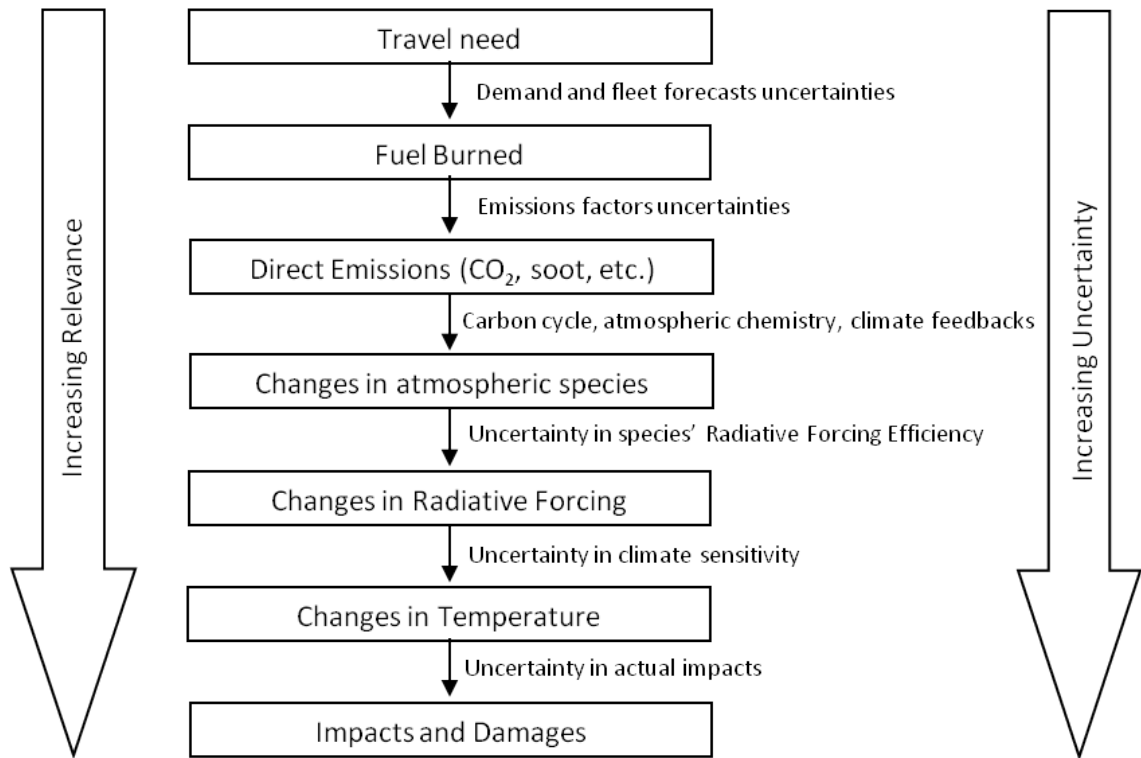
Figure 66: Uncertainties in climate impact assessment (adapted from Dallara et al. [29])

In order to introduce policies and assess their impact, the right metric for policy assessment needs to be identified, hence the following research question:

Research Question 2.2: What metric is appropriate for transportation climate impact assessment?

To answer this question, a tradeoff between relevance and uncertainty is inevitable as depicted in Figure 66. The current understanding and the state of the science is such that the effects of anthropogenic emissions are increasingly better modeled and understood. Consequently the uncertainty may be reduced, which shows that

the relevant metric for policies might evolve through time. The Aviation-Climate Change Research Initiative report on climate metrics and aviation [179] lists the characteristics that such metrics must have:

- Provide flexible, rapidly available input regarding the ability to minimize impact of human activities on climate system

- Assess the relative contributions of emissions

- Compare and rank climate effects from competing technologies

- Rank emissions from various countries

- Establish a basis for comparing reductions in various countries

- Function as a signal for policy considerations

- Analysis tool for industries and countries to determine the best approach for meeting commitments to reduce climate impact

It must be scientifically well grounded, but also simple to use and easy to understand.

As introduced in Section 2.5.3 on radiative transfer theory and Section 2.5.1 on the transportation climate impact, a number of species emitted by transportation modes have an impact on the climate. Depending on a number of characteristics, their effect on the energy balance of the planet will vary. Some species may have a stronger impact on radiative transfer through the atmosphere than others. Emission-based metrics are a necessary step toward policy making and have the advantage of having more limited uncertainty. But to assess the relative contributions of emissions on climate impact, RF is a more relevant metric, and is used by the IPCC and throughout the literature. Hence the following assertion:

Assertion 2.2: To fully assess transportation climate impact, all gases and aerosols need to be considered and radiative forcing is an appropriate metric.

5.2.2 Main Species for Transportation Climate Impact

Emissions from transportation affect the atmosphere in a number of ways. As described in Chapter 2, a number of gases and particles from transportation modes impact the energy balance of the Earth atmosphere. The RF from each species needs to be estimated in order to decide which species to include in the framework to assess climate impact and make decisions on policies and technologies. Hence, the following research question:

Research Question 2.3: What is the RF of the species with the most impact? First the impact of different species is estimated through literature review, and the species with the main impact are chosen and incorporated into the eGAME framework.

Below is a list of short and long lived gaseous species and their impact:

- CO_2 is emitted by both modes of transportation. It is also emitted by electricity generation for electric vehicles. Its lifetime in the atmosphere vary between 30 years and thousands of years. It has a warming effect with a radiative efficiency of $1.4.10^{-5} W.m^{-2}.ppb^{-1}$ [75]. Its global mean radiative forcing due to all emissions is $1.46 W.m^{-2}$ [74]. The level of understanding for CO_2 is good.

- NO_x (NO and NO_2) is produced by both the air and ground transportation modes. Its impact is associated with significant uncertainty [70]. Due to spatial and temporal dependence, the radiative efficiency of NO_x has no prescribed value [119]. Wild et al. [177] estimated the RF for different regions and the study showed that NO_x had a cooling effect due to the combined O_3 and CH_4 effects. However without the CH_4 effect, the NO_x-O_3 radiative efficiency of $6.10^{-13} W.m^{-2}.kg^{-1}$ is obtained [119].

- O_3 from NO_x comes from both the aviation and the ground modes of transportation. It is short lived and has a warming effect. Its total gobal mean RF

from IPCC's Third Assessment Report (TAR) [74] is $0.35W.m^{-2}$ with a poor level of understanding.

- CH_4 impact from NO_x is produced by both modes of transportation as well. CH_4 has a 12 years lifetime in the atmosphere and NO_x-CH_4 has a cooling effect. The radiative efficiency of CH_4 is $3.7.10^{-4}W.m^{-2}.ppb^{-1}$. The total global mean radiative forcing from TAR is $0.48W.m^{-2}$ with a poor level of understanding.

- H_2O produced by both modes has a lifetime of approximately 1 week and a small warming effect. The concentration of water vapor is not significantly changed by anthropogenic emissions.

- CO produced by both modes of transportation is short lived and has a warming effect.

- Volatile Organic Compounds (VOC) are produced by both modes and have a warming effect.

Aerosols and clouds resulting from transportation activity also have a significant impact on the Earth Radiative Balance.

- Sulfate aerosols are produced by both modes and have a cooling effect.

- Soot, also called black carbon, is short-lived (3.8 to 11.4 days based on Bond et al. [17]) and has a warming effect with a forcing efficiency of 90 to 270 $W.m^{-2} per AAOD$ varying regionally and seasonaly. These values are obtained by comparing radiative transfer (RT) calculations with and without BC emissions.

- Contrails are generated by aircraft engines under certain atmospheric conditions. They are short-lived and their positive radiative forcing is fairly well understood. Previous studies quantified contrail cloud cover and resulting radiative forcing.

- Cirrus clouds. Contrails sometimes become cirrus clouds which have a warming effect but the transition from contrail to cirrus is poorly understood.

Physical properties of aerosols are important for correct estimation of their radiative efficiency. Regional and seasonal variations are observed with short-lived species due to significant spatial and temporal variability of emissions and parameters with influence on the radiative transfer calculations. Hence the following hypothesis:

Hypothesis 2.3: Radiative Forcing efficiencies vary based on the mode of transportation, location and season of emission.

In this research, the CONUS is the spatial limit. Seasonal variations in emissions can be captured using the quaterly version of demand models. This study will focus on the effect of aerosol species with a warming effect and a good or fair level of understanding. The goal is to assess the difference in demand and emissions resulting from "CO_2 only" policies versus policies that include short-lived aerosols effects.

After estimating the impact of the different species emitted by the main transportation modes, CO_2, black carbon and contrails are considered and are included in the eGAME modeling and simulation environment. Black carbon is considered as the second most significant warming species [17]. As can be observed in Figure 12, contrails are the second most significant warming effect for aviation. For each species, a radiative forcing efficiency of transportation emissions is defined. This forcing efficiency can be quantified using radiative transfer codes [13, 102, 53, 67]. Surface albedo and clouds have a non negligible impact on the radiative effects of aerosols. Remote sensing techniques are commonly used to derive aerosol optical depth. A common metric is the aerosol radiative efficiency defined as the ratio between direct radiative forcing and optical depth at 550 nm. It is determined by aerosol size distribution, single-scattering albedo and phase function [183]. Remote sensing data is used to determine necessary characteristics for radiative transfer simulations.

5.2.3 Regional and Seasonal Characteristics Based on Remote Sensing Data

Due to the regional and seasonal variations, impacts of aerosols have a range of uncertainty. For policy making, an average effect will be considered, with given ranges of uncertainty, that are determined through radiative transfer calculations. A number of parameters need to be determined for radiative transfer calculations. The BC aerosol optical depth used for the simulations is based on retrievals from a global network of ground-based sun-/sky-radiance observation (AERONET), and is estimated at 0.01 by Bond et al. [17]. The aerosol vertical profile is obtained from the CALIOP lidar aboard the CALIPSO (Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations), which measures backscattered radiation at 532 and 1064 nm. Seasonal and regional variations may be observed. Therefore, multiple images are retrieved for different seasons and regions. Aerosols are found in the lower 3 to 5 km depending on season. Different profiles were indeed observed for the winter and summer seasons. Summer is characterized by higher aerosol mixing (as was observed by Andrews et al. [8]). Ground aerosols are distributed up to 3 km in winter, 5 km in summer. An example is given in Figure 67 for the East coast in the summer. It is difficult to identify emissions from aircraft, however they can be assumed to be concentrated at cruise altitude (around 10 km). Aircraft emitted aerosol were thus distributed between 9 and 11 km for the high cruise altitude case, and between 7 and 9 km for the low cruise altitude case. The surface albedo has a significant impact on radiative forcing. Regional and seasonal variations may therefore be observed due to the surface albedo of different regions at different seasons. A combination of snow, seawater, sand and vegetation can be defined. A study of land cover for the chosen regions at different seasons helps determine appropriate conditions. Land cover was estimated for each region using the USGS land cover viewer. The East coast is mostly covered by the vegetation type. Some land cover that could be categorized

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under the sand type is observed in the South West region. Monthly snow cover data from NOAA's national snow analyses (Figure 68) was retrieved for multiple years. It showed significant snow cover over the North East and North West regions in winter. Four regions were selected based on observed land cover. Two seasons were defined to account for snow cover variations at higher latitudes.
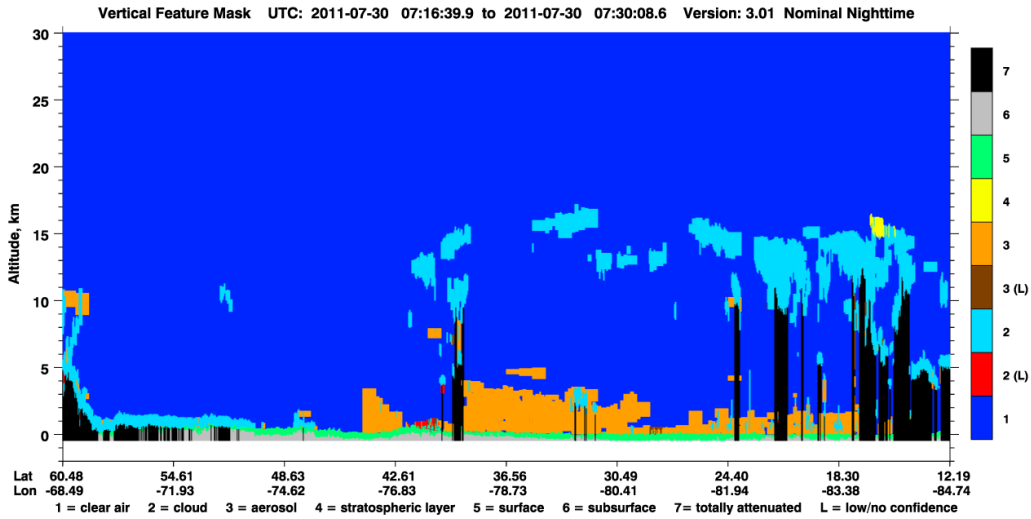
Figure 67: Calipso vertical feature mask for 30 July 2011

5.2.4 Radiative Forcing Efficiencies from Main Species

For each one of the considered species (CO_2, black carbon and contrails) the radiative forcing due to transportation needs to be determined. The approach is to obtain radiative forcing efficiencies (radiative forcing per emissions), which can then be used with emissions forecasts to determine future radiative forcings, and help quantify transportation's climate impact. Radiative forcing efficiencies (RFE) are derived from the Santa Barbara DISORT Atmospheric Radiative Transfer (SBDART) radiative transfer code.

The basic equation for plane-parallel atmospheres describes the physical phenomena of absorption, scattering and emission [99] (Equation 15). On the right hand side of the equation, the first term relates to absorption, the last term relates to emission

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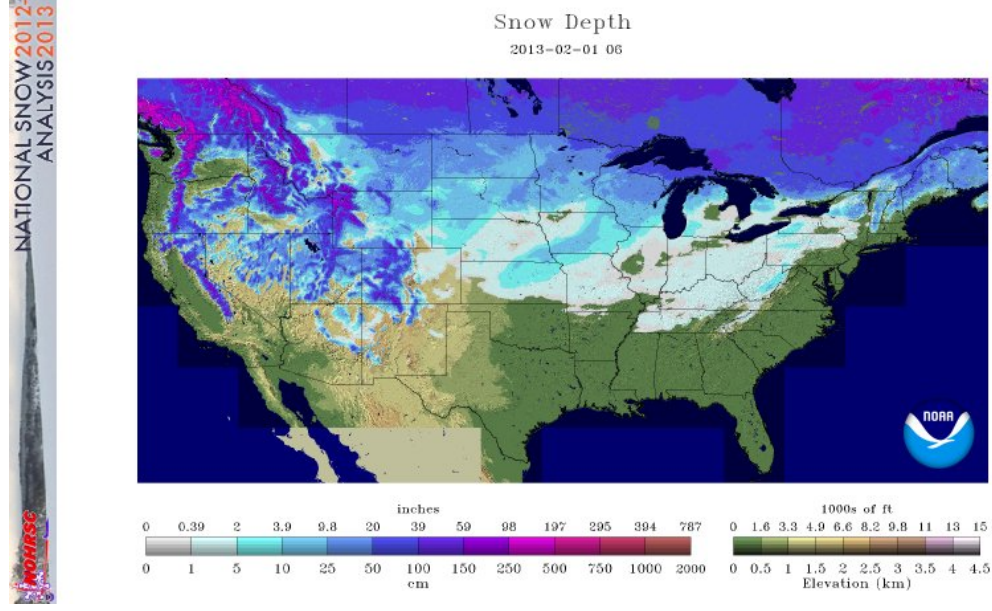
Figure 68: Snow Cover on 1 February 2013

and the other terms relate to scattering.

$$\mu \frac{dI(\tau, \Omega)}{d\tau} = I(\tau, \Omega) - \frac{w_0}{4\pi} \int_{4\pi} I(\tau, \Omega')P(\Omega, \Omega')d\Omega'$$
$$- \frac{w_0}{4\pi} F_O P(\Omega, -\Omega_0)e^{-\tau/\mu_0} - (1 - w_0)B[T(\tau)] \tag{15}$$

- with $\mu = cos\Theta$ and Θ is the inclination to the upward normal

- $I(\tau, \Omega)$ is the intensity, τ the optical depth, Ω the direction of propagation

- $\Omega = (\mu, \phi)$ with ϕ the azimuthal angle

- $\tau = \int_\tau^\infty \beta_e d\tau'$ the optical depth, which is the vertical path from a given altitude to outer space.

- $\beta_e = \beta_a + \beta_s$ the extinction coefficient, sum of the absorption β_a and the scattering β_s coefficients

- $w_0 = \frac{\beta_s}{\beta_e}$ the single scattering albedo, ratio of scattering efficiency to total extinction efficiency.

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- $P(\Omega, \Omega')$ the phase function, which is the angular distribution of light intensity scattered by a particle at a given wavelength.

- F_O the solar flux density at the top of the atmosphere

- $B[T]$ the Planck function, which defines the electromagnetic radiation emitted by a black body in thermal equilibrium at a definite temperature.

Simulations are run for different concentrations of gases and aerosols under given environmental conditions (surface, atmosphere). A spectral resolution of 5 nm for the shortwave (SW) and 20 cm^{-1} for the longwave (LW) is used. Net fluxes are computed for LW and SW (Equation 16). The Radiative Forcing Effiency (RFE) is obtained from Equation 17. The RFE is computed at the top of the atmosphere (TOA), and the surface. The RFE of an aerosol layer is the difference between the RFE at the TOA and the RFE at the surface. Atmospheric heating rates can be calculated using Equation 18.

$$F_{net} = F_{down} - F_{up} \tag{16}$$

$$RFE = \frac{\Delta F_{net}}{\Delta AOD(550nm)} \tag{17}$$

$$\frac{dT}{dt} = -\frac{1}{c_p}\rho\frac{dF_{net}}{dz} \tag{18}$$

A number of settings have an impact on the radiative transfer, which result in regional differences for the climate impact of transportation:

- Atmospheric profiles: US62 is used, and sensitivity studies are run with other atmospheric profiles based on location and season (mid-latitude summer and winter in this research).

- Surface albedo: combination of land cover categories, based on observations of land cover.

- Cloud cover: simulations are run with and without low level cloud cover.

- Solar zenith angle (SZA): reasonable solar angle based on location and season. The NOAA solar position calculator was used to obtain seasonal solar zenith angle for each region.

BC optical properties need to be characterized: aerosol optical depth (AOD), effective radius, extinction efficiency, single scattering albedo and asymmetry parameter. These parameters were obtained from the Optical Properties of Aerosols and Clouds (OPAC) data. A contrail cloud thickness of 0.2 and a cloud drop effective radius of 10 micrometers were used [150]. Based on the data obtained from remote sensing for land cover, snow cover, and aerosol vertical distribution, the parameters listed in Table 17 were chosen to simulate plausible characteristics for the given regions and seasons. A first set of simulations was run assuming clear sky conditions. However, a cloud cover is also likely, therefore more simulations were run with a cloud cover chosen to be a layer of low level stratus clouds, between 1 and 2 km, with optical depth 8 and effective radius 10 micrometers [46]. Different atmospheres were used (midlatitude summer and midlatitude winter) to account for seasonality but little impact on the results was observed, thus standard US62 was used to quantify regional and seasonal variations due to albedo and solar zenith angle.

Results were computed for both SW and LW, at the TOA and surface. The total soot RFE at the top of the atmosphere is almost entirely SW. It is given for different regions and seasons, and for both ground and air modes of transportation. For the air transportation, two different altitudes of emissions were considered.

Large regional and seasonal variations are observed for short-lived soot/black carbon aerosols (Table 18). This verifies hypothesis 2.3. These variations are due to

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Table 17: Regional and seasonal characteritics

Region	Season	Solar Elevation Angle	Albedo
South East (R1)	Summer	75	vegetation
South East (R1)	Winter	30	vegetation
North East (R2)	Summer	70	vegetation
North East (R2)	Winter	25	vegetation-snow
South West (R3)	Summer	75	vegetation-sand
South West (R3)	Winter	30	vegetation-sand
North West (R4)	Summer	65	vegetation
North West (R4)	Winter	20	vegetation-snow

Table 18: Regional soot total RFE at the TOA for different modes of transportation

Region	Season	RFE TOA Ground $(W/m^2/AOD)$	RFE TOA Aviation High $(W/m^2/AOD)$	RFE TOA Aviation Low $(W/m^2/AOD)$
R1	Summer	365	490	475
R1	Winter	225	369	350
R2	Summer	357	483	469
R2	Winter	596	721	706
R3	Summer	323	449	434
R3	Winter	196	341	322
R4	Summer	348	475	460
R4	Winter	512	649	630

Table 19: Regional soot total RFE at the TOA for different modes of transportation with low level cloud cover

Region	Season	RFE TOA Ground $(W/m^2/AOD)$	RFE TOA Aviation High $(W/m^2/AOD)$	RFE TOA Aviation Low $(W/m^2/AOD)$
R1	Summer	352	927	924
R1	Winter	117	900	889
R2	Summer	343	931	927
R2	Winter	264	997	987
R3	Summer	306	905	901
R3	Winter	100	889	878
R4	Summer	333	938	933
R4	Winter	196	918	903

the sensitivity to surface albedo and solar zenith angle (SZA). For regions with no snow cover, summer RFE is higher due to lower SZA. Regions with sand cover have lower RFE. In the presence of snow, RFE increases significantly. Soot is indeed an absorbing aerosol, which is less efficient over darker surfaces because solar radiation is absorbed anyway [117]. North East (R2) and North West (R4) winter surface albedo includes snow and results in higher RFE. The altitude of soot aerosol also appears to be a factor. The higher the aerosol, the higher the RFE is. Therefore, under clear sky conditions, aviation emitted soot aerosols have a higher RFE than ground transportation emitted soot aerosols. A lower cruise altitude results in a slightly lower RFE.

Under cloudy sky conditions, soot aerosols emitted above the cloud layer have a significantly higher RFE as can be observed in Table 19. Ground emitted soot RFE is decreased, especially in northern region's winters. Bond et al. found that aerosol forcing tends to be higher for aerosols over stratus clouds, and over snow. The results of this research are consistent with this observation.

Contrails trap outgoing LW radiation, which results in LW positive RF, and reflect SW radiation resulting in SW cooling, with the LW warming impact dominating.

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Table 20: Regional contrail total RFE at the TOA for different altitudes

Region	Season	RFE TOA Aviation High ($W/m^2/\%coverage$)	RFE TOA Aviation Low ($W/m^2/\%coverage$)
R1	Summer	0.211	0.165
R1	Winter	0.087	0.046
R2	Summer	0.207	0.161
R2	Winter	0.113	0.073
R3	Summer	0.207	0.162
R3	Winter	0.080	0.040
R4	Summer	0.201	0.156
R4	Winter	0.090	0.051

Contrails result in positive total RF at TOA (given in Table 20 for 1% contrail coverage). As can be observed in Table 20, the higher the flight altitude, the higher the impact is. A low level cloud cover tends to decrease the LW RFE. Most of the observed regional and seasonal variations (especially significant under clear sky conditions) come from the SW RFE, resulting in higher RFE in the summer. LW forcing is about 0.21 $W/m^2/\%coverage$ for high altitude cruise under clear sky condition, 0.17 $W/m^2/\%coverage$ at lower cruise altitude, 0.18 $W/m^2/\%coverage$ at high cruise altitude under cloudy condition, and 0.14 $W/m^2/\%coverage$ at lower cruise altitude under cloudy conditions. The lower values under cloudy conditions are due to the fact that the lower level cloud cover traps some LW radiation, resulting in smaller fluxes at the TOA.

From these values high and low values of soot RFE and contrail RFE were derived for each mode and used in eGAME to generate ranges of RF.

5.2.5 Radiative Forcing from Main Species

The different species emitted by transportation have different lifetime in the atmosphere. Long-lived species accumulate over time while short-lived species have only a temporary impact. This calls for different treatments. For the long-lived CO_2,

Table 21: Regional contrail total RFE at the TOA for different altitudes with low level clouds

Region	Season	RFE TOA Aviation High $(W/m^2/\%coverage)$	RFE TOA Aviation Low $(W/m^2/\%coverage)$
R1	Summer	0.138	0.093
R1	Winter	0.141	0.099
R2	Summer	0.140	0.094
R2	Winter	0.142	0.101
R3	Summer	0.135	0.089
R3	Winter	0.139	0.098
R4	Summer	0.141	0.096
R4	Winter	0.134	0.094

Table 22: Impulse Response Function coefficients

a_0	0.2173
a_1	0.2240
a_2	0.2824
a_3	0.2763
τ_1	394.4 yr
τ_2	36.54 yr
τ_3	4.304 yr

concentration is obtained using a carbon cycle model. Due to the high computational cost of state-of-the art atmospheric models, a simpler representation of the complex carbon cycle-climate model is needed in order to enable fast computation of multiple scenarios. Impulse response functions or Green's functions are introduced as described by Joos et al. [79] to represent the response to a delta-function forcing at a given time t.

$$IRF_{CO_2}(t) = a_0 + \sum_{i=1}^{3} a_i e^{\frac{-t}{\tau_i}} \tag{19}$$

The values of the different variables are listed in Table 22. The coefficient a_i are taken from Joos et al. [79], which performed a multi-model study.

Knowing the impulse response functions, the concentration can then be determined:

$$C(t) = \int_0^t IRF * E d\tau \tag{20}$$

with E the emissions in kg.

The Radiative Forcing of CO_2 is obtained from CO_2 concentration using equation 21.

$$\Delta F = 5.35 ln \frac{C}{C_0} W.m^{-2} \tag{21}$$

where C is the CO_2 concentration and C_0 is the reference concentration in parts per million by volume.

Short-lived species have a forcing only for the year considered. Their Radiative Forcing is equal to

$$RF_{sl}(t) = RFE_{sl} * AOD_{sl}(t) \tag{22}$$

Radiative forcing of aerosols is computed using a box model as done by Reddy and Venkataraman, 2000 [138]. Equation 23 gives the aerosol optical depth τ based on the mass extinction coefficient α, and the aerosol burden B. The aerosol burden is obtained from Equation 24 with Q the aerosol emission rate ($g.day^{-1}$), L_t the aerosol lifetime (day) and A the area of the box (m^2). Using the box model, it appears that a change in aerosol emission rate will result in a change in aerosol burden and in AOD, thus a change in RF.

$$\tau = \alpha B \tag{23}$$

$$B = \frac{QL_t}{A} \tag{24}$$

For contrail and cirrus induced clouds, a common assumption is based on the work of Stordal et al. [160] and states that cloud cover increases linearly with RPM.

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Other studies have used fuel burn as a substitute for flight density [142]. A forcing per distance can be determined: knowing the traveled distance (13.5 billion nautical miles), the cloud cover 0.2 and the forcing per cloud cover obtained from radiative transfer calculations ($0.2\ W.m^{-2}$ per cloud cover using a cloud thickness of 0.2 and a cloud drop effective radius of 10 micrometers [150]), a forcing of $3.10^{-12}W.m^{-2}.nmi^{-1}$ is obtained. As highlighted in Haywood et al. [64], this number can vary greatly and further studies are needed to assess the reliability of contrail and contrail-induced cirrus impact estimation. Another source of uncertainty is due to the very specific atmospheric conditions required for contrail formation. A number of studies have been performed in order to quantify contrail coverage over time for different regions using remote sensing data from MODIS and other instruments as described in section 2.5.4. The reference contrail coverage of 0.15% is obtained from Minnis et al. [113]. The RF per contrail coverage is determined using the RT code. eGAME uses the following equation for RF from contrail and scales contrail RF with aircraft fuel burn:

$$RF_{contrail}(t) = \frac{AircraftFuelburn(t)}{AircraftFuelburn(ref)} * RF_{contrail}(ref) \tag{25}$$

The global mean radiative forcing can be associated with a global mean surface temperature change when the system has reached a new equilibrium [89].

$$\Delta T_s = \lambda RF \tag{26}$$

5.2.6   Baseline Climate Impact and Policy Considerations

The baseline Radiative Forcing is shown for the species of interest. As observed in Figures 69, 70 and 71, contrails have the most impact, followed by aviation soot and ground transportation soot. The uncertainty in the estimation of the impact of soot and contrail remains relatively large due to the variations in regional characteristics that impact the RF. Uncertainty may be reduced by using a higher granularity for the distribution of emissions through a grid within the continental U.S., and by using

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a shorter time step. In spite of this uncertainty, insight is given into the relative climate impact of each mode of transportation when species other than CO_2 are included. In this research, total emissions are quantified and an average value of RF efficiencies is considered. As can be seen in Figures 72 and 73, under a high level of technology scenario (N+2 aircraft included, and MPG improvement of 50% in 2035), CO_2 emissions may be stabilized, but due to the long lifetime of CO_2 in the atmosphere, the concentration keeps increasing and therefore the RF increases.
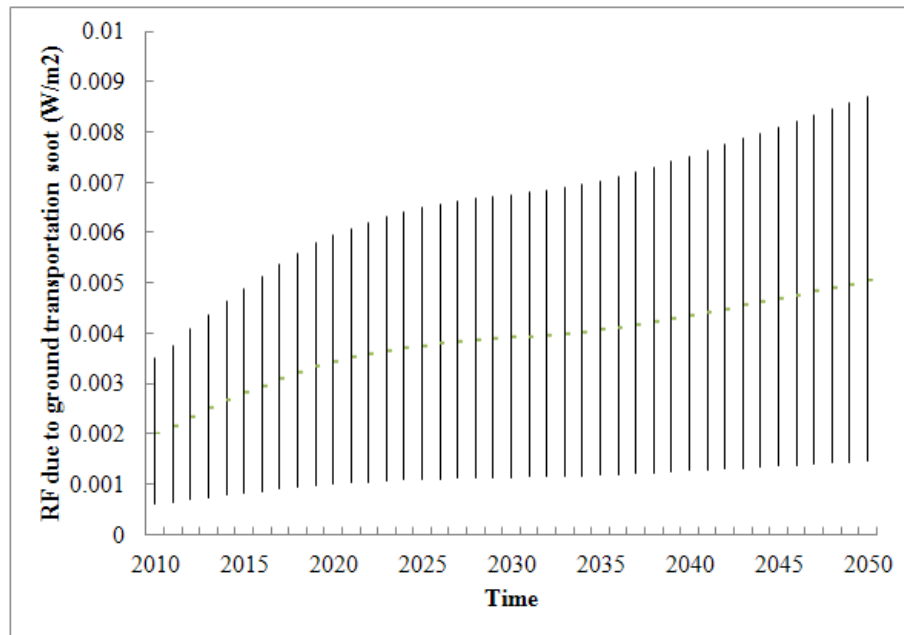
Figure 69: Baseline RF due to ground transportation emitted soot

5.2.7 Summary and Policy Relevance

Transportation emissions result in radiative forcing. Quantifying these effects is done through the use of radiative transfer models with characteristics derived from remote sensing data. A number of regional characteristics result in significant variations in regional impacts. For best climate impact assessment, emissions need to be distributed in a grid based on demand from models with high granularity such as *Mi*. Using the methods presented in the previous sections, it is possible to quantify climate metrics for each mode of transportation and each trip. Policies can then be envisioned that

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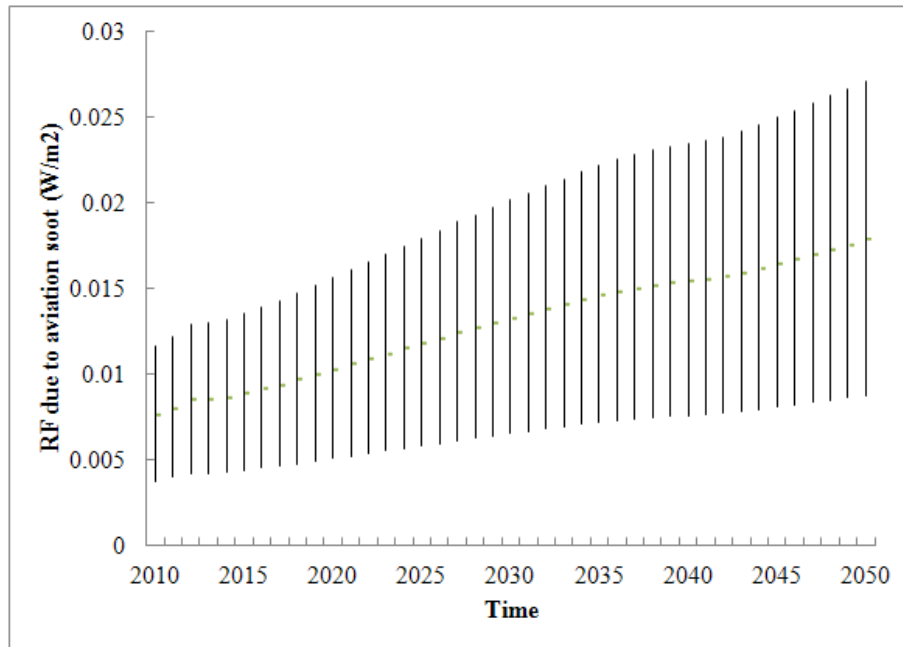
Figure 70: Baseline RF due to aviation emitted soot

put a price on these impacts to shift demand towards more fuel efficient modes of transportation, and motivate fuel efficiency improvements. However, implementing policies with high regional and seasonal variations may be challenging. Therefore, an average climate impact may be computed for each mode of transportation and policies can be envisioned that increase the cost of travel accordingly. More details are provided in the following chapter, which discusses policies and gives results from eGAME for different policy and technology scenarios.
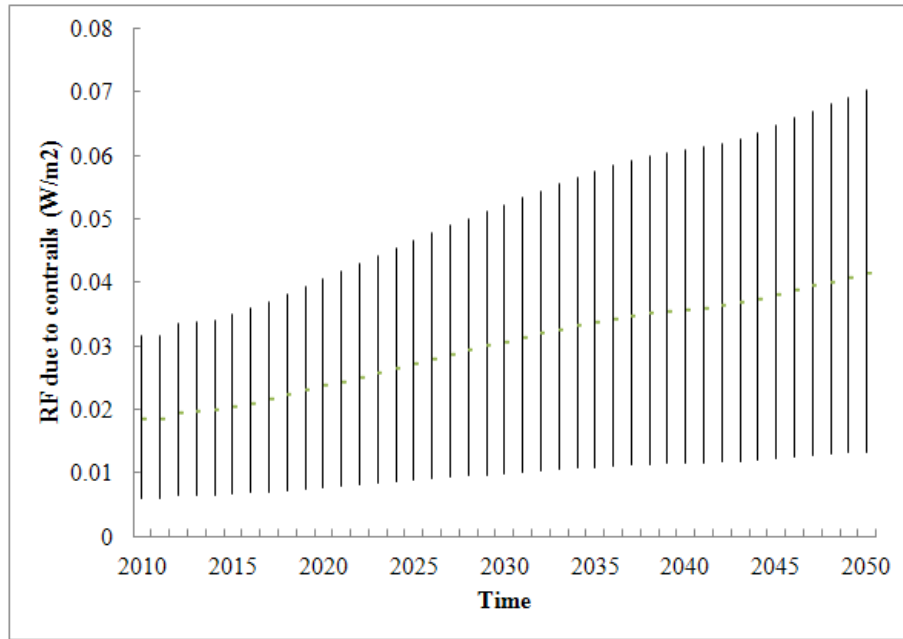
Figure 71: Baseline RF due to contrails
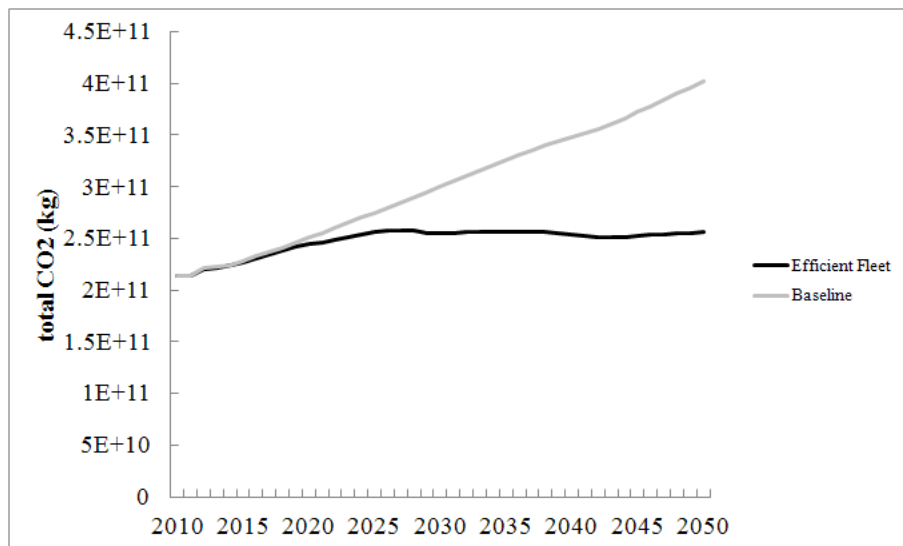
Figure 72: Baseline total CO_2 emissions

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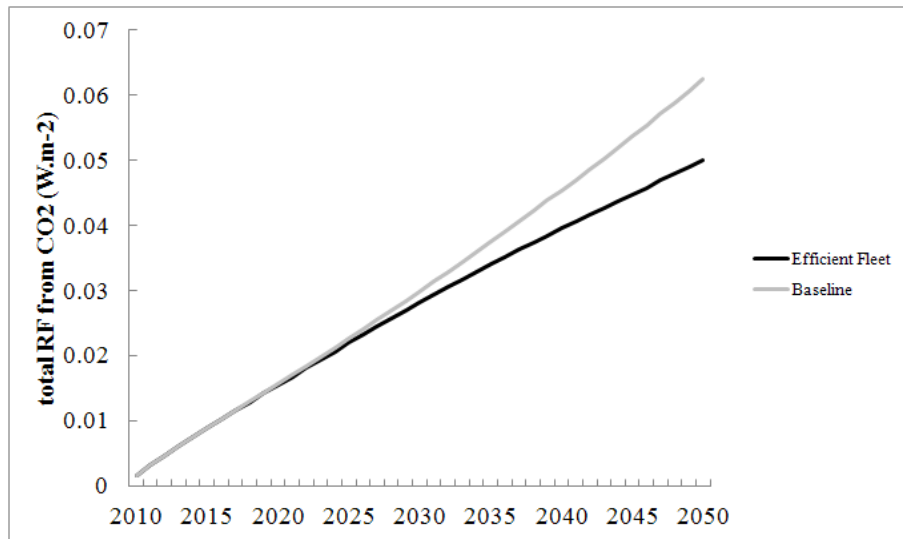
Figure 73: Baseline CO_2 RF

CHAPTER VI

POLICY AND TECHNOLOGY SCENARIO EXPLORATION

As demonstrated in the previous chapter, both air transportation and ground transportation have an impact on the Earth radiative budget through different species, with CO_2, BC and contrails having the most warming effects. With increasing mobility and concerns about climate change, regulations and policies are discussed. The International Civil Aviation Organization (ICAO), Committee on Aviation Environmental Protection (CAEP) plans on implementing Market-Based Measures (MBM) by 2020 [48]. How would these policies affect the transportation system in terms of demand for different modes and fleet efficiencies? By how much can policies reduce climate impact? To gain insight into these challenging questions, scenario-based simulations are needed. With the framework described in Figure 74, it is possible to explore a number of policy and technology scenarios for the long distance transportation in the continental U.S. and address the following research question:

Research Question 3: What are the impacts of policies and technologies on the demand and fleet of different modes of transportation?

The climate impact determined in Section 5.2.6 was based on the demand in a scenario without any climate policy implemented. The demand was determined with a given socio-economic scenario and a given level of technology (a given fleet replacement scenario) for each mode. This level of technology was assumed based on expected introduction dates of new aircraft or new fuel efficient cars. However, in the case where the climate impact exceeds targets, multiple policies can be envisioned and implemented in order to try to limit emissions and reduce climate impact

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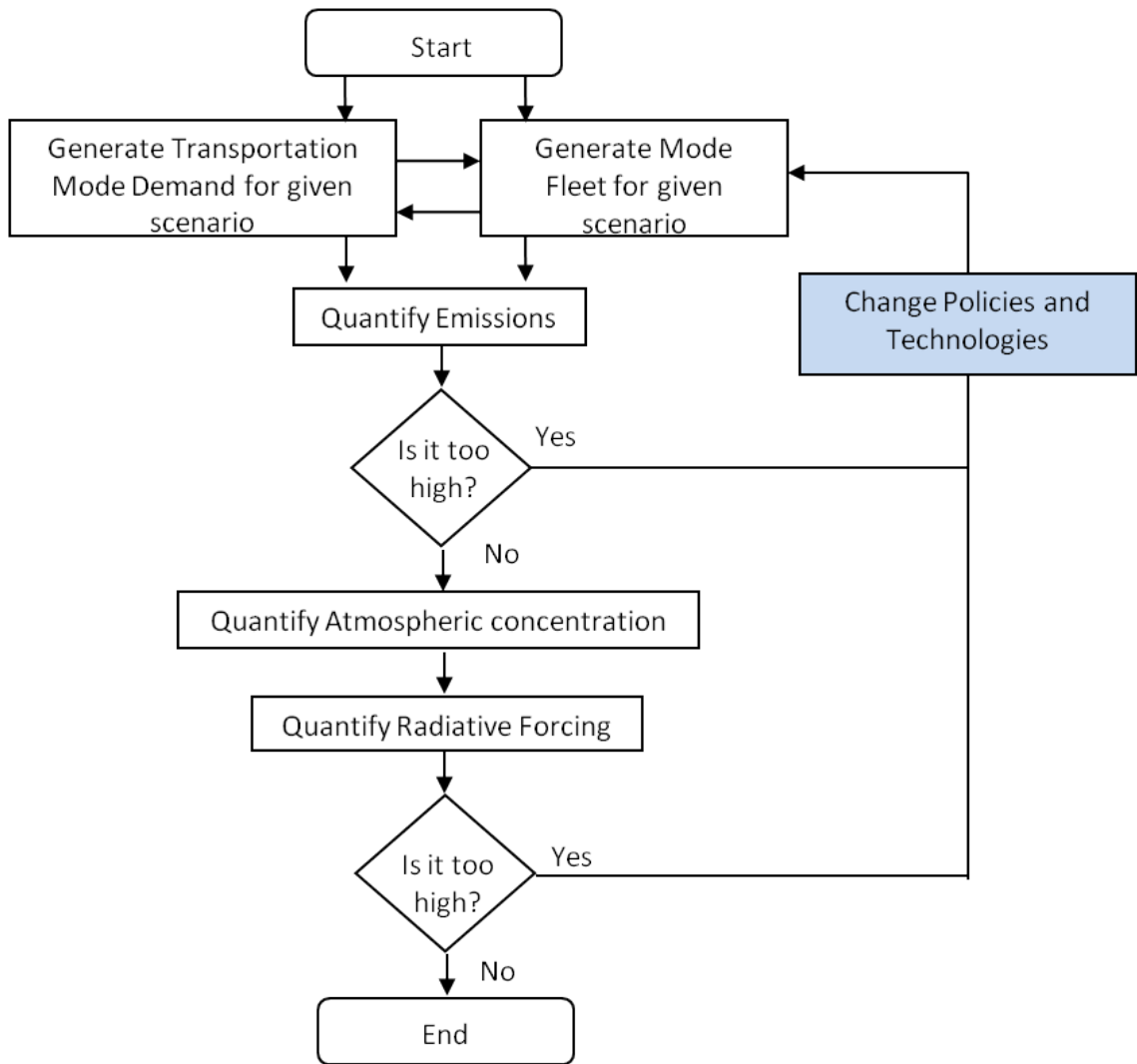
Figure 74: Step 4: Climate policy assessment

through demand reduction and faster introduction of more fuel efficient vehicles. It is challenging to predict the extent of the impact of these policies and decide on the right policy. By using the eGAME framework (shown in Figure 74), insight can be obtained. Policies may target a specific mode of transportation, specific species (greenhouse gases or aerosols). They may aim to reduce demand, or introduce new efficient technologies faster. Their impact on the demand for each mode of transportation, fleet changes, and the resulting emissions and climate impact can be quantified. It then becomes possible to decide on the most appropriate climate impact metric

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and associated policies in order to reach a given target.

6.1   Climate Policies

Based on the climate impact of the different modes of transportation described in the previous chapter, it appears that both modes of transportation affect the atmosphere through a number of species that absorb, scatter and emit radiation. With the quantified climate impact of transportation for the main species, new policies can be envisioned to curb gases and aerosols emissions in order to maintain a sustainable transportation system. This is a complex problem to address since these policies would change the demand for the different modes, as well as encourage the introduction of new technologies. These are competing effects. It is indeed expected that increasing the cost of traveling through policies would have a negative impact on the demand for transportation, but if new technologies are introduced faster, a rebound effect may be observed. These types of behavior can be captured with eGAME.

Once the climate impact is quantified, policies may be implemented and a new simulation can be run to assess the changes in emissions and radiative forcing. In most cases, policies will result in a change of travel cost for a given mode, which is likely to be passed on to the customer. In this case, the demand is likely to change. A wide variety of policies can be envisioned. Market-Based measures such as a carbon tax result in an increased cost of travel. This increase needs to be quantified. Then using eGAME the impact of this increase on demand and fleets can be assessed. Other policies include regulations such as gas mileage standards. In this case fuel efficiency standards have to be implemented and can be directly used in the model. The following sections focus on how different types of policies may be introduced into the framework. Policies impact demand and fleets through an increased cost of travel. Therefore, changes in fuel price can be used to investigate sensitivities and assess the effect of policies that would result in increased average trip cost.

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6.1.1 Carbon Tax and Carbon Trading

Some policies aim to reduce emissions through the introduction of a price of emissions which affects the cost of transportation. Instances include carbon trading and CO_2 tax. The main difference between a cap and trade system and an emission fee relate to uncertainty. In a cap and trade system, the emission limit is fixed and uncertainty exists on the price of carbon defined by the established market (thus called quantity-based instrument), whereas with a carbon tax the price is known while there is uncertainty on the resulting emissions (this is a price-based instrument). Each policy has advantages. Emission trading is appealing to private industries that can make profit by selling their allowances. A cap and trade system responds to inflation, recessions by adjusting prices automatically. Based on demand, the price on the carbon and other species markets is adjusted. When emissions increase, the price increases. On the other hand, trading systems sometimes do not adjust to sudden changes. With a carbon tax, it is more difficult for organizations to use strategic behavior in an attempt to influence the cost of abatement. Carbon taxes can target more sectors. Trading systems may be envisioned for private companies and countries, but it would be difficult to target individual consumers. Therefore, trading systems are not directly applicable to individual transportation users. Finally, carbon tax revenues may be used to encourage technology investments. Due to the challenge of appropriately model market dynamics of a trading scheme, the uncertainty in the price of carbon allowances and in the exact value of a tax, it was decided that an increase in the cost of fuel be used in this study to represent policies and assess their potential in terms of changing demand and fleets with the purpose of reducing climate impact.

As mentioned above, a fee would result in an arbitrary increase in the cost of transportation. Different introduction time, and amounts can be envisioned and they would apply no matter what the total emissions are. Carbon taxes result in a higher price of gasoline, natural gas or coal. They can also apply to electricity consumption

on a per kilowatt-hour basis. They may be implemented at a given year using a step function, or gradually using a ramp function, as depicted in Figure 75.
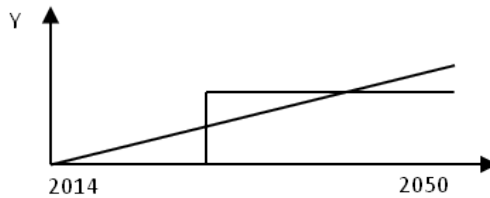
Figure 75: Carbon Tax gradual versus step introduction

An often mentioned metric for policy quantification is the social cost of carbon (SCC), which can be seen as a carbon tax. It is recognized that there is a large uncertainty in the SCC value since it aims to monetize the damages caused by increases in CO_2 emissions. Estimates of SCC may be used to approximate an initial guess for an appropriate carbon tax. The eGAME framework then allows to change the value of this initial carbon tax to explore the effects on transportation, which is the main goal of this research. The social cost of carbon emissions is discussed in the technical support document from the working group on social cost of carbon [73], and values are suggested for use in regulatory analyses. Previous values that have been used are: 7 dollars per ton CO_2 increasing at 2.4 percent per year used by the Department Of Transportation in 2008, up to 20 dollars per ton CO_2 used by the Department Of Energy in October of 2008. EPA used global mean values of 68 and 40 dollars with discount rates of 2 and 3 percent respectively. For a SCC of 52 dollars per ton of CO_2, calculations result in a carbon tax of about 50 cents per gallon. This value is used as a baseline carbon tax in the simulations.

6.1.2 Tax Based on Radiative Forcing

Based on the previous discussions on climate impact, policies can target different species and physical phenomena. Carbon taxes have long been discussed and even

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implemented, but as the impact of short term effects, notably due to aerosols, becomes better understood, they might be included in policies. Depending on what species the policies target, it is expected that different modes of transportation will be at an advantage depending on how they affect the atmosphere. From the previous sections on emissions and climate impact, an emission or radiative forcing per passenger per mile traveled can be determined. With the granularity of eGAME, this mode efficiency can be determined for each distance group, which is especially important for modes such as the commercial air transportation, for which the fuel burn per mile decreases with distance traveled. Once this metric has been derived, policies can be designed in order to target less efficient modes. An average climate impact for each mode of transportation across all trips is considered and a tax is implemented separately for each mode.

A RF forcing tax that would take into account all gases and particles described in the climate impact section of this document is envisioned based on the same principles as the carbon tax. Using the baseline scenario, the total Radiative Forcing can be determined and the ratio between RF from the main species considered in this study and the Radiative Forcing due to CO_2 only can be computed. A time frame of 40 years (looking at 2050) is chosen to compute this ratio, which decreases with time due to the long lifetime of CO_2. From this value, the pricing strategy can be adjusted. With the species considered in this research for transportation's main impacts, results show that the ratio of total RF (considering CO_2, BC and contrails) to RF due to CO_2 only has an average value of 2.3 for aviation, and 1.2 for ground, resulting in a tax of 1.1 dollar per gallon for aviation versus 0.6 dollars for ground. This type of ratio applied to the carbon tax has been discussed and an example is given in Reference [31] (page 227). Due to the uncertainty associated with the soot and contrail RF quantification (observed in Section 5.2.6), this factor could vary from about 1.5 to 3 for aviation, and 1.1 to 1.3 for ground. The average values are used in this study, and any increase

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or decrease in the value of this factor would emphasize or reduce the effects observed when going from a carbon tax to a tax based on RF. This "imbalanced" tax would result in mode shift and/or faster fuel efficient vehicle adoption rates. These effects are further quantified in the following sections.

6.1.3 Carbon Budget

Another concept is introduced for completeness: the carbon budget. This concept is sometimes referred to as personal carbon allowance or personal carbon trading in the literature. This differs from the industry level trading scheme which would apply to the airlines, because it is applied at the household level or individual level. Each person or household would be given a certain amount of carbon allowances, and would use them when purchasing airline tickets and gasoline for their personal vehicle. Paul et al. [128] discuss the impact of a household level cap policy versus a tax policy and conclude that high income households would be affected by both and reduce their amount of emissions, whereas low income households' emissions would be reduced in a tax policy scenario and increased in a trade policy scenario due to the extra cash obtained from selling allowances. This type of behavior can be explored with this framework through simulations with Mi, which is suitable since the policy would be introduced at the agent level. Similar to the time and monetary budget introduced in Mi, a carbon budget could be added and the resulting budget space is represented in Figure 76.

6.1.4 Technology Infusion and Other Policies

Policies that change the cost of travel aim to motivate changes in mobility, demand, and fleet composition. However these effects may not be sufficient to reach climate impact targets and standards imposed on manufacturers may be needed to achieve a given fleet efficiency in a given year. This is done through fuel economy standard, new aircraft standards, etc. Policies that alter fuel consumption through reduction

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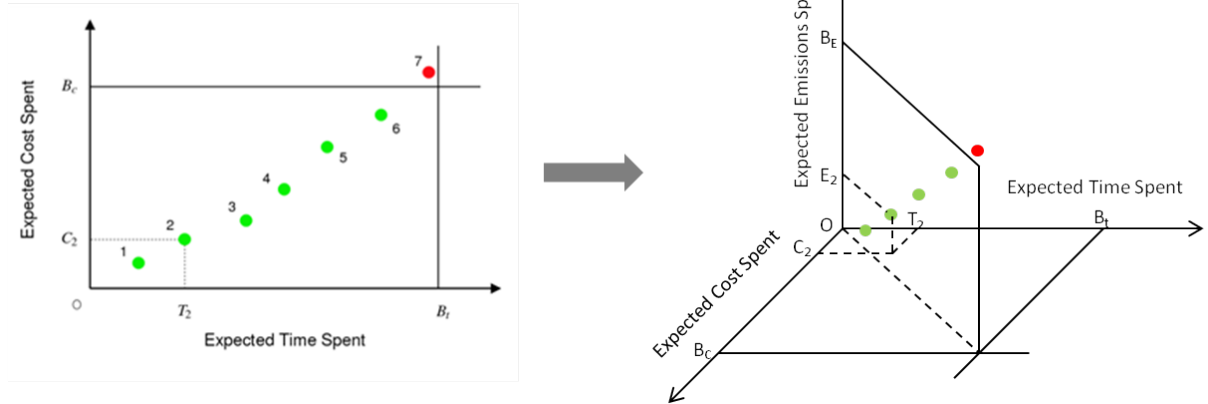
Figure 76: Mobility budget space with personal carbon budget

of fleet age are also possible, using for example scrappage schemes (which encourage the replacement of old vehicles with more recent ones through the use of monetary incentives). Other types of policies include regulations such as the CAFE standards, or low-carbon fuel standards. Regulations on the operations can also be implemented such as speed limits. Policies may aim to encourage technology introduction and/or curb demand. Johansson [78] advocates the combined use of technology and demand based measures to meet climate goals. Malina et al. [104] argues that the European Trading Scheme would only have a small impact on airlines and emissions. Some tradeoff situations may exist. For example, although diesel gets better mileage and emits less CO_2, they emit more particulates which may offset and create more positive forcing. The climate impact reduction using technologies and policies is thus a very intricate problem, and simulation tools such as eGAME are needed to explore multiple scenarios that include all these parameters. Simulations are run using eGAME to answer the following research question:

Research Question 3.1: Can transportation emissions and climate impact stabilization goals be achieved through market measures alone?

Reasonable changes in cost of travel are expected to have limited impact on overall

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demand and emissions, hence the following hypothesis:

Hypothesis 3.1: Climate impact goals may be achieved through a combination of technologies and policies.

In order to fully assess the effects of policies, it is necessary to quantify the impact on demand as described above, but also on technology introduction. The following sections focus on the effect of variations in travel cost (due to a carbon tax ot a tax based on RF) on demand, fleet efficiency and the resulting climate impact.

6.2   Effect of Policies on Demand

A number of scenarios are run in eGAME to quantify the effect of policies on demand (RPM and VMT). These policies are essentially similar to changing the cost of fuel in the modeling and simulation environment. Policies can be implemented by mode, using a ramp function or a step function. This corresponds to a carbon tax implemented gradually, or suddenly at a given year. The tax scenarios are defined as follow:

- ALN: gradual tax on airline mode

- GND: gradual tax on ground mode

- both: gradual tax on both mode

- RF: gradual tax on both modes based on RF

- ALN YYYY: tax on airline mode implemented fully at year YYYY

- GND YYYY: tax on ground mode implemented fully at year YYYY

- both YYYY: tax on both modes implemented fully at year YYYY

- RF YYYY: tax on both modes based on RF implemented fully at year YYYY

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6.2.1   Mode Shift

Depending on which mode is taxed, or the relative tax on each mode, shifts in demand from one mode to other modes of transportation may be observed, which justifies the use of a multimodal approach. As expected, a tax on the air transportation mode only, would result in the most significant decrease in RPM, and increase in VMT. A tax on the ground mode would result in an increase in RPM compensating for the decrease in VMT. A tax on both modes would lie somewhere in the middle, with a small decrease in demand for both modes, as can be observed in Figures 77 and 78. These figures show the difference between the baseline with no tax and cases where a gradual tax of 50 cents per gallon is implemented on different modes. The impact on the two main modes of transportation depends highly on a number of parameters such as technological level (ground fleet fuel economy for example), or how airline pass the extra cost on to the customer. Here the following assumptions are made: full pass through for the airlines, BAU scenario for airline fleet and no mpg improvement for ground vehicles. With different GND mode efficiency assumptions and different pass through and ALN fleets, results could look very different. For example a zero pass through assumption for the airlines would result in no variation in demand in the case of a tax on the ALN mode, and identical variations for a tax on GND and a tax on both, since increases in cost for the ALN mode would not be passed on to the customer. The more fuel efficient and cheaper mode will be less negatively affected by a tax on climate impact.

A gradual carbon tax of 50 cents per gallon would result in long term changes in VMT and RPM. As listed in Table 23, a carbon tax implemented on a single mode would result in a decrease in demand for the targeted mode and an increase in the demand of the other due to the relative increase in attractiveness of the mode that is not taxed. The mode shift is not a one to one relationship because some travelers may cancel their trip, or switch mode and reduce the distance traveled (likely to

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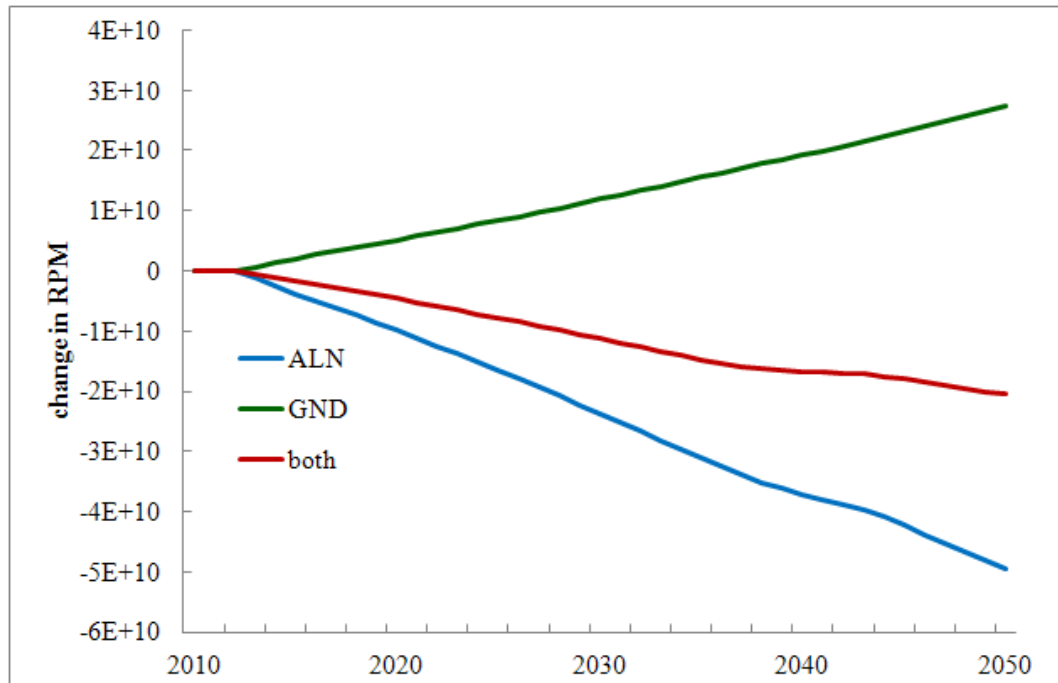
Figure 77: Change in RPM due to a gradual carbon tax with BAU fleets

Table 23: Changes in RPM and VMT in 2050 with a carbon tax

Mode taxed	change in RPM	change in VMT
ALN	-3.32%	+0.98%
GND	+1.84%	-1.18%
both	-1.38%	-0.21%

be the case when switching to the ground mode), or travel further (using the air transportation). When both modes are taxed, the demand for both decreases. With the settings used here, the air transportation mode is more significantly affected than ground transportation.

Table 24 shows that with higher fuel efficiency aircraft and automobiles, the carbon tax would result in a smaller mode shift, which can be explained by the fact that the extra cost introduced by the carbon tax is smaller due to lower fuel consumption. The relative effects also change depending on the fuel efficiency improvement. In this case aviation is less affected than ground transportation by a tax implemented on

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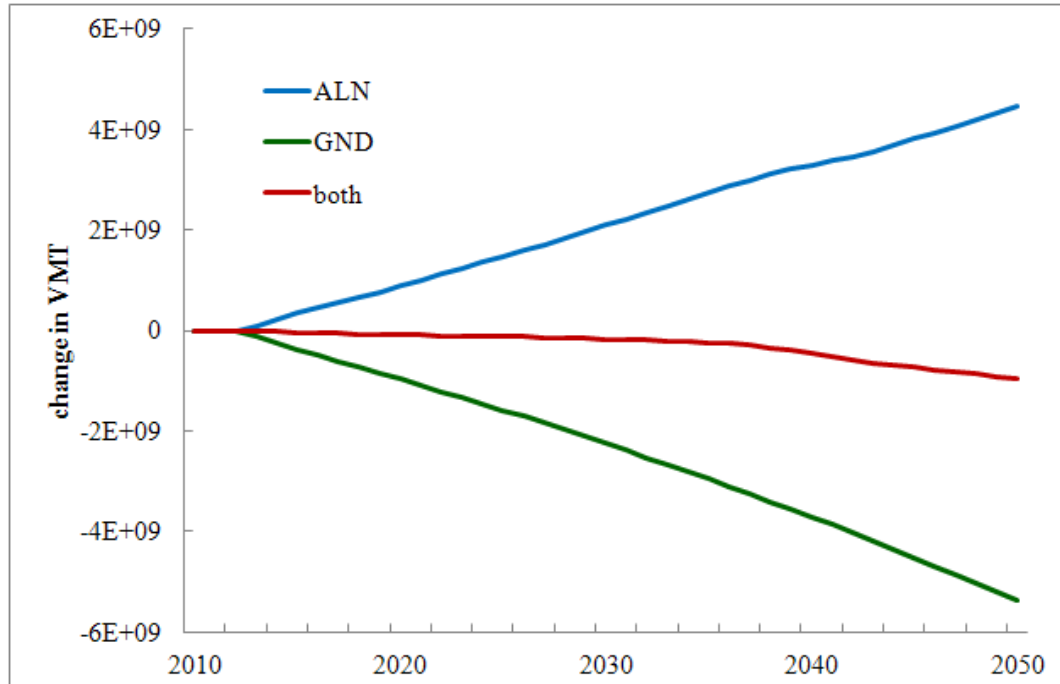
Figure 78: Change in VMT due to a gradual carbon tax with BAU fleets

Table 24: Changes in RPM and VMT in 2050 with a carbon tax with higher fuel efficiency scenario

Mode taxed	change in RPM	change in VMT
ALN	-1.42%	+0.60%
GND	+1.27%	-0.81 %
both	-0.11%	-0.22%

both modes.

With the granularity offered by eGAME, it is observed that each Distance Group will be affected differently. With a tax on air transportation, most of the mode shift will occur in the mid-distance groups (Table 25). Two effects appear here. The first one is the relative increase in fuel cost for the distance considered, the second is the attractiveness of the other mode for the distance considered. Short distance trips do not have a very significant change in price due to the tax, and the ground mode keeps its significant advantage. Long distance trips cannot as easily be done with the ground mode and the air transportation remains at an advantage in spite of the tax.

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Table 25: Changes in RPM by DG in 2050 with a carbon tax

Distance Group	tax on ALN	tax on GND	tax on both modes
DG 1	-1.99%	+1.20%	-0.81%
DG 2	-3.40%	+2.71%	-0.74%
DG 3	-5.89%	+5.26%	-0.62%
DG 4	-3.88%	+2.53%	-1.04%
DG 5	-2.06%	+0.06%	-1.99%

Similarly, a tax on the ground mode results in more significant increase in RPM for mid-distance groups. This can be explained by the fact that short distances remain cheap enough that the advantage of the ground mode holds, but as distance increases air transportation becomes more attractive. There is very little demand for long distances with the ground mode to begin with, which explains the almost negligible increase in RPM for that distance group. Finally, when a tax is implemented on both modes, demand for air transportation decreases mostly for longer distances which are most affected by an increase in fuel cost. Similar observations are made with higher fuel efficiency fleets, but the effects on longer distances is reduced due to the smaller fuel cost. In this case, and with a tax on both modes, an increase in RPM for distance groups 3 and 4 is observed in the long term due to the reduced fuel consumption and the rebound effect.

6.2.2 Carbon Tax versus RF Based Tax

As introduced in Section 6.1.2, the Radiative Forcing from the main species to the CO_2 RF ratio is different for each mode, thus resulting in a potentially different tax on each mode. If a RF based tax is implemented, the aviation mode is penalized further, which may negatively affect demand for this mode and further increase the demand for the competing mode, as shown in Table 26. Similar to the carbon tax case, with higher vehicle fuel efficiency, the effect of the tax is attenuated, as can be

Table 26: Changes in RPM and VMT in 2050 with different policies

tax type	change in RPM	change in VMT
CO_2	-1.38%	-0.21%
main species	-6.86%	+1.29%

Table 27: Changes in RPM and VMT in 2050 with different policies and high efficiency fleets

tax type	change in RPM	change in VMT
CO_2	-0.11%	-0.22%
main species	-1.17%	+0.29%

seen in Table 27.

6.2.3 Gradual versus Sudden Tax

The modeling and simulation environment provides the option to gradually implement the tax, with a ramp function reaching the target carbon tax in a future year (2035 here), or implement the full tax at a chosen year, for example 2020, or 2030, as represented in Figure 75. As expected, demand would be more significantly and suddenly affected when the tax is introduced fully at a given year. The gradual tax is implemented using a ramp function starting at the beginning of the simulation time, and reaching the full value in 2035. It then continues to increase past 2035. Figures 79 and 80 show the time series of change in RPM compared to the baseline scenario with no tax, and using the BAU airline fleets and no mpg improvement. As can be observed, the effect on demand would be similar in 2035, but the time series look different. Since some of the emitted species resulting from this demand have a long lifetime in the atmosphere, the implementation year is a significant parameter. As already observed in subsection 6.2.1, a tax on the ALN mode results in the most decrease in RPM, followed by a tax on both modes, while a tax on the GND mode results in an increase in RPM. These changes occur suddenly or gradually and have

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the same effect in 2035, as expected from the definition of the ramp and step function in Figure 75. As can be observed in Figures 81 and 82, under higher fleet efficiency scenarios, the initial decrease in demand due to the increase in fuel price may be partially recovered over time due to the improvement in fleet efficiency and associated rebound effect on demand. The effect of the fuel price increase on technology introduction and demand is further discussed in the following section.
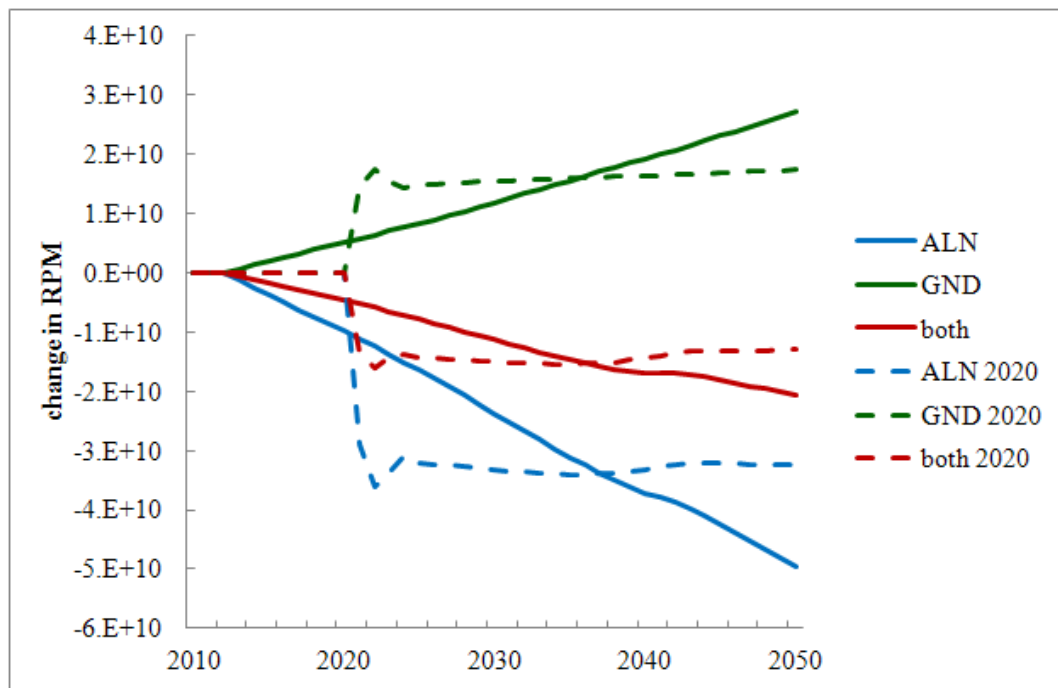
Figure 79: Change in RPM due to a carbon tax implemented in 2020 or gradually with BAU fleets

6.3   Effect of Policies on Technology Introduction

In order to fully assess the effect of policies, both changes in demand and fleet composition need to be accounted for. Fleets are changed based on the relative costs of operating each vehicle, resulting in different fuel efficiencies. In the airline and ground fleet models, the implementation of a tax will result in a higher operating cost and the value of aircraft or vehicles with high fuel consumption will decrease, resulting in a faster switch to more fuel efficient aircraft or automobiles.
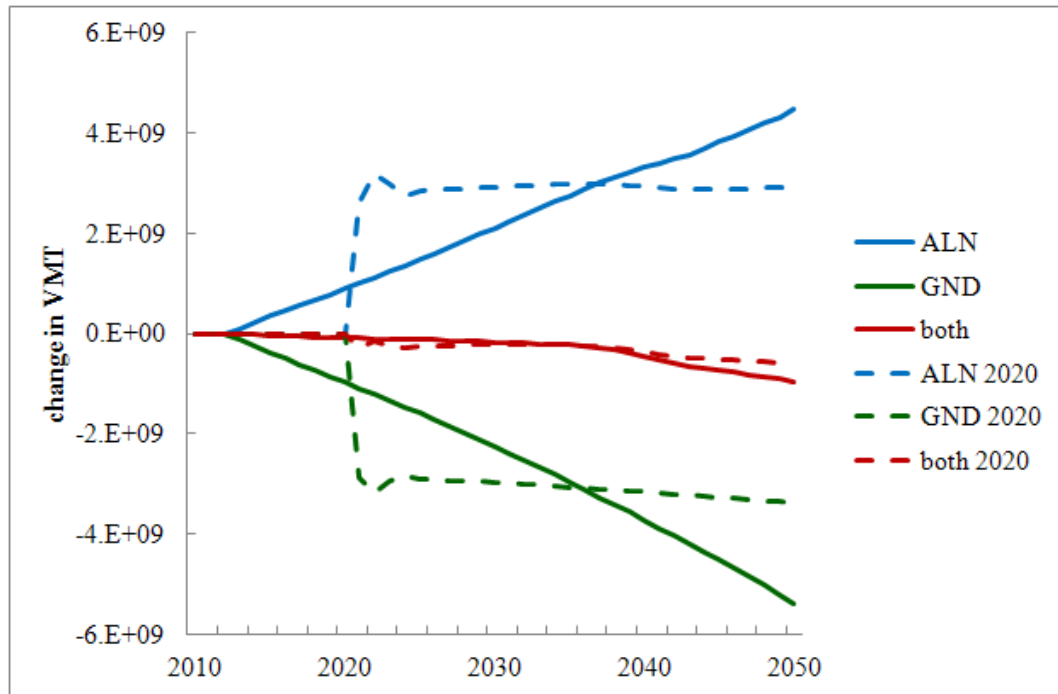
Figure 80: Change in VMT due to a carbon tax implemented in 2020 or gradually with BAU fleets

6.3.1 Air Transportation

When a policy is implemented in the airline fleet model, the attractiveness of a given aircraft changes and airlines switch to new available aircraft faster. With new policies on emissions, the direct operating cost increases, thus changing the airlines decision to retire old aircraft and replace them with new more efficient aircraft.

Based on the net present value approach used in IDEA for aircraft fleet strategies, airlines will replace older aircraft faster under strict climate policy situations. An example is shown in Figure 83 where the N+2 scenario is used, allowing for new industry aircaft and N+2 to replace current aircraft. As can be seen in Figure 83, the higher the tax, the faster airline switch to new more fuel efficient aircraft, resulting in a better system's fleet efficiency. Changes start after 2020, as more fuel efficient aircraft become available.

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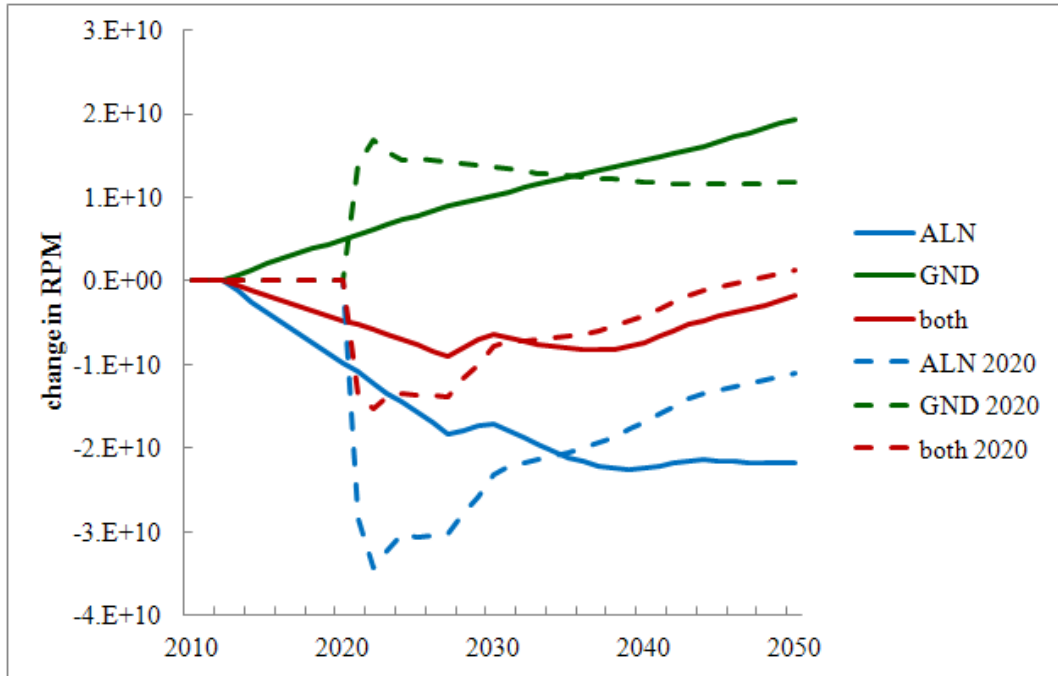
Figure 81: Change in RPM due to a carbon tax implemented in 2020 or gradually with high efficiency fleets

6.3.2 Ground Transportation

Based on the ground module described in Subsection 5.1.2, with the attractiveness of a vehicle based on multiple factors, including fuel cost, a carbon tax would result in a different fleet composition. As can be observed in Figure 84, a carbon tax would accelerate the introduction of EVs in the fleet, as the cost of operating high mpg internal combustion engine would increase. The average fuel efficiency of internal combustion engine vehicles would increase with the replacement of less fuel efficient vehicles (Figure 85). The initial positive slope is due to the retirement of older less efficient vehicles still in the fleet. After 2025, no more improvement is observed due to the scenario chosen, which introduces no mpg improvement in the future. However, a slight improvement is observed with policies due to changes in market shares of different vehicles types.
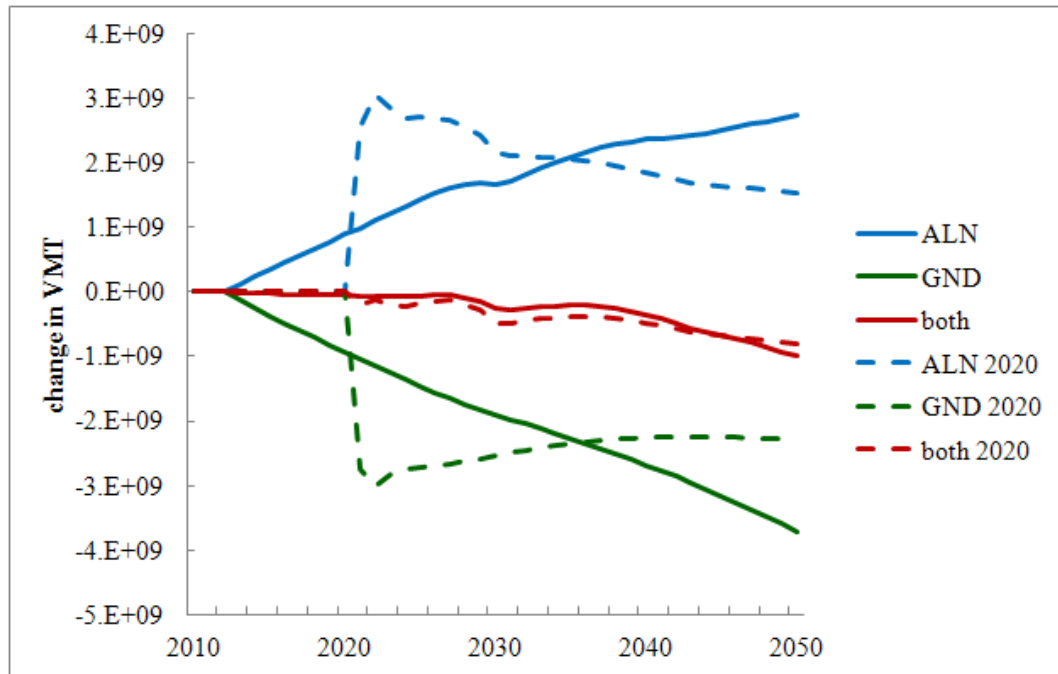
Figure 82: Change in VMT due to a carbon tax implemented in 2020 or gradually with high efficiency fleets

6.3.3 Technology Effect on Demand

Fuel efficiency improvements for the ground mode directly affect the cost of travel in GAME and therefore define the demand which may increase through the rebound effect. Any improvement in fuel efficiency will result in a lower operating cost for airlines, which may be passed on to the customer through a reduced ticket price. It is observed that with higher fuel efficiency, the decrease in demand due to a carbon tax is smaller than in the BAU fleet scenario. This is due to the fact that the reduction in fuel burn results in a decrease in the fuel cost portion of the ticket price, which, under full pass through assumptions, helps to maintain mobility in spite of increased fuel costs as observed in Figures 81 and 82. For example, a carbon tax under BAU fleet assumptions result in a decrease in RPM of 3.32% in 2050, but with N+2 technologies it is reduced to 1.42%. Through these observations, it appears that policies impact demand and fleets through the increased cost of travel. The following section discusses the effect of policies on climate impact.
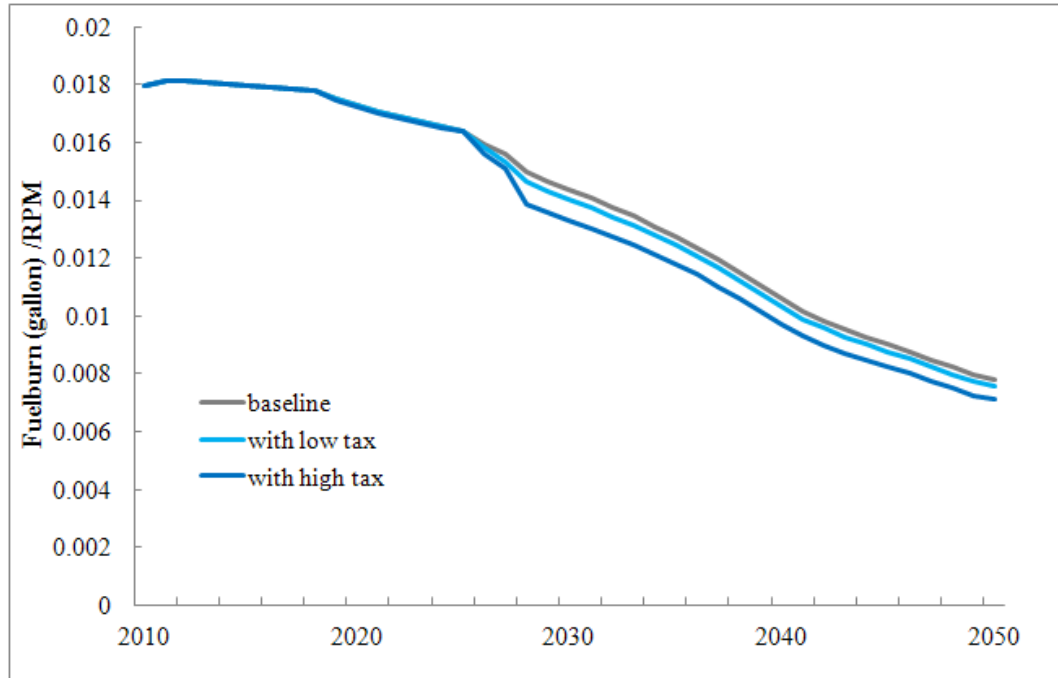
Figure 83: Fuel burn per RPM under different policy scenarios for N+2 scenario

6.4 Effect of Policies on Climate Impact

To quantify the effect of policies on climate impact, the combined effect of these policies on demand and fleets needs to be taken into account. This is done through the eGAME framework and the iterations between the airline fleet model and the demand models as described in Subsection 5.1.1. From the changes in demand and in fleet efficiency, and the climate module described in Section 5.2, the effect of policices on climate impact is obtained. As discussed in Section 5.2, the climate impact is quantified through Radiative Forcing. The RF from each mode and each species can be quantified with eGAME.

6.4.1 Long-lived versus Short-lived Species

Radiative Forcing from CO_2 is based on the concentration of CO_2 in the atmosphere. Due to its long life time, a reduction of CO_2 emissions due to demand and/or fleet changes does not necessarily result in an immediate reduction in CO_2 RF, as discussed in subsection 5.2.6. Furthermore, the total CO_2 RF needs to be considered since a
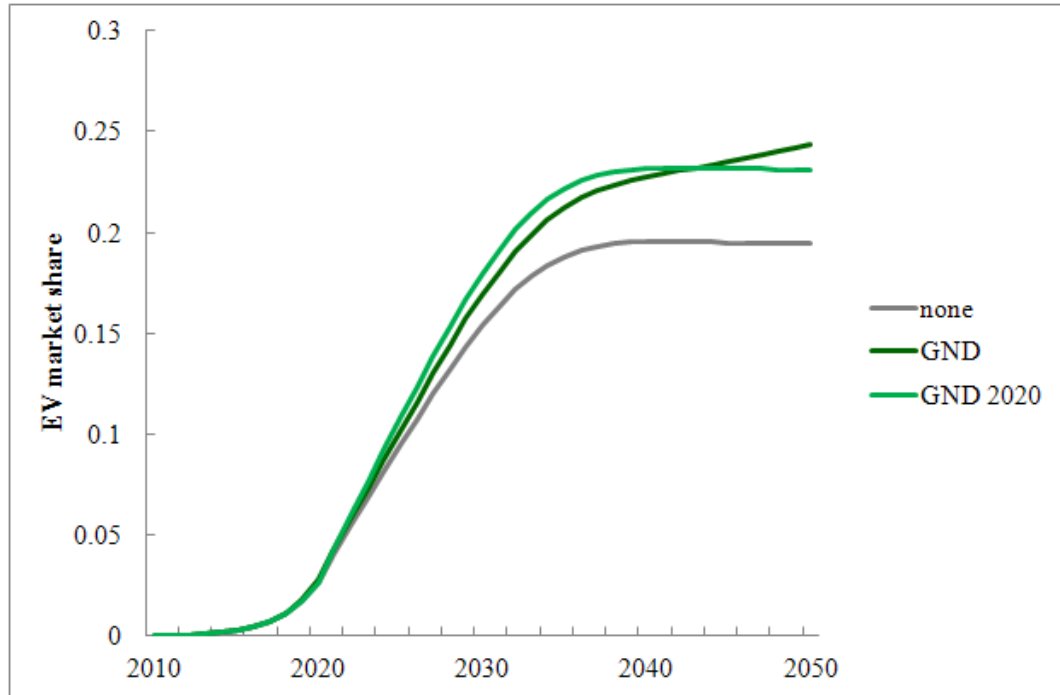
Figure 84: EV market share under different policy scenarios

decrease in emissions for one mode of transportation might come with an increase in emissions for another mode. The total CO_2 RF from both modes of transportation shows some interesting results. In cases where a tax is applied to only one of the two modes (in this example, the ground mode), a tax may in fact, under certain conditions, result in an increase in overall tranportation CO_2 RF, as seen in Figure 86. This is likely due to the fact that people switch to the ALN mode, which in some cases may be less fuel efficient, and maybe fly farther, thus increasing their CO_2 emissions. The average distance flown decreases when a tax is implemented on the GND mode due to the mode switch from GND to ALN which is mainly shorter distances. In the case of a tax on the ALN mode only, the opposite is observed where shorter distance trips are switched to the GND mode thus increasing the average distance flown.

However, under other circumstances, the effect of the tax may be reversed. This is the case under the high technology scenario, as depicted in Figure 87. If the tax on GND is implemented in 2020, the same effect is observed with an increase in CO_2 RF.

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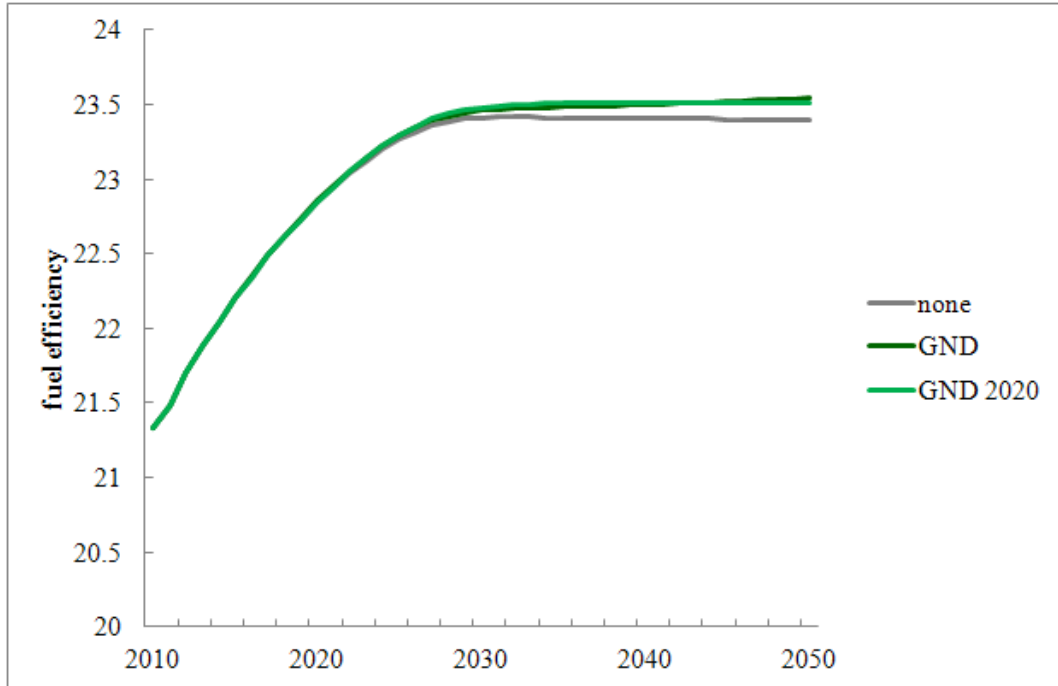
Figure 85: Fuel efficiency under different policy scenarios

But when implemented in 2030, it is the tax on ALN that would result in an increase in CO_2 RF. This can be explained by the significant reduction in fleet fuel burn per RPM between 2020 and 2030 due to new technologies. Therefore, in this particular case, switching to the ground mode by making the ALN mode more expensive is not beneficial from a System-of-Systems point of view.

For short-lived species the effect may be beneficial faster due to their short life time in the atmosphere. Under the BAU fleet scenario, a sudden tax indeed results in a sudden reduction in RF from contrail (Figure 88) and soot (Figure 89) due to the change in demand. This may be used in policy making to show direct effects of policies on RF. However, in the long term, RF may still be increasing due to the long lifetime of some species. This further shows why time series of RF from these species is a significant piece of information for policy and technology scenario exploration.
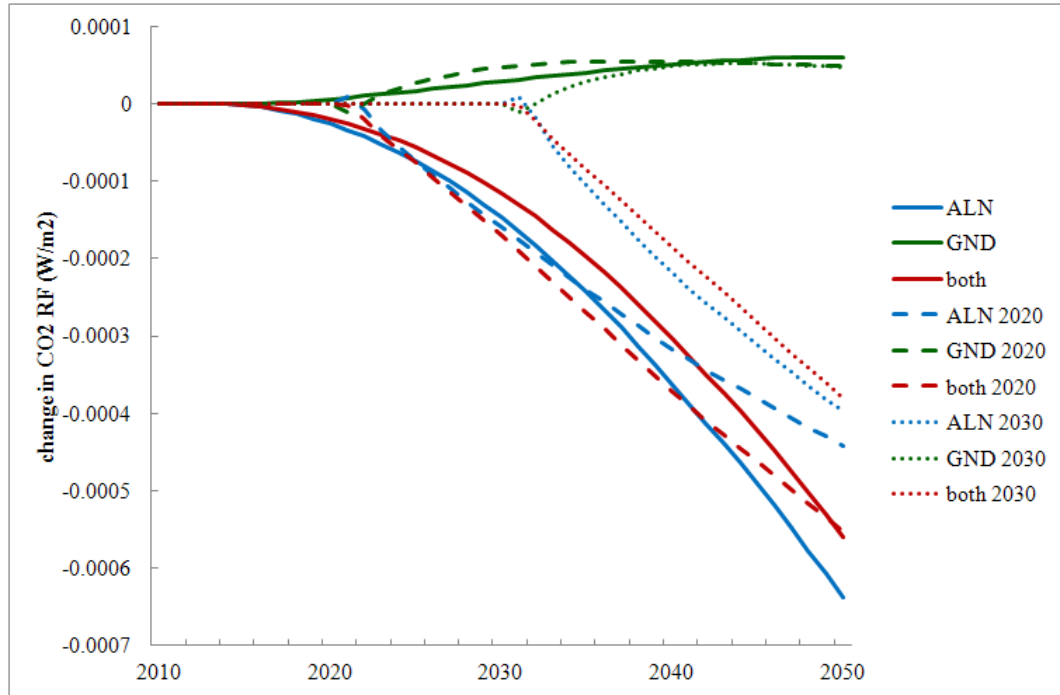
Figure 86: Total CO_2 RF under baseline fleet scenarios

6.4.2 Hypothetical Past Policy

Models predicting the impact of policies are hard to calibrate. Very limited data exist for validation. In this section, a comparison is made with a study by Sgouridis et al. [151], which found a 3% decrease with a 0.5 dollar per gallon tax and 9% decrease with a 2 dollars per gallon tax. With a carbon tax implemented in 2011 in eGAME, demand in 2012 would have decreased by 6.32% overall. This value is of the same order of magnitude as found by Sgouridis et al [151].

A more detailed analysis shows a 2.7% decrease for DG1, 4.3% for DG2, 7.9% for DG3, 5.1% for DG4 and 2.7% for DG5. Long distance flight demand is not strongly affected due to the much higher attractiveness of this mode for long distance. Short distance attractiveness does not change significantly. The most affected are the mid distance groups where most of the competition between modes is going to happen. CO_2 emissions would have been reduced by 1.23% for air transportation and increased by the same amount for ground transportation due to the increase in

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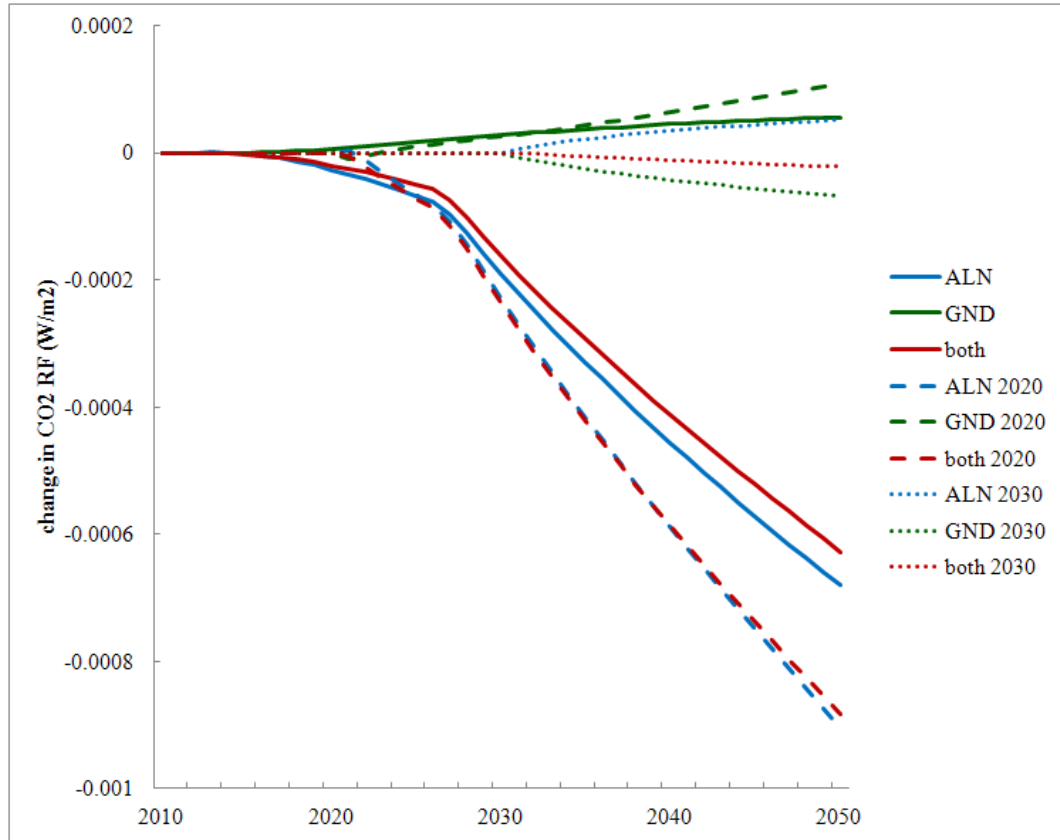
Figure 87: Total CO_2 RF under high fuel efficiency fleet scenarios

demand. Therefore no significant environmental benefits would have been obtained
with a carbon tax exclusively on ALN.

6.4.3 Realistic Target and Technology and Policy Portfolios

The reduction obtained with policies (CO_2 and RF based taxes) is limited. Among
the gradual options explored in this study (on each mode, and on both modes based
on CO_2 only and RF) the reduction in emissions achieved is at most 5.1% in the
baseline fleet assumption, and 6.7% in the N+2 fleet assumption. But the reduction
obtained from making N+2 aircraft available and increasing ground vehicle fuel effi-
ciency is about 33.6%. This shows that it is necessary to motivate new technologies
concurrently with the implementation of policies to encourage mobility changes and
fleet renewals. With no new technology available, all savings come from reduction

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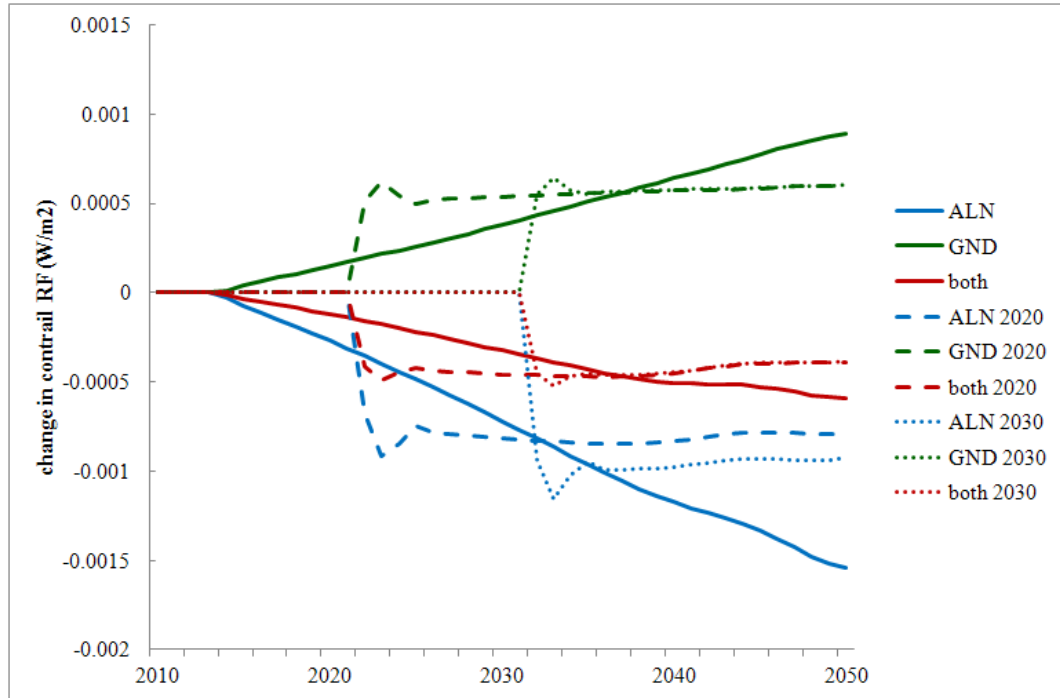
Figure 88: Contrail RF under baseline fleet scenarios

in mobility. With new technologies, significant reduction can be achieved, and policies result in a faster introduction of technologies, and a smaller negative impact on mobility.

As can be seen in Figure 90, a combination of technologies and carbon tax would result in the stabilization of CO_2 emissions. Due to the long lifetime of CO_2 in the atmosphere, the RF would keep increasing for a few years as can be observed in Figure 91. Without technology infusion, policies would not be sufficient to stabilize CO_2 emissions, which is a target of many policies. Only relatively small reductions are obtained with reasonable market based measures alone. This verifies **hypothesis 3.1**. And it is concluded that with sufficient policy **and technologies**, emissions and climate impact goals can be achieved.

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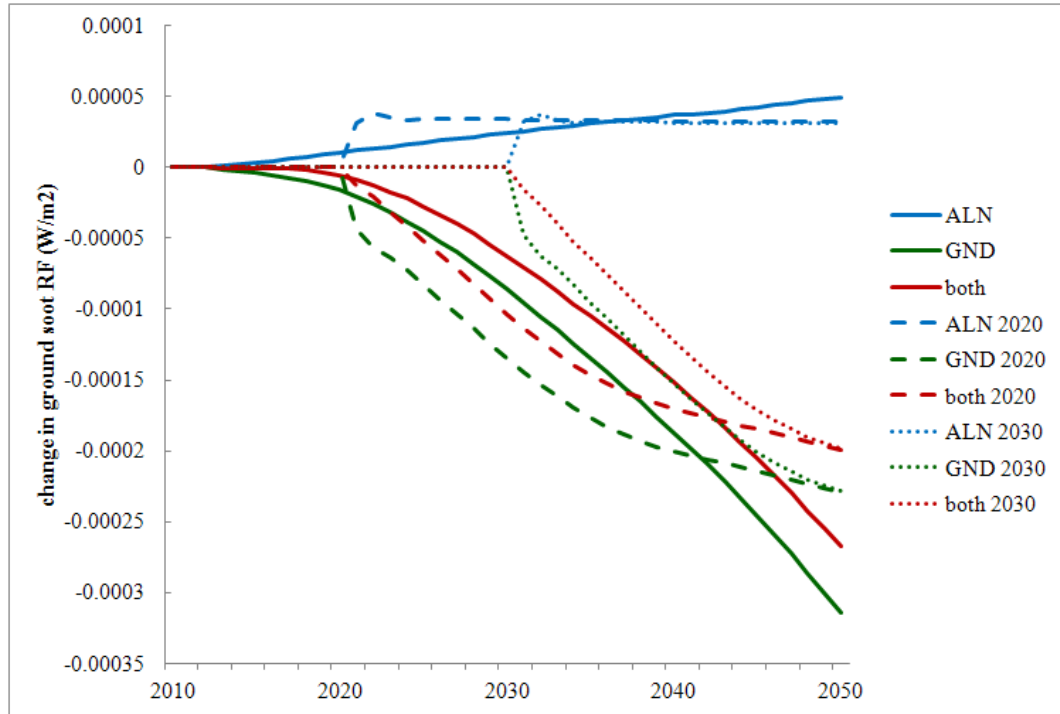
Figure 89: Ground BC RF under baseline fleet scenarios

6.5 Policy Evaluation and Selection

With the eGAME framework described above, it becomes possible to run simulations with and without climate policies, and with different climate policies and different sets of technologies. This results in different output demand, emissions and climate impact. It is then possible to assess the performance of each scenario with respect to these metrics. In terms of transportation, the goal is to maintain a satisfying level of mobility without excessive impact on the atmosphere. Some decision making techniques can be applied in order to identify the best scenario based on a series of criteria, address the following research question:

Research Question 3.2: How can different policies and technologies be assessed?

and verify the following hypothesis:

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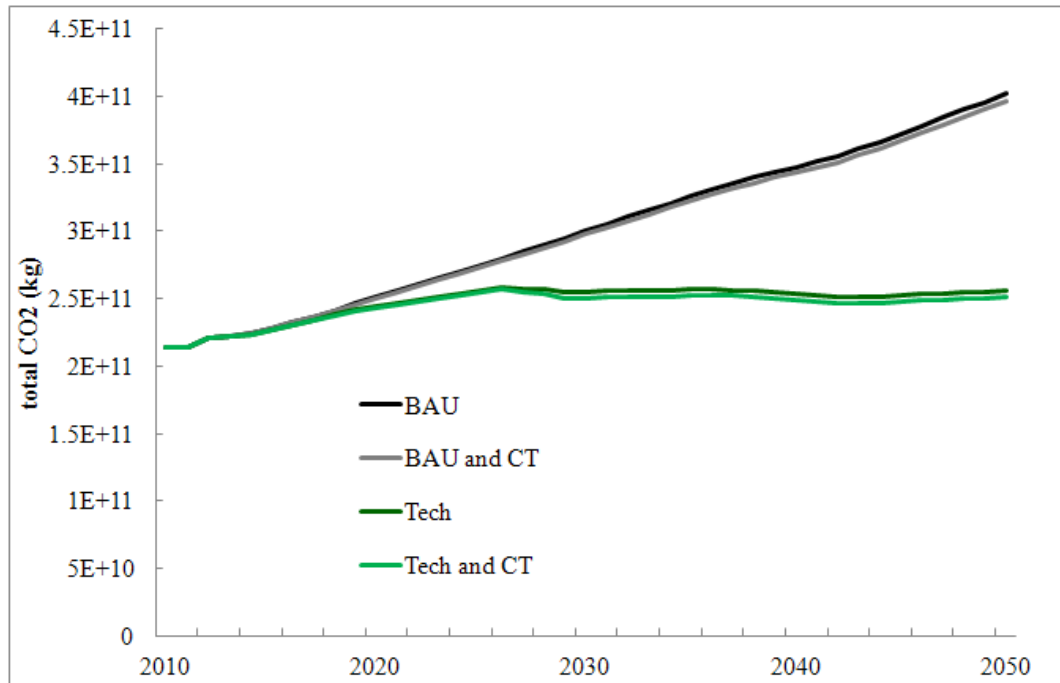
Figure 90: Transportation system's CO_2 emissions under different policy and technology scenarios

Hypothesis 3.2: Due to the many interdependencies involved in transportation sustainability, a scenario-based approach is best to assess different policies and technologies.

6.5.1 Pareto Frontier

In order to make decisions on the best climate policy and sets of technologies, several factors need to be taken into account and decision making needs to be performed. Total demand and climate impact are competing, with technology level being the mean to having a high demand with limited climate impact. Therefore some mobility metrics and climate metrics are used for decision making. Mobility metrics may be the average or total time and/or cost it takes to travel a given distance, or the average or total distance traveled. Climate metrics may be any of the metrics described in section 5.2. Each scenario is run and these outputs are obtained and plotted. It is then straightforward to identify a pareto frontier of the best scenarios as can be
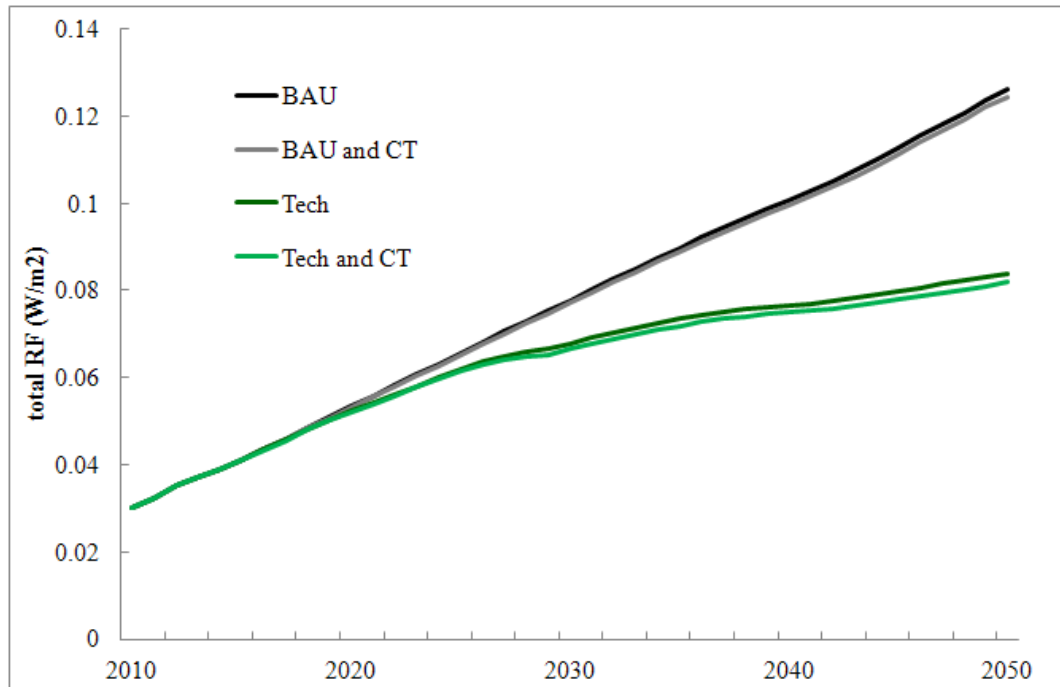
Figure 91: Transportation system's RF under under different policy and technology scenarios

seen in Figure 92. On the left, the total distance traveled (RPM and VMT) and the climate impact metric of interest are considered. The objective is to maximize distance traveled and minimize climate impact. Non-dominated solutions can be identified as scenarios A, B and C. Scenario A will be prefered if the emphasis is on reducing climate impact, no matter what it implies in terms of mobility, whereas scenario C will be prefered if the goal is to maintain a satisfying level of traveled distance. Scenario B represents a compromise between the two objectives. When time and cost of traveling are also considered (right graph), complexity is added because the previously non-dominated solutions may not be optimum (scenario A for instance). Multi-attribute decision making can be performed and the best solution identified based on priorities on objectives. The abstract scenarios A, B, C, D and E can be mapped to a given set of policies and technologies, providing the decision makers with the necessary policies and technological improvements to achieve the desired mobility and climate goals.

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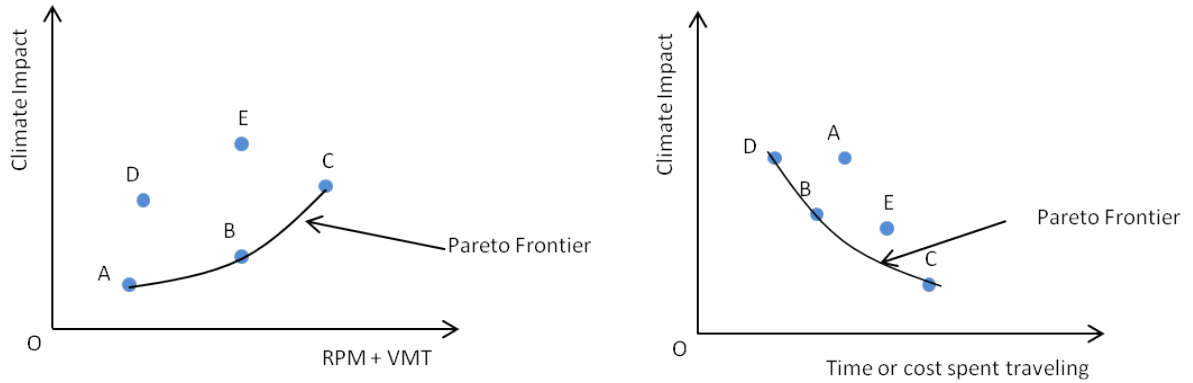
Figure 92: Scenarios pareto frontiers

6.5.2 Mobility versus Climate Impact

Different technology and policy packages are simulated as described in Table 28. As can be observed in Figure 93, significant reduction in climate impact with increase in mobility is obtained when technologies such as N+2 and higher mpg are implemented. Policies result in a small decrease in climate impact, but a decrease in mobility. The effect of policies is reduced with higher fuel efficiency of the fleets as shown by the spread of the data points. When going from a policy on ALN only with high fuel efficiency scenario to a tax based on RF, a decrease in RF and an increase in mobility is observed, which is possible with the extra fuel savings obtained with faster replacement of airline fleets. The best choice, in terms of climate impact, based on this plot is the high technology scenario with a tax based on RF.

6.5.3 Travel Cost versus Climate Impact

The same scenarios were run and compared with a new metric, the average cost of travel, which is computed based on the weighted cost spent traveling with each mode. Figure 94 shows that technologies help reduce the cost of travel while reducing the climate impact, and policies increase the cost of travel slightly while reducing the climate impact. The best choice for low cost of travel is, as expected, the high technology, no tax scenario. The best choice for climate impact reduction is the high

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Table 28: Policy and Technology scenarios

scenario	Socio-economic	Tax	ALN Fleet	GND Fleet
A	Baseline	None	BAU	MPGx1
B	Baseline	ALN gradual	BAU	MPGx1
C	Baseline	GND gradual	BAU	MPGx1
D	Baseline	both gradual	BAU	MPGx1
E	Baseline	RF gradual	BAU	MPGx1
F	Baseline	None	N+2	MPGx1.5
G	Baseline	ALN gradual	N+2	MPGx1.5
H	Baseline	GND gradual	N+2	MPGx1.5
I	Baseline	both gradual	N+2	MPGx1.5
J	Baseline	RF gradual	N+2	MPGx1.5

technology, RF tax scenario.

6.5.4 Travel Time versus Climate Impact

Mode switch and changes in traveled distance may result in variations in average travel time, as depicted in Figure 95. A tax results in a decrease in time spent traveling, and the higher the tax, the lower the time spent traveling. With technologies, the climate impact is reduced and more time may be spent traveling due to the reduced cost.

If the goal is to minimize climate impact, scenario J is the best. If the goal is to minimize the cost of travel, scenario F is the best. If the goal is to maximize the miles traveled, scenario H is the best. Thus hypothesis 3.2 is verified. In order to rank the alternatives based on the multiple attributes, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is applied as described in the following section.

6.5.5 Ranking of Alternatives

Ranking the alternatives based on multiple alternatives (distance traveled, time and cost, climate impact) may be challenging and the two dimension representations

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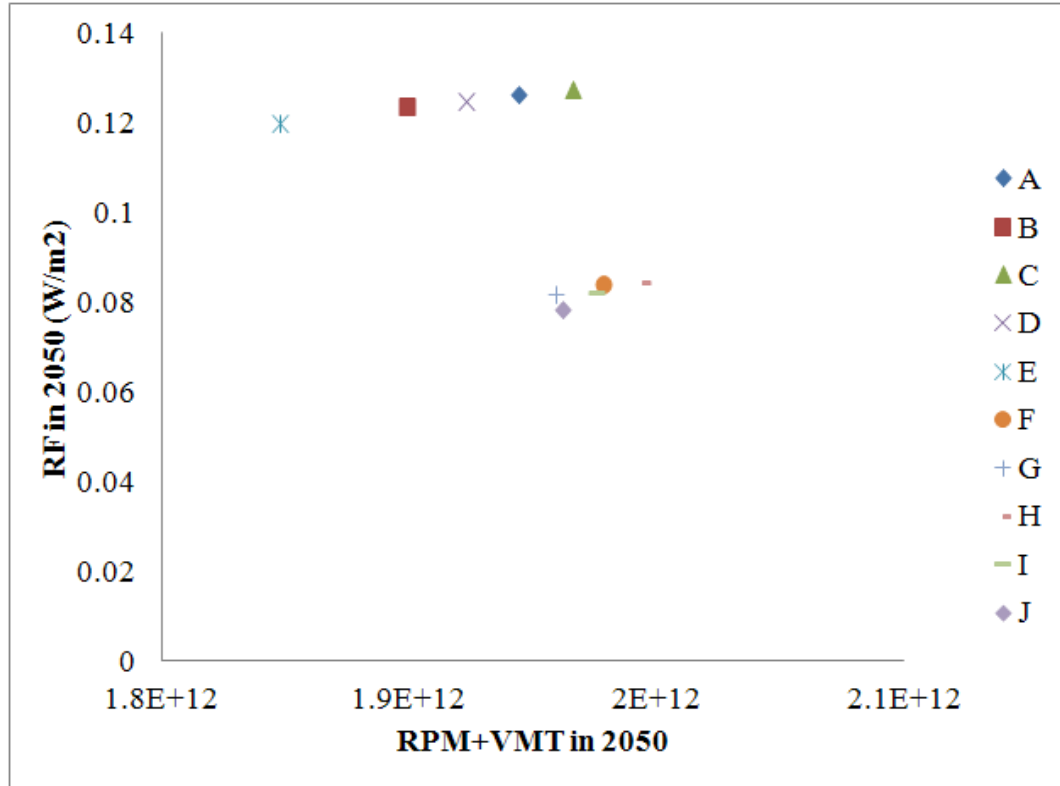
Figure 93: Climate impact (RF) versus mobility (RPM+VMT)

shown in the previous subsections are not sufficient. Therefore a Multi Attribute Decision Making (MADM) technique is used, TOPSIS, in order to show how eGAME scenarios may be used for policy and technology decision making. In TOPSIS, weights of different attributes must be defined. Depending on these weights, the results of the ranking may be different. Four main attributes were identified to quantify the climate impact and mobility metrics:

- total transportation RF in 2050

- total RPM and VMT in 2050

- average time spent traveling

- average cost spent traveling

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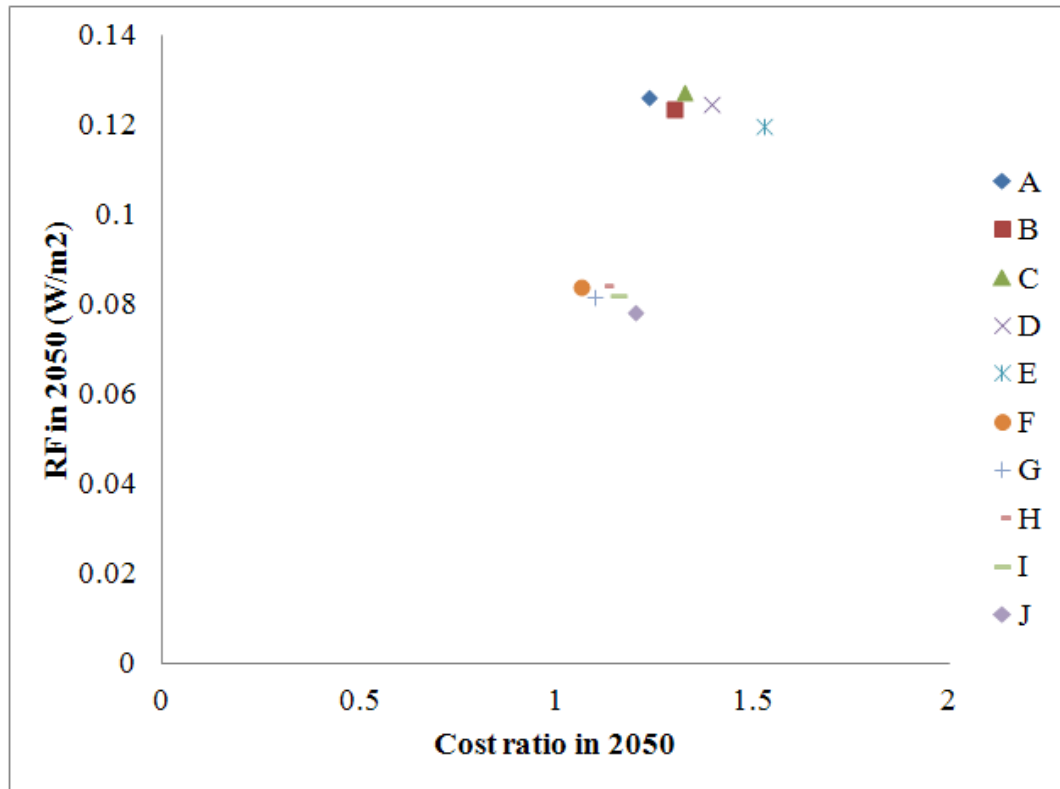
Figure 94: Climate impact (RF) versus cost of travel

A number of weighting scenarios were chosen as listed in Table 29. As shown in Table 30, all weighting scenarios favor the policy and technology scenarios that include high fuel efficiency technologies, because they all result in lower environmental impact, while lowering the cost and improving mobility. However when it comes to policies, depending on the weighting scenarios, the best technology and policy package may be different. For example, the "environmental" weighting scenario favors strong policy scenarios such as a policy based on RF, which, as previously described, results in a higher tax on both modes, especially on the ALN mode. On the other hand, the weighting scenario with strong emphasis on mobility favors scenarios with little or no tax. These policy and technology scenarios represent a small subset of all possible scenarios that may be run in eGAME. As demonstrated here, eGAME enables the evaluation of a number of policies and technologies for transportation at the System-of-Sytem level, which can provide useful insights into the effects on a number of high

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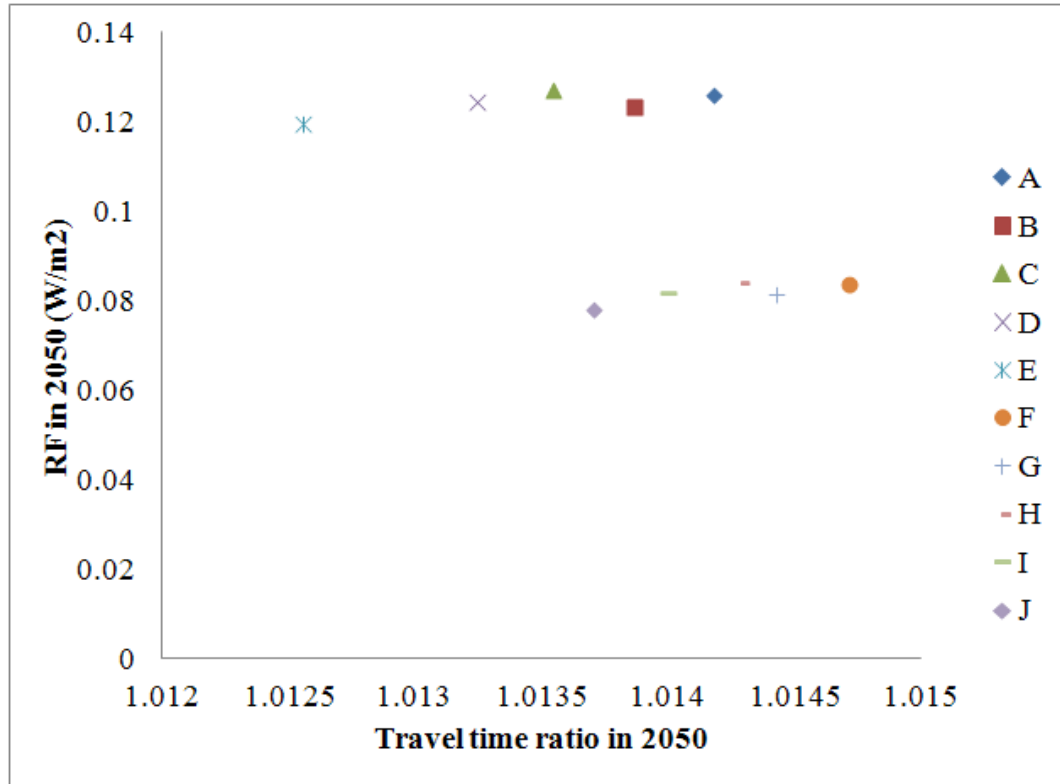
Figure 95: Climate impact (RF) versus time spent traveling

level metrics.

Table 29: TOPSIS weighting scenarios

weighting scenario	RF	RPM+VMT	Time	Cost
"environmental"	0.7	0.1	0.1	0.1
balanced	0.5	0.3	0.1	0.1
emphasis on mobility	0.3	0.3	0.2	0.2
strong emphasis on mobility	0.1	0.3	0.3	0.3

Table 30: TOPSIS results for policy and technology scenarios

	environmental	balanced	emphasis on mobility	strong emphasis on mobility
A	0.072	0.109	0.260	0.537
B	0.093	0.109	0.221	0.429
C	0.050	0.094	0.202	0.398
D	0.063	0.083	0.149	0.267
E	0.149	0.148	0.129	0.056
F	0.886	0.887	0.900	0.953
G	0.931	0.928	0.924	0.919
H	0.880	0.880	0.879	0.874
I	0.922	0.919	0.886	0.815
J	0.968	0.952	0.872	0.739

CHAPTER VII

CONCLUSION AND RECOMMENDATIONS

The increasing concern for climate impact of human activities and the looming policies associated with this impact may change the way we use transportation. It is crucial to better forecast how the system would react to different scenarios in order to make decisions and avoid severe consequences in terms of mobility and climate impact. The literature review showed an increasing number of discussions on integrated assessments which enable this type of scenario exploration including both economic and climate impact aspects. The scope and the level of detail of integrated assessments is of paramount importance and should be relevant to each country and sector that are affected by given policies. The transportation sector is one of the main emittors in the United States. Therefore an assessment of the U.S. transportation system is needed, including all modes of transportation. Powerful tools exist but are not currently linked to enable these scenarios' explorations. Furthermore their approach and computation time may not be appropriate. Therefore a new approach is proposed: a system dynamics model (GAME) is developed and expanded to include all aspects of transportation, including emissions and climate policies. The proposed framework (eGAME) is depicted in Figure 96. This integrated tool aims to assess demand, emissions and climate impact under given technology and policy scenarios. With this new approach to perform scenario exploration of different technologies and policies in the U.S. transportation system, insight is given into the extent of the effect of climate policies on the system and what should the future system look like.

The purpose of this research was to explore the long distance transportation system-of-systems behavior under climate constraints. This implies exploring the
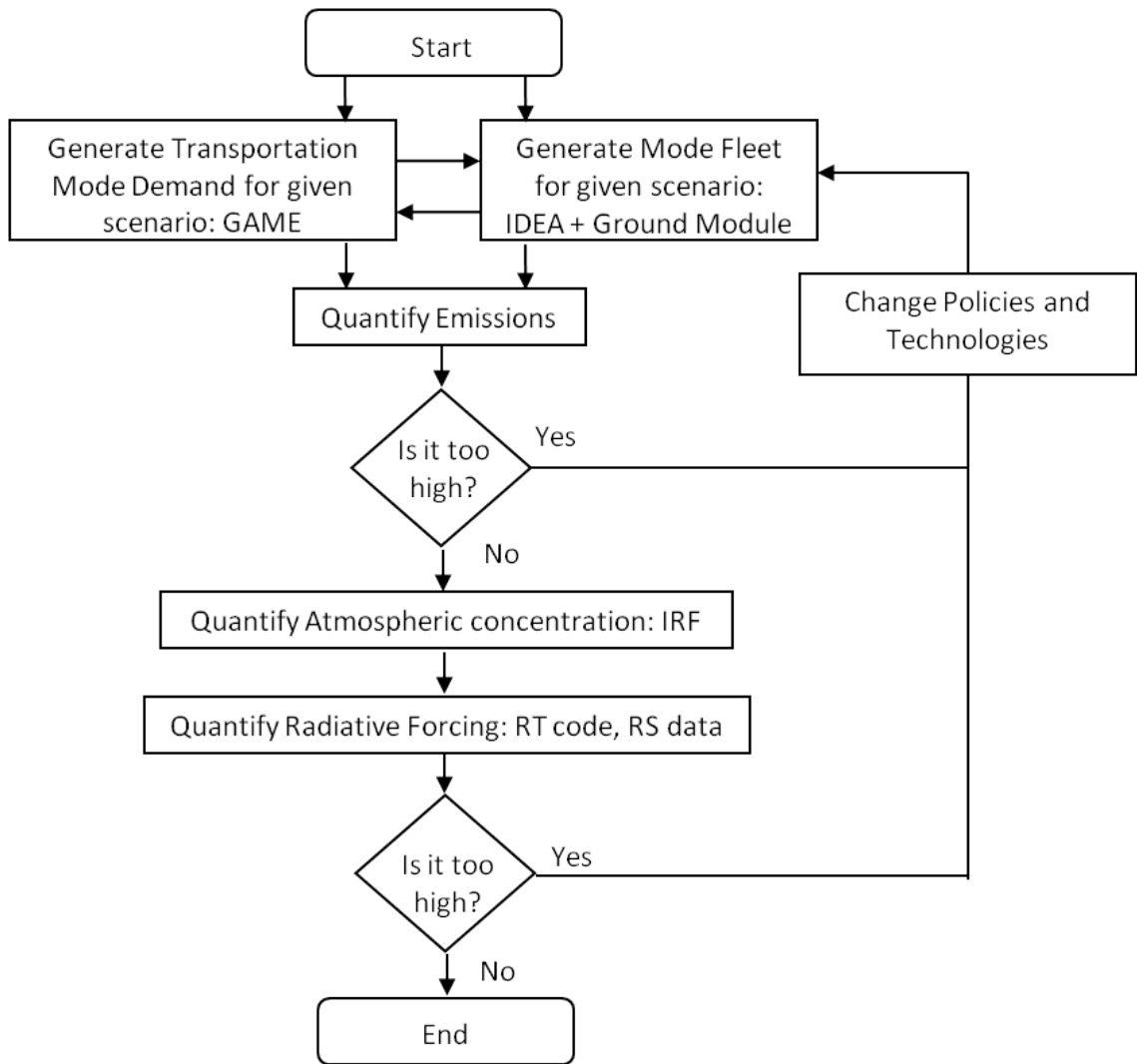
Figure 96: US Transportation SoS integrated assessment framework with tools

changes in demand and fleets with newly added policies such as the widely discussed
carbon tax. Two research areas are presented in this dissertation: the first relates
to new techniques to better represent the system-of-sytems, the second relates to the
quantification of the transportation system's climate impact and the possible policies
that can be envisioned. Through this research, a tool is developed, the environmen-
tal Ground and Air Mode Explorer (eGAME) that incorporates the results of the
research and thus enables policy and technology scenario exploration.

7.1 Contributions

The design and analysis of transportation systems can be facilitated by the development of parametric simulation environments that may be used to explore multiple scenarios and perform decision-making. Rigorous calibration is needed to gain confidence in simulations' results. The complexity of the transportation System-of-Systems makes these tasks challenging and requires methodologies and mathematical analysis with a holistic approach. It is shown that both micro- and macro-level views - in the form of multi-paradigm Agent-Based Modeling (ABM) and System Dynamics (SD) - are suitable and have long remained disconnected. A literature review across a wide variety of fields indicates that their use in a synergistic manner is increasingly advocated. A large number of hybrid methodologies, sometimes with strong similarities, appear with limited conceptual framework to build on. In an attempt to streamline efforts to create hybrid models, a complete and succinct classification is formulated. A new hybrid approach is developed that could help expand the use of these techniques for transportation systems' analysis. An SD model is developed for long distance transportation in the continental United States. Generally, SD models lack numerical accuracy and their validity has been a subject of debates. The confidence in the model's results is improved through previous research that resulted in an Agent-Based Model with proven ability to replicate historical data of multimodal inter-city travel demand. ABM is used to derive the structure and mathematical formulation of the SD model, thus verifying

Hypothesis 1.1: With proper analysis, derivations, and aggregation, a SD model can be derived from an ABM.

The purpose of the SD model is to replicate the behavior of the ABM within a bounded region which defines acceptable ranges for reliable forecasts. This is achieved through a cross-calibration and verified using multiple data points. Through this process, we show how to obtain better numerical accuracy with model refinement

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using ABM. This structured methodology ensures that the SD model inherits the proven predictive power of the ABM and verifies

Hypothesis 1.2: Through a cross-calibration process, SD can produce results similar to ABM within given ranges.

The hybrid methods classification aspires to establish a common ground for ABM and SD modelers who may use it as a starting point for model development. The methodology described in this research for the creation and calibration of an SD model based on an ABM may be used as a guideline for other applications. The SD surrogate created in this research may be used as a decision-making framework for transportation problems. Its fast computation time and parametric nature make it a good candidate for decision making through exploration of a wide variety of policy and technology scenarios for intercity multimodal transportation design.

The demand model is linked to fleet models of each mode of transportation to quantify fuel burn and emissions resulting from this demand. Interactions between the models are considered in order to capture potential rebound effects of technologies on demand. It is indeed observed that fuel efficiency improvement may result in an increase in demand depending on airlines pricing strategies. A ground fleet model is created based on the attractiveness of different vehicles, and life cycle emissions are quantified using existing tools.

Hypothesis 2.1 is verified: The integration of parametric demand and fleet replacement models, and the use of life cycle emission factors enables scenario based environmental analysis.

With these emissions, climate impact is then quantified using the Radiative Forcing metric which from literature is an appropriate metric for climate impact studies (**Assertion 2.2**). The species with the main warming impact are chosen here: CO_2 RF is quantified through Impulse Response Functions that model the carbon cycle,

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RF from soot and contrails is quantified using a radiative transfer code. These radiative transfer simulation show large regional and seasonal variations, and thus verify

Hypothesis 2.3: Radiative Forcing efficiencies vary based on the mode of transportation, location and season of emissions.

With the quantified demand, fuel burn and climate impact, eGAME enables policy and technology scenario exploration. A number of policies are considered, which essentially result in an increased fuel price. Policies impact demand and fleets through an increased cost of travel. Though non-negligible, the results show relatively small effects of policies on demand, and fleets, and thus little effect on climate impact, which verifies

Hypothesis 3.1: Climate impact goals may be achieved through a combination of technologies and policies.

Policies need to be associated with technology infusion in order to have sufficient impact. By making fuel efficient technologies available, a significant decrease in climate impact is observed with limited impact on demand. Policies such as MBM can then accelerate and increase the magnitude of this decrease, through faster replacement of fleets. A number of policy and technology scenarios are run and the resulting high level metric for mobility and climate impact quantified.

Hypothesis 3.2 is verified: Due to the many interdependencies involved in transportation sustainability, a scenario-based approach is best to assess different policies and technologies.

With a sustainable transportation goal in mind, multi-attribute decision making may be performed in an attempt to identify potential policy and technology packages that help maintain mobility with limited climate impact and thus achieve sustainability.

The main contributions are summarized here:

- Create a framework for integrated assessment of the US transportation system

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(eGAME)

- Establish a methodology to create a System Dynamics surrogate of an Agent-Based Model applied to the transportation demand

- Link multimodal transportation demand models with fleet models to quantify fuel burn under different scenarios

- Explore different climate impact metrics for the transportation SoS

- Quantify the climate impact of the transportation SoS including both gaseous and aerosols species

- Implement climate policies and quantify their impact on the demand, fleets and climate impacts of different modes of transportation

7.2   *Lessons Learned and Potential Research Paths*

It is a significant advantage to have both bottom-up and top-down views because it enables the representation of a wide variety of behaviors and policies. By bringing air transportation systems together with other transportation systems, a more complete picture on long distance transportation in the United States is obtained, and enables the exploration of more possible futures. By using radiative transfer codes and remote sensing techniques, a better and more complete assessment of climate impact is obtained.

This thesis established the foundation for a hybrid ABM-SD for long distance transportation systems. A number of research paths may be envisioned to further improve the modeling capability and expand its scope.

- The current model does not represent the complex interactions related to competition between airlines. The air transportation system is represented as a

single supplier, and to better capture the dynamics within the air transportation system, an airline "agent" may be created.

- The tradeoffs considered in this study for climate impact of transportation focused on the two existing modes. The multimodal approach used here enables the expansion to other modes as was demonstrated with the P2P mode. Significant changes in mobility and climate impact may be observed if new modes such as high speed train are introduced. With the granularity of the ABM at the MSA level and/or the SD at the market level, this mode can be introduced on some specific markets and competition with other modes can be assessed. Some research would be needed to quantify the design variables and climate impact associated with the life cycle emissions of potential new modes.

- As mentioned in the climate policy section, a carbon budget for agents may be envisioned and introduced into the ABM view of the system.

- Large uncertainty remains in the assessment of demand, and climate impact, which may be reduced by refining the assessment through gridded demand and refined climate model simulations including more species.

- This research focused on the impact of transportation on climate. Another interesting research field is in the effect of climate change on transportation, and more generally on the economy. It is usually challenging to quantify but some relationships could be envisioned that would create a feedback between the quantified climate impact and the inputs of eGAME.

- Finally, this kind of approach may be repeated for other sectors of the economy, and in other geographic locations. Since climate change is a global issue with recognized uncertainty which makes it the topic of many debates, gaining knowledge by attempting to better model regional and sectoral impacts, and

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assessing the potential for sustainable systems by using policy and technology infusion is a challenge that can be tackled by breaking down assessments to then aim for global sustainability.

APPENDIX A

CALIBRATION OF THE AGENT-BASED MODEL

A.1 Databases

Mi was originally calibrated against the 1995 American Travel Survey (ATS) which gives information on long distance travel patterns. Since this survey has not been repeated, more databases were investigated and a set of databases was identified to perform a multi-year calibration of *Mi*. For the air transportation, T-100, which lists data from the operator's standpoint, and the Airline Origin and Destination Survey (DB1B), which lists data from the traveler's standpoint, were used. T-100 gives the complete data of airline operations, and the domestic data was retrieved for calibration of *Mi*. DB1B is a 10-percent sample of airline ticket information from reporting carriers and is the best way to track passenger itineraries with publicly available data. For ground transportation, VMT is tracked and data on long distance travel is not readily available. However, a set of databases was identified, which include the National Personal Transportation Survey (NPTS) from 1995, and the National Household Transportation Survey from 2001 and 2009. Both the NPTS and NHTS provide data on ground transportation, which include the mode of transportation, the duration of the trip, the distance and the purpose of the trip. They also gather demographic, geographic and economic data. Even though long distance trip data is not directly available, it can be obtained using VMT estimates for long and short distance trips, as well as total VMT from National Transportation Statistics [92]. Other databases were used to define socio-economic variables such as the GDP, the Consumer Price Index, Consumer Sentiment Index, population growth. A list of databases is provided in Figure 97 from Lewe et al. [92]. A quaterly time

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period was chosen for model calibration. Not all databases were quarterly and some treatment was required. For lower time periods, values were added or averaged, depending on the type of data. For longer time period, a seasonality factor was derived from the U.S Product Supplied of Finished Motor Gasoline for ground transportation and from T-100 for the air transportation. The ground transportation factor showed smaller seasonal variability due to the inclusion of short distance trips. Since the study focuses on long distance travel, the seasonality from T-100 was used.

Category	Data Used	Database Source
Air	Jet Fuel Price	BTS Statistics, Airline Fuel Cost and Consumption
	Operations	T-100D Segment
	Enplanements	T-100D Segment; DB1B
	Revenue Passenger Miles (RPM)	T-100D Segment
Auto	Business Mileage Reimbursement Rate (BMRR)	Internal Revenue Service (IRS)
	Maintenance and Tire Cost	American Automobile Association (AAA)
	Low Duty Vehicle (LDV) Short Distance Vehicle Mile Traveled	1995 American Transportation Survey (ATS)
		1995 National Personal Transportation Survey (NPTS)
		2001 National Household Transportation Survey (NHTS)
		2009 NHTS
	LDV Petroleum Consumption	National Transportation Statistics (NTS)
	LDV Total Vehicle Mile Traveled	
	U.S. Product Supplied of Finished Motor Gasoline	Energy Information Administration (EIA)
	Average Retail Gas Prices (regular grade all formulations)	
Socioeconomic	Gross Domestic Product	Bureau of Economic Analysis
	Consumer Price Index	Bureau of Labor Statistics
	Population	U.S. Census Bureau
	# of Household	
	Consumer Sentiment Index (MCSI)	University of Michigan

Figure 97: Databases used for calibration of Mi [92]

A.2   Calibration

A number of adjustments were made to Mi to ensure that it was able to replicate past data, and thus be considered to be calibrated. The simulation strategy was to iteratively change Mi until its outputs were close enough to actual data. Some modifications were applied, such as the seasonality mentioned in section A.1. A discontinuity was introduced due to 9/11 which resulted in a massive disturbance

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in aviation operations. A consumer confidence effect was added to account for the budget space variations with traveler's perception of the economy. The inputs used for the calibration are shown in Figure 98.
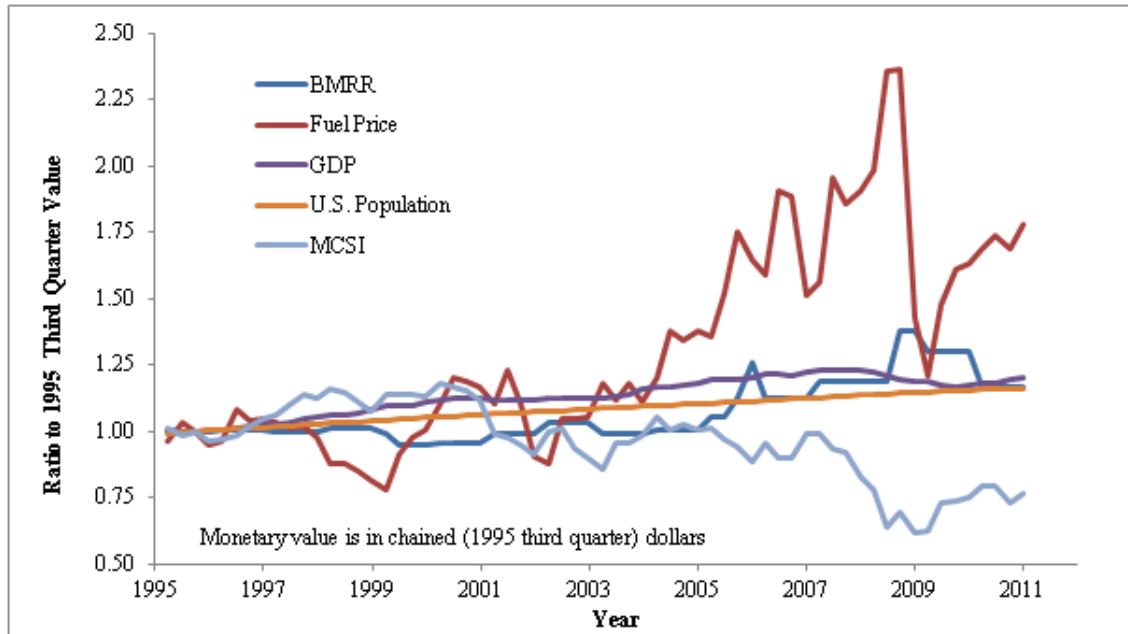
Figure 98: Simulation Inputs used for Mi calibration [92]

Through the calibration process, the adjusted model is able to replicate past data for RPM and VMT with a good level of accuracy. Resuls for RPM are shown in Figure 99, and results for VMT are shown in Figure 100. For the VMT, uncertainty ranges were determined to account for the fact that individual trips are more difficult to track than for air transportation. Due to the availability of long distance data, the uncertainty grows from 1995 NPTS which was compared to 1995 ATS, to 2009, which does not include long distance travel data. With the calibrated *Mi*, it is possible to generate forecast for RPM and VMT with a higher level of confidence, by using forecast data for the input variables. Some simulation were run in Lewe et al. [92] and RPM data was compared to the FAA forecast.

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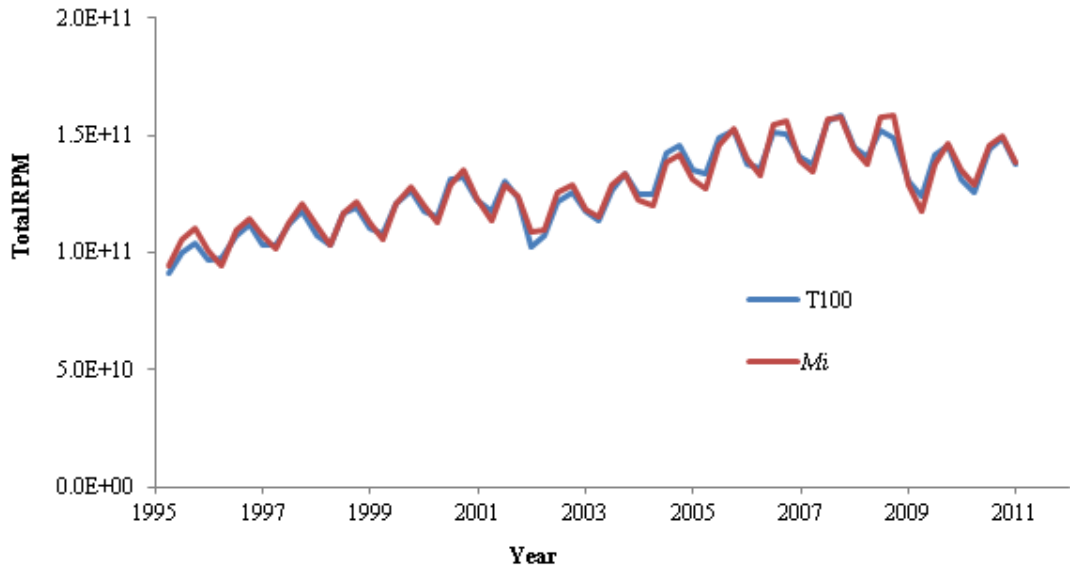
Figure 99: Mi and T-100D RPM [92]
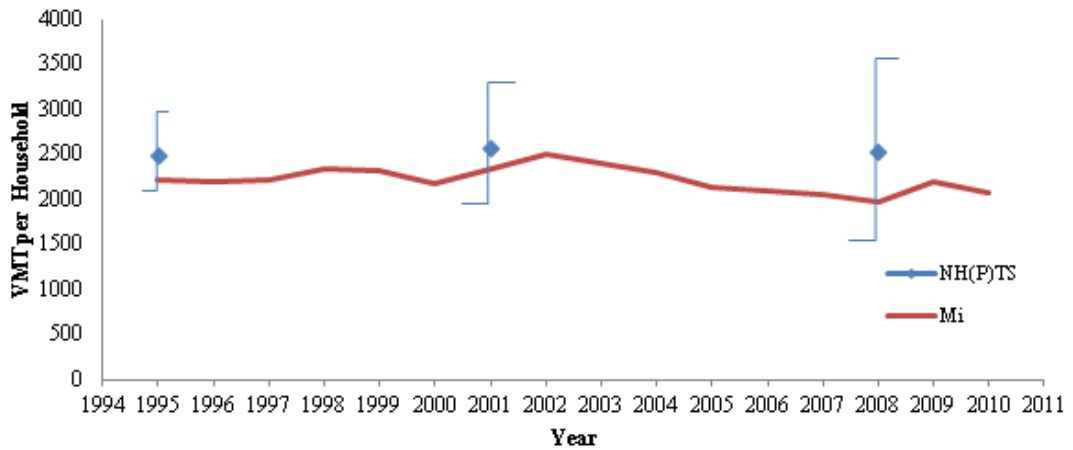
Figure 100: Mi and NPTS/NHTS VMT [92]

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APPENDIX B

AN ANALYSIS OF HISTORICAL TRENDS IN AIRLINE FLEET AND TICKET PRICE IN RESPONSE TO FLUCTUATING FUEL PRICES

The fuel price has been fluctuating significantly over the past few years, putting cost pressure on the airlines and forcing them to rapidly adapt. Airlines net loss reached record high values, requiring decisions to be made at many different levels. Airlines had to make tradeoffs and modify their ticket price, their fleet, their route structure, salaries, and the number of employees in order to make profit in the long term. Decisions made by airlines involve many parameters. Correlations are therefore not easily identified. The purpose of this appendix is to analyze airline historical data in order to try to find some correlations between fuel price and other variables, such as ticket price or type of aircraft in the airline fleet. These findings can then be used in air traffic demand models, as well as fleet forecast models. First, the procedure used for this research is presented, then the data used is described, followed by the results.

The objective of this research is to identify potential correlations between fuel price and airline responses focusing on ticket price and fleet structure. Airlines make decisions based on revenue and cost, trying to maximize net income. Facing financial difficulties, layoffs and fleet reduction are common. Airlines determine the ticket fare based on a number of parameters. Different airlines use different strategies. They also need to make decisions on their fleet based on aircraft age, advantages of switching to a new aircraft. These decisions are mostly based on current and expected demand. In recent years, fuel price volatility emerged, bringing another parameter in the picture, which impact on airline behavior is not very well known. Traditional air

traffic forecast tools base their forecast on parameters such as economic growth and fuel price. The uncertainty associated with these parameters has grown with the fuel price volatility observed in the past few years. To address this issue, the procedure is to look at historical data in order to identify some trends and potential correlations in cost, ticket price, fleet of different airlines. The focus should be on the last ten years since the fuel price has fluctuated significantly during this period (up to a factor three-fold increase in 2008). A given set of airlines was chosen for the analysis, as well as a given time of year in order to reduce variability and uncertainty of the results. Observing the airlines' responses to an increase in fuel price and their outcome, future decisions can be made based on previous experiences. The results could help predict the response to future fuel price fluctuations, anticipate the demand for new aircraft, and forecast future activity. The airline industry was divided into airline categories and airlines with a high market share from each category were chosen for the analysis. Total time period studied and frequency of the data analyzed were chosen in order to try to isolate the effect of fuel price. The focus of the study is on fleet and ticket price. The data was taken from the Bureau of Transportation Statistics aviation data library online.

B.1 Preliminary Considerations

Two main types of airlines are identified: Network Legacy Carriers and Low Cost Carriers. Other types such as Regional Carrier and Commuters are not considered in this analysis. Both Network Legacy Carriers and Low Cost Carriers are certified under Part 121 of Title 14 of the Code of Federal Regulations. Network Legacy Carriers are airlines that flew interstate routes before deregulation, and have international operations. Low Cost Carriers are airlines that have a stated low fare business model.

Seasonality is a very important factor in the transportation industry. During holidays, the demand for travel tends to increase significantly. The number of passengers

varies significantly from month to month. Therefore it is necessary to choose a time of year and keep the same time each year for comparison. By averaging over a long period of time, short time exceptional events may distort the results. Hence the need to choose a period of time that is as short as possible. However the data available also has a time period. Some data sets are reported monthly, but most are reported on a quarterly basis. Thus the first quarter of each year has been chosen for the analysis.

B.2   Database Description

Air Carriers (both passenger and cargo airlines) are required by US federal law to report financial and operating information to the Department of Transportation. Form 41 contains financial information on large certified U.S. air carriers such as balance sheet, income statement, cash flow, aircraft inventory, aircraft operating expenses, and air carrier operating expenses. Certified Carriers are carriers that hold Certificates of Public Convenience and Necessity issued by the U.S. Department of Transportation authorizing the performance of air transportation with annual operating revenues of 20 million dollars or more. Data is available starting in 1990. The time period is different for each schedule: one month, quarter, or 6 months. Balance sheets are found in schedule B-1 and schedule B-11. The first one represents quarterly reports from major, national and large regional carriers. The second represents semiannual reports for smaller carriers. The profit and Loss Statements are found in schedules P-12 for large carriers, P-11 for smaller ones. More detailed data can be retrieved from schedule P-12 Aircraft Operating Expenses, which provides expenses for each aircraft and each region of the world. This is of interest for studies on the impact of jet fuel price on a given carrier or aircraft. The following schedules are particularly interesting for this study:

- Schedule P-12A contains reported fuel costs and gallons of fuel consumed by air carrier and category of fuel use. It includes both schedule and non-scheduled,

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domestic and international service. Data is available starting in 2000, and has a time period of one month.

- Schedule P-52 gives aircraft operating expenses such as payroll expenses, fuel costs, maintenance, and depreciation costs for large certificated U.S. air carriers. The time period is a quarter.

- Schedule P-10 lists the number of employees each year, and schedule P-6 contains quarterly operating expenses including salaries and benefits.

The T100 Segment contains non-stop segment data for domestic flights and international flights leaving from or arriving in the U.S. For each city pair, it gives information on the air carrier, the aircraft type, the available capacity, the number of scheduled departures and departures performed, the distance and the aircraft hours. The Load Factor was retrieved by averaging the number of passengers to number of seats ratio.

Form 41 Schedule B43 table tracts the aircraft inventory. It contains the information on the year the aircraft was first placed in service, its status (owned or leased), and its operating status. Data is presented for major U.S. carriers and is available for only 2006, 2007 and 2008 (the data is reported on a yearly basis). Using this database and the Form 41 Schedule P-52 total air hours metric, the utilization of each aircraft can be determined.

The Airline Origin and Destination Survey is a 10 percent sample of airline tickets from reporting carriers. The data include ticket information such as fare, distance, carrier information, itinerary information, credibility of the reported fare. Data is available starting in 1993, and is reported on a quarterly basis.

The Ticket Fare varies significantly, even for a given origin, a given airline and a given distance. Therefore a process is needed in order to try to identify some trends over time and potential correlations with fuel price. The methodology is as follow: for

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each airline, an average of the ticket fare is calculated for each distance group (from 0 to 3000 miles, with increments of 500 miles). Only domestic flights are considered and values that are not credible are removed (values higher than 10,000 dollars and below 50 dollars, which are assumed to be the result of Frequent Flying programs). Correlations for the one coupon data, and the two coupons roundtrip data (which represent the 50-70 percent of the flights) were calculated.

B.3   Results and Analysis

Market Fuel prices increased by a factor five between 2002 and 2008, and reached their highest values in the summer of 2008. Since most of the data is obtained for the first quarter of each year, the fuel price data was averaged over the first three months of each year. The correlation between different variables and the fuel price are presented below, and regressions are implemented. The R-squared value is computed. The R-squared value represents the proportion of the variance in the considered variable that is attributable to the variance in fuel price.

B.3.1   Cost

The direct impact of fuel price is observed on the cost data of the airlines. The data was obtained using the Form 41 schedule P-52 database. The increase in fuel price resulted in an increase in fuel cost per hour for the airlines. The correlation is very high for most airlines. Airlines that hedged fuel show a lower R squared value (Table 31). It is observed that the fuel cost became a very significant part of the Direct Operating Cost, going from a ratio of 30 percent to 60 percent during the fuel price peak time. This ratio is relatively constant across all airlines at a given point in time. Correlations of this ratio to the fuel price are relatively high. Hedging strategies explain the lower value of some airlines during the peak. The Direct Operating Cost increased when fuel price increased, and the correlation is high. Network Legacy Carriers have a higher Direct Operating Cost than Low Cost Carriers (about 50

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Table 31: R-squared values for Cost and Fuel Issued

Airline	Airline Fuel Cost	Fuel Cost/DOC	DOC	Fuel Issued
NLC 1	0.7960	0.8490	0.5990	0.6856
NLC 2	0.9925	0.8492	0.9070	0.0023
LCC 1	0.7968	0.9294	0.6846	0.5377
LCC 2	0.9774	0.9206	0.9592	0.5394

percent higher). Thanks to hedging strategy, some airlines managed to minimize the impact of fuel cost on their operating cost during the fuel price peak of 2007-2008.

Low Cost Carrier pay a lower fuel cost and a lower Direct Operating Cost than Network Legacy Carriers. The ratio of fuel cost to DOC ratio is very similar for all LCC and NLC. For all airlines, the fuel cost increase was more significant than the DOC increase, which explains the increase in fuel cost to DOC ratio.

The airlines reported the Fuel Issued as well as the total air hours. From this data, the Fuel Issued per hour was determined. The trend is a slight decrease in fuel issued over the past few years for most airlines, even when the fuel price was not increasing significantly. The correlation to fuel price is low. It can be noticed that the decrease seems to have been more significant in 2007 and 2008 (higher slope for most carriers). Low Cost Carriers tend to have lower fuel issued since they operate different aircraft and different routes (and therefore have a lower fuel cost and a lower Direct Operating Cost as presented before). The fuel issued is the best airline estimate for the actual fuel use. The correlation to fuel price is not obvious, since fuel consumption is highly dependant on the fleet composition, air traffic, payload, and weather.

B.3.2 Ticket Price

A rapid and direct way for airlines to increase revenue in order to account for the operating cost increase depicted above is to increase air fares. The correlation between air fare and fuel price is not very high for most airlines. A lot of other parameters

Table 32: R-squared values for Ticket Price 2 coupons round trip data

Airline	Average R-squared (all distances), 2000-2010	Average R-squared (all distances), 2005-2010
NLC 1	0.1934	0.3051
NLC 2	0.2702	0.3717
LCC 1	0.6650	0.3101
LCC 2	0.9058	0.8437

can have an impact on air fare, such as lower competitor's fare, changing demand, etc. Data includes the ticket price, taxes and airport fees, but does not include extra fees charged by airlines such as baggage fees, internet in-flight and select coach fee. It can be observed that airlines increased their fares when fuel price went up, and that long distance flights were more sensitive to fuel price than short distance flights (peaks appear more clearly for longer distances than short distances).

The correlations between fuel price and ticket price are relatively low for most airlines as listed in Table 32. LCC 2 fares are well correlated with fuel price. A slight increase in R-squared value can be observed for NLC when focusing on the 2005-2010 period. LCC 1 low correlation may be related to hedging strategies which help reduce the airline fuel cost and the correlation to market fuel price. The ticket price to fuel price linear regressions for LCC 2 (which ticket price has a good correlation to fuel price) are listed in Table 33. From the slopes of the linear regression, the sensitivity of longer flights ticket prices to fuel prices is highlighted. The longer flights have a higher slope, which represents a higher sensitivity to fuel price.

An interesting point to mention is the significant decrease in airfare in 2002-2003 for long distance 1 coupon flights on Network Legacy Carriers. The 1 coupon data from NLC shows a significant decrease between 2000 and 2004. During this period, the airline industry went through a massive restructuration with a realigned fare structure that narrowed the gap between premium and walkup fares and leisure

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Table 33: Ticket Price Linear Regression for LCC 2 (2 Coupons, 2001-2010)

Distance Group	Linear Regression
0-500 miles	y=0.404x+132.7
500-1000 miles	y=0.5718x+110.89
1000-1500 miles	y=0.5697x+158.49
1500-2000 miles	y=0.5777x+237.51
2000-2500 miles	y=0.7334x+225.47

fares, due to the availability of internet booking and a drop in demand in the early 2000s. Two periods can be identified: between 2000 and 2005, the airline industry was restructuring, between 2005 and 2010, it responded to higher fuel prices. This explains the better correlations obtained previously on the NLC 2 Coupons data by focusing on the 2005-2010 period.

B.4 Airline Fleet

The impact of the fuel price variation on the fleet represents crucial information when trying to quantify the magnitude of the variation that is necessary for airlines to become interested in small decreases in fuel consumption of newer aircraft. The two Legacy Carriers decreased the number of aircraft in their fleet between 2006 and 2008, whereas the two Low Cost Carriers increased the number of aircraft in their fleet. Airlines decrease their number of operating aircraft and employees to reduce capacity. It is uneasy to isolate the effect of fuel price since the data is available for a short period of time and the situation faced by NLC and LCC were significantly different. It is observed that the trends in fleet size are very different for the airlines considered, which suggests that fuel price is not a determining factor for fleet size. Fleet size is more likely to be determined by other factors such as routes, financial situation, competition and global economical situation. It is not an easy task to isolate the effect of fuel price since other parameters were changing at the same time.

The airlines' fleets were analyzed. For Low Cost Carrier, it is similar to their

domestic operations' fleet since LCC operate mostly domestic routes. But for NLC, it is important to realize that some of the aircraft listed would operate international routes. Overall, Low Cost Carriers operate a much smaller variety of aircraft. It can also be observed that airlines fleet composition is relatively stable: the seat class distribution of aircraft operated by each airline does not change significantly from year to year. Generally speaking, the number of old, less efficient aircraft decreased.

Due to the difficulty of observing trends looking at the aircraft fleet reported by each airline in Schedule B43, which presents data for only the years 2006, 2007 and 2008, System-wide data was analyzed using the T100 Segment data, presenting aircraft operations. System-wide, the number of departures of older aircraft such as the MD-80 decreased in the past years while its competitors the A320 and B737 increased their shares. This supports the observation that airlines replaced older and less efficient aircraft by newer more efficient aircraft. However the trends seem to be relatively constant over the 2005-2010 period, without significant changes during the peak, showing that the fuel price increase magnitude in the past years did not result in a significant change in aircraft operations.

B.5   Route Structure

In order to better understand the observations on ticket price and airline fleets, some data on the route structure of each airline has been retrieved from the T100 Segment data for domestic flights. The purpose is to confirm the trends in airline expansion or contraction: from the fleet analysis, it was observed that the Network Legacy Carriers decreased the number of aircraft in their fleet whereas the Low Cost Carrier increased them. This suggests that NLC decreased their number of flights, whereas LCC increased them. It can be noticed that LCC2 started with a very low number of flights since it was created recently. The correlations with fuel price are relatively low: Negative correlation for NLC with R-squared values of 0.59 and 0.74, positive

correlation with R-squared values of 0.85 and 0.84 for LCC. Although the R-squared values are relatively high for the two Low Cost Carriers, the trends are opposite. Trends may be better explained by the fact that LCC expanded their market when the fuel price was increasing (and when demand was increasing). NLC decreased their number of destinations, while LCC increased them. The correlations with fuel price are also relatively low. Similarly to the number of departures, the different trends between LCC and NLC are better explained by the competitive market between airlines and the changes in market share. Overall, Low Cost Carriers are increasing their domestic market share, at the expense of the Network Legacy Carriers.

The average distance flown by passengers on each airline also changed: NLC 2 flies the longer domestic routes with an average of 1100 miles, relatively stable over the past ten years. NLC 1 and LCC 1 increased their average passenger distance by 200 miles over the past ten years. LCC 2 opened new routes and increased its average distance between 2000 and 2005.

B.6   Conclusion

Fuel Price fluctuations directly impact the operating cost of the airlines: the fuel cost per hour increases, becoming a more significant part of the Direct Operating Cost, which increases as well. As seen in this analysis, in order to respond to these changes, airlines have several options: they can modify their fleet, change their ticket price, their route structure, their number of employees and their salaries, and hedge fuel. Most of these changes cannot happen too quickly: decisions associated with fleet replacement are long term decisions, and airlines must weigh the pros and the cons of changing aircraft now instead of later. Ticket price changes need to be minimized otherwise the airline risks a loss of demand.

The airlines' fleet and ticket price changed when fuel price increased. Airlines increased their ticket price, especially for long routes. The correlations with fuel

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price remain relatively low for most of the data over the past decade. Two periods were identified: The first half of the past decade was associated with an adaptation of NLC fares to be able to compete on the changing market, and the second half of the past decade was associated with an increase in ticket price due to fuel price increase. LCC 2, a relatively small and new airline, has a high correlation between fuel price and ticket price. For other airlines, the low correlation observed may be due to the fact that airfares are highly dependent on other parameters such as demand, competition, and financial situation of the airline. Therefore any attempt to link fuel price to ticket price must be carefully made: some sort of equilibrium in market share and other parameters that may have an impact on demand must be reached. Network Legacy Carrier, which faced the growing market share of Low Cost Carrier, and financial difficulties, reduced the number of aircraft they operate. Airlines retired less efficient aircraft. Aircraft utilization and load factor increased in the past few years.

Fuel price is not the only parameter that influences airlines' decisions. Airlines' behavior is also highly dependent on economical growth. The time period studied here includes an increase in fuel price, followed by an economical downturn and a decrease in fuel price. Some trends have been identified, some with good correlation with fuel price, some with very low correlation. The results that show good correlation can be used for studies of air traffic demand forecasts, and fleet forecast, based on fuel price forecast and policy induced fuel price changes. Further study including more parameters is needed to explain the trends that show low correlation with fuel price.

APPENDIX C

AGGREGATION FROM ABM TO SD

The output from Mi is a 204x204 OD matrix. A portion of this matrix is given as an example in Figure 101.

0	0	2	0	0	1	22	4	0	0	0	8	0	0	1	0	0	2
0	0	6	6	0	5	7	5	0	3	0	1	0	1	0	0	2	2
0	0	0	0	0	0	2	1	0	1	0	0	0	0	0	0	3	0
1	0	0	0	1	0	8	0	0	0	0	0	0	0	0	0	2	0
0	0	3	0	0	1	3	0	3	0	3	0	0	0	0	0	3	0
0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	0
2	0	11	0	0	10	0	23	10	16	1	13	15	6	4	2	28	2
1	3	1	0	0	0	3	0	0	0	2	1	0	0	0	0	0	0
0	0	4	0	0	0	1	2	0	0	0	2	0	0	0	0	1	0
0	0	3	0	0	0	20	7	0	0	0	0	2	0	0	0	0	1
0	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0	1	4
4	15	7	0	2	3	58	0	15	2	2	0	3	0	6	2	10	4
0	0	1	0	1	0	16	1	0	9	0	1	0	0	2	0	5	2
0	2	0	1	0	0	11	0	0	0	0	0	2	0	0	0	0	0
5	0	14	0	0	0	40	0	0	5	2	25	1	0	0	0	16	6
0	0	0	0	0	0	2	0	0	2	0	0	0	0	0	0	0	0
1	0	1	0	0	0	32	6	5	2	2	7	8	1	0	0	0	2
0	0	4	0	0	0	3	0	0	0	1	1	1	0	0	0	1	0
11	23	22	13	5	4	97	170	15	8	10	53	10	4	7	9	15	7
0	0	12	0	0	0	8	2	0	5	4	0	0	0	0	0	0	0
3	7	6	0	2	6	10	18	1	0	0	14	0	2	0	0	0	1
0	2	0	0	0	0	6	0	0	1	0	0	0	3	0	0	0	2
0	0	1	0	0	0	34	0	0	0	0	1	0	0	0	0	1	0
0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	1
0	0	1	4	0	2	106	13	2	3	2	7	5	0	3	0	9	2
0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	4	49	2	14	16	211	38	29	29	16	35	12	12	5	4	60	15
5	5	3	0	5	4	83	2	6	2	4	5	2	2	2	0	16	0
0	5	6	3	0	4	45	9	2	8	0	18	0	5	3	0	10	3
0	0	7	0	0	0	5	7	0	0	0	0	0	0	0	2	0	0
2	0	3	0	0	0	41	0	0	0	3	0	0	0	4	1	5	0

Figure 101: Mi output

Using the latitude and longitude data of each MSA, the great circle distance can be determined using the following code.

LatLong = xlsread('MSALatLong.xlsx');

for i=1:204

for j=1:204

GCD(i,j)=deg2sm(distance(LatLong(i,1),LatLong(i,2),LatLong(j,1),LatLong(j,2)));

end

end

csvwrite('GreatCircleDistance.csv',GCD)

Table 34: GAME ALN DG1 initialization data

DG-MMG	initial demand
DG1-LL	4.11006e+006
DG1-LM	6.23184e+006
DG1-LS	5.2118e+006
DG1-LN	6.85605e+006
DG1-MM	1.85109e+006
DG1-MS	4.67987e+006
DG1-MN	2.1653e+006
DG1-SS	938874
DG1-SN	1.67513e+006
DG1-NN	418405

The aggregation of data between the 204x204 OD matrix from $\boldsymbol{Mi}$ to the data by DG and MMG for GAME is then done by going through the cells of the OD matrix and counting trips for each DG and MMG combination using the code listed below (given for DG1 and Large to Large MSA as an example):

```
for i=1:204
for j=1:204
if strcmp(LMSN(i,2),'L') && strcmp(LMSN(j,2),'L') && GCD(i,j)>=100 && GCD(i,j)<200
LLDG1=LLDG1+data(i,j)*GCD(i,j);
end
end
end
```

If the number of passenger is desired instead of the passenger miles traveled, then replace LLDG1=LLDG1+data(i,j)*GCD(i,j) with LLDG1=LLDG1+data(i,j). This code is repeated for each DG and MMG combination.

GAME's initialization data is given in Table 34, through Table 43.

Table 35: GAME ALN DG2 initialization data

DG-MMG	initial demand
DG2-LL	1.42627e+007
DG2-LM	3.49161e+007
DG2-LS	2.0109e+007
DG2-LN	1.54749e+007
DG2-MM	1.29371e+007
DG2-MS	1.70047e+007
DG2-MN	1.11023e+007
DG2-SS	4.51596e+006
DG2-SN	6.9168e+006
DG2-NN	2.08823e+006

Table 36: GAME ALN DG3 initialization data

DG-MMG	initial demand
DG3-LL	1.00573e+007
DG3-LM	2.7009e+007
DG3-LS	1.73963e+007
DG3-LN	2.10796e+007
DG3-MM	1.52175e+007
DG3-MS	1.80486e+007
DG3-MN	1.95471e+007
DG3-SS	6.48207e+006
DG3-SN	1.19417e+007
DG3-NN	4.44876e+006

Table 37: GAME ALN DG4 initialization data

DG-MMG	initial demand
DG4-LL	1.21771e+007
DG4-LM	3.76009e+007
DG4-LS	1.77226e+007
DG4-LN	2.29271e+007
DG4-MM	1.72424e+007
DG4-MS	2.11266e+007
DG4-MN	2.21056e+007
DG4-SS	5.4318e+006
DG4-SN	1.30884e+007
DG4-NN	6.04548e+006

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Table 38: GAME ALN DG5 initialization data

DG-MMG	initial demand
DG5-LL	1.21831e+007
DG5-LM	2.25389e+007
DG5-LS	1.62328e+007
DG5-LN	1.44562e+007
DG5-MM	8.26628e+006
DG5-MS	1.40622e+007
DG5-MN	9.67638e+006
DG5-SS	4.97617e+006
DG5-SN	7.7774e+006
DG5-NN	2.45813e+006

Table 39: GAME GND DG1 initialization data

DG-MMG	initial demand
DG1-LL	7.58662e+007
DG1-LM	1.15509e+008
DG1-LS	1.55229e+008
DG1-LN	1.45774e+008
DG1-MM	5.2526e+007
DG1-MS	1.34328e+008
DG1-MN	1.04527e+008
DG1-SS	5.47742e+007
DG1-SN	9.37119e+007
DG1-NN	5.03142e+007

Table 40: GAME GND DG2 initialization data

DG-MMG	initial demand
DG2-LL	3.34427e+007
DG2-LM	9.0041e+007
DG2-LS	4.7233e+007
DG2-LN	6.47532e+007
DG2-MM	3.03283e+007
DG2-MS	5.77203e+007
DG2-MN	7.09511e+007
DG2-SS	2.23583e+007
DG2-SN	5.82564e+007
DG2-NN	3.26101e+007

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Table 41: GAME GND DG3 initialization data

DG-MMG	initial demand
DG3-LL	1.70678e+006
DG3-LM	8.48003e+006
DG3-LS	5.13661e+006
DG3-LN	1.10268e+007
DG3-MM	5.26852e+006
DG3-MS	8.53143e+006
DG3-MN	1.91301e+007
DG3-SS	3.97688e+006
DG3-SN	1.27655e+007
DG3-NN	1.0827e+007

Table 42: GAME GND DG4 initialization data

DG-MMG	initial demand
DG4-LL	537465
DG4-LM	1.83452e+006
DG4-LS	884976
DG4-LN	2.26599e+006
DG4-MM	900805
DG4-MS	1.24145e+006
DG4-MN	2.78981e+006
DG4-SS	410771
DG4-SN	2.06845e+006
DG4-NN	2.26078e+006

Table 43: GAME GND DG5 initialization data

DG-MMG	initial demand
DG5-LL	243967
DG5-LM	421147
DG5-LS	322133
DG5-LN	323131
DG5-MM	165891
DG5-MS	272965
DG5-MN	246117
DG5-SS	81087.6
DG5-SN	177419
DG5-NN	75101

APPENDIX D

GROUND EMISSIONS

This section gives more information on the experimental approach to derive the main parameters that determine the ground vehicle emissions using existing tools. EPA's tool MOVES (Motor Vehicle Emissions Simulator) is used to estimate national inventories and fuel consumption projections at the county level. It allows for different scenarios and generates results on various species. MOVES consists of many different components including various databases and analysis modules. Its execution requires many assumptions for a large number of variables which include vehicle types, fleet age distribution, fuel types, meteorological data, road types, speed distribution, day and month vehicle mile traveled (VMT) fractions, etc. Screening tests were performed to identify the most essential variables. Three variables were found to be the most affecting factors for CO_2 emission and thus fuel consumption: vehicle speed, vehicle age and outside temperature. The objective was to obtain a surrogate model of MOVES using a DOE on the three variables. Vehicle speeds of 1.25 mph, 5 mph, 10 mph, 20 mph, 45mph and 75 mph were used. Temperatures ranging from 16 to 104 with 8 degree increment, and vehicle ages of 0 to 30 years with 1 year increment were used. Full factorial is desired which makes 2232 data points. Results are shown in Figure 102.

The surrogate model for CO_2 emissions is based on the following equation:

$$\Phi_{CO_2}(v, t, a) = V(v).T(t).A(a) \tag{27}$$

where v, t and a are the vehicle speed, the outside temperature and the vehicle age respectively.
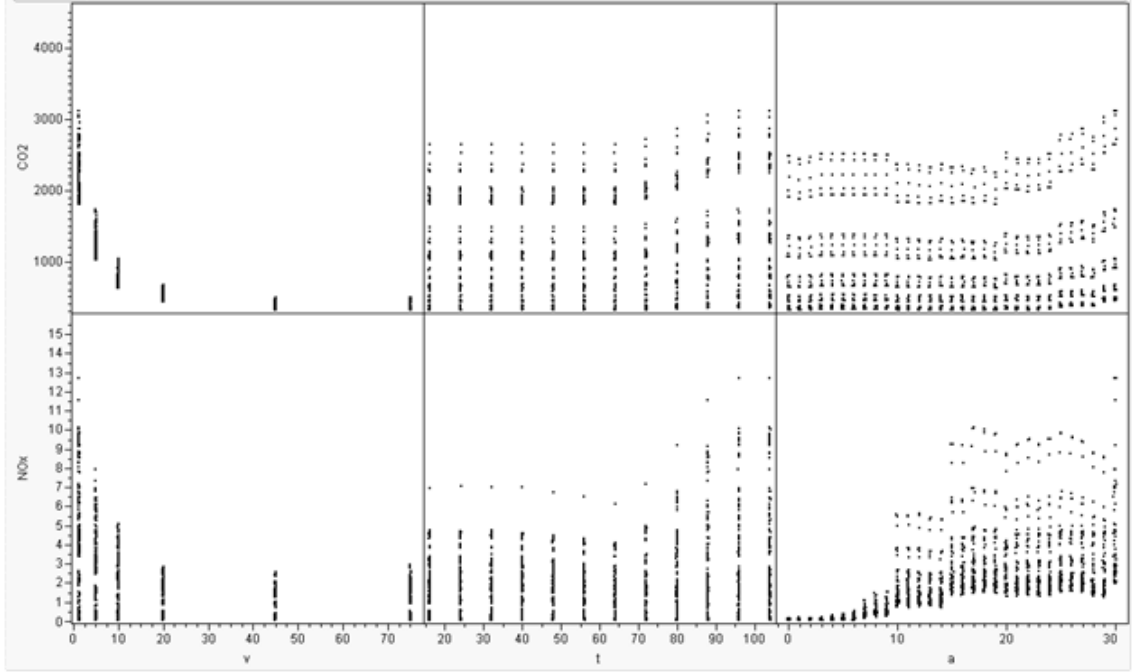
Figure 102: MOVES simulation results

The equation for speed has the following form:

$$V(v) = \beta_0 + \beta_1.v + \beta_2.v^2 + \beta_3.v^{-\beta_4} \tag{28}$$

where β_i are the regression parameters.

The equations for temperatures and age are as follow:

$$T(t) = \Theta_0 + (\Theta_1 - \Theta_0)(1 + \Theta_2 e^{-\Theta_3(t-\Theta_4)})^{\frac{-1}{\Theta_5}} \tag{29}$$

$$A(a) = \alpha_0 + (\alpha_1 - \alpha_0)(1 + \alpha_2 e^{-\alpha_3(a-\alpha_4)})^{\frac{-1}{\alpha_5}} \tag{30}$$

The best regression parameters were identified and gave an R-squared value of 0.9935. The emissions are then quantified using the following equation:

$$E = VMT \int \int \int \Phi(v, t, a).\rho(v, t, a).dv.dt.da \tag{31}$$

where ρ is the VMT density distribution function. MOVES uses speed distribution for each road type. In this research focusing on long distance travel, the rural and

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urban restricted access roads are most used and their speed distributions are given in Figure 103. Two speed bins, which vary based on congestion and driving speed, are used.
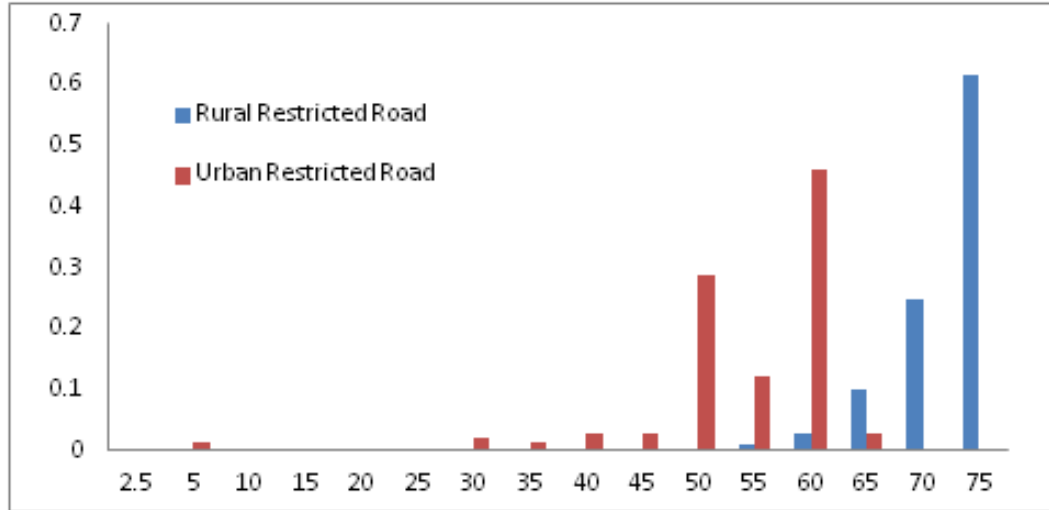
Figure 103: MOVES speed distribution

MOVES includes a relatively detailed database of hourly average temperature and humidity for each county and each month. A national temperature distribution can be obtained. Weighted values were computed to account for the fact that most VMT occurs at a given time of the day and certain regions of the country. Monthly variations were taken into account but are negligible. As can be seen in Figure 104, the distribution resembles a triangular distribution, which is the approximation used in the ground module.

For vehicle age distribution, two sets of data were used. The default database in MOVES was compared to some data from www.georgiaair.org, sample MOVES Input Files. Both show similar trends which can be approximated by a trapezoidal distribution as can be observed in Figure 105.

Figure 104: MOVES temperature distribution
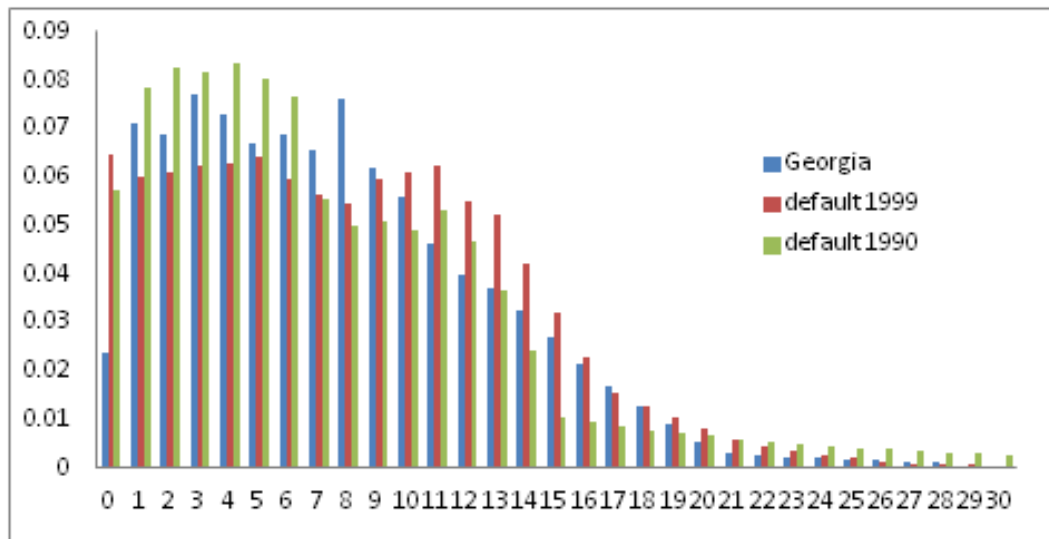
Figure 105: MOVES age distribution

APPENDIX E

POLICY AND TECHNOLOGY SCENARIO
EXPLORATION WITH EGAME

The eGAME GUI is shown in Figure 106. A set of input is defined on the upper left corner. They include a number of variables that may be used to explore a wide variety of scenarios:

- a set of exogenous variables, such as GDP and fuel price

- policy variables with the date of introduction and value of a tax

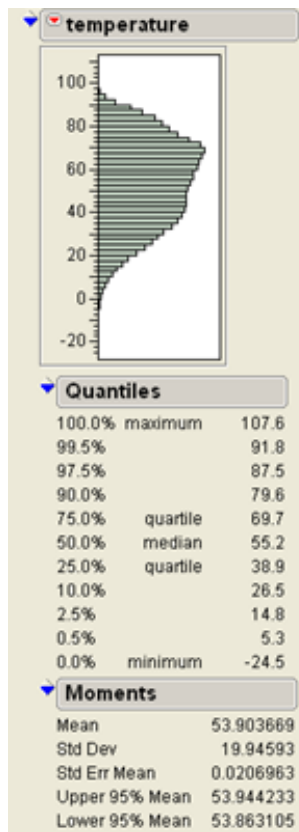- variables related to the air transportation system, such as pass through, capacity, fleet replacement scenario

- ground transportation variables, including the expected MPG improvements, the price premium of EV, the average driving speed

- variables related to the new mode (P2P) such as aircraft size and range.

Simulation can be run from the buttons at the bottom left corner. It is possible to run the demand model and the fleet model independently, or run them successively with iterations to obtain the final demand and emissions with potential rebound effects. Results for demand and emissions of each mode of transportation are observed on the right-hand side of the eGAME GUI. Further analysis may be performed using the time series of the results from the demand and fleet models which are listed in a separate tab. From this data, the radiative forcing module is used to compute the impact of different emitted species and the total radiative forcing is obtained. It is then used to compute policies based on radiative forcing, using the ratio of

total radiative to the radiative forcing due to CO_2 only. This ratio can be used to appropriately scale the CO_2 tax, which is computed based on the fuel CO_2 content and the social cost of carbon. These policies may then be used to adjust the inputs and run the model again in order to quantify the potential improvements from the implemented policies and technologies. The user may compare different scenarios by keeping track of the desired data at each run and use the decision making tool with the scenarios results to plot each scenarios against the main metrics of interest and rank them using the methodology described in section 6.5.
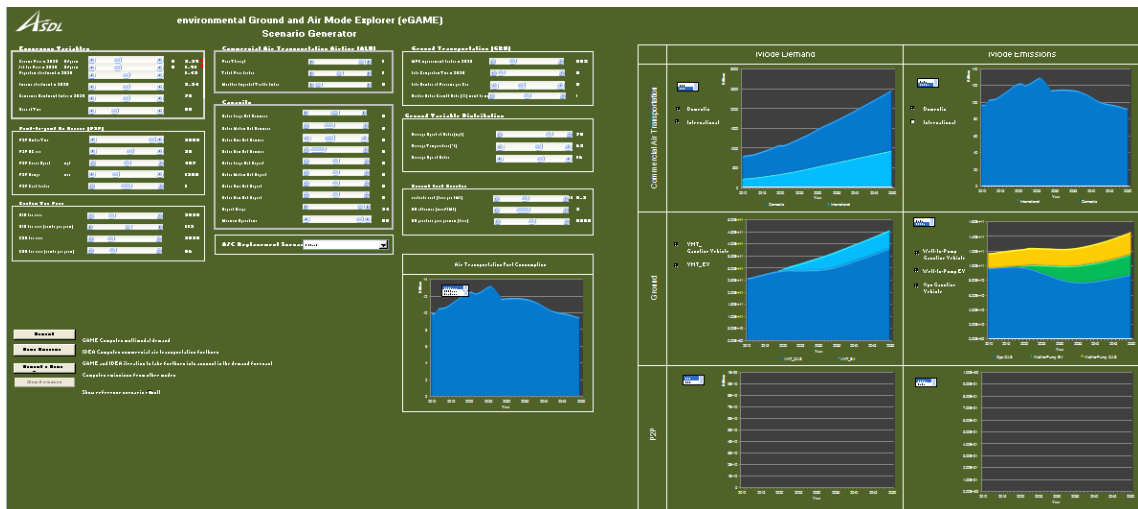

Figure 106: eGAME GUI

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