MODELING SUSTAINABILITY IN COMPLEX URBAN TRANSPORTATION SYSTEMS

A Thesis
Presented to
The Academic Faculty

by

Kyle K. Azevedo

In Partial Fulfillment
of the Requirements for the Degree
Master of Science in Mechanical Engineering in the
George W. Woodruff School of Mechanical Engineering

Georgia Institute of Technology

December 2010

MODELING SUSTAINABILITY IN COMPLEX URBAN TRANSPORTATION SYSTEMS

Approved by:

Dr. Bert Bras, Advisor
School of Mechanical Engineering
Georgia Institute of Technology

Dr. Chris Paredis
School of Mechanical Engineering
Georgia Institute of Technology

Dr. Valerie Thomas
School of Industrial and Systems Engineering
Georgia Institute of Technology

Date Approved: August 25th, 2010

To the students of the Georgia Institute of Technology, and my coworkers in the Sustainable Design and Manufacturing Program.

ACKNOWLEDGEMENTS

I wish to thank Dr. Bert Bras for the opportunity, knowledge, and valuable guidance he has given me over the past several years. My time at Georgia Tech has been a learning experience in every sense of the word. Also, I owe thanks to Tina Guldberg for her own teachings, and for being the glue that keeps all of the SDM parts held together. Thanks to my thesis committee, Dr. Chris Paredis and Dr. Valerie Thomas, for their guidance, support, and academic insight. I owe thanks to the Georgia Institute of Technology and the Woodruff School of Mechanical Engineering for the opportunities they have afforded me. I am grateful to all those who helped me perform my research in any way, including No Magic Inc., InterCAX Inc., all of my professors, my contacts at the City of Atlanta and Atlanta Regional Commission, and Ford Motor Company for their financial support. Thanks to Dave Berdish for his mentorship and real-world teachings.

Thanks to my coworkers in SDM for constantly being there, whether it be to discuss ideas, provide assistance on a tough problem, or simply just to share a laugh. Special thanks go to the viaCycle team: Koji Intlekofer, Mike Culler, Sid Doshi, Yuriy Romaniw, and Zach Zacharia. They made day-to-day research a team effort, and above all, made it fun. Thanks also to my friends elsewhere, for making hundreds or even thousands of miles a small hurdle.

I owe thanks to my family, for everything. My mother, father, brothers and their families, and grandmother have given so much love and support that I have no doubt I would not be where I am without them. I can only hope to repay it in full whenever and wherever I am able.

Lastly, thanks to Katie. Her love has carried me through the highs and lows of my time here in Atlanta, and has turned many of the latter into the former. She is truly one of a kind.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

C_{fuel}	Fuel carbon content by mass percentage
$CO2_{fuel}$	Fuel CO_2 output
$CO2_{out}$	Pump-to-wheel CO_2 output
$CO2_{rate}$	CO_2 output per unit of electricity produced
$CO2_{WTPE}$	Well-to-pump CO_2 production per unit energy
E_{WTP}	Well-to-pump energy consumption per unit volume
η_{WTP}	Well-to-pump energy efficiency
E_{PTW}	Pump-to-wheel energy consumption
E_{WTW}	Well-to-wheel energy consumption
HHV	Higher heating value
LHV	Lower heating value
m	Mass
Oc_{avg}	Average occupancy
PKT	Passenger kilometers traveled
VMT	Vehicle miles traveled
VKT	Vehicle kilometers traveled
VDT	Vehicle distance traveled
BRT	Bus rapid-transit
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
ISO	International Organization for Standardization
LCA	Life cycle analysis
LCI	Life cycle inventory

MBSE	Model-based systems engineering
OMG SysML^{TM}	Object Management Group Systems Modeling Language
UML	Unified Modeling Language
WTP	Well to pump
PTW	Pump to wheel

SUMMARY

This thesis proposes a framework to design and analyze sustainability within complex urban transportation systems. Urban transit systems have large variability in temporal and spatial resolution, and are common in lifecycle analyses and sustainability studies. Unlike analyses with smaller scope or broader resolution, these systems are composed of numerous interacting layers, each intricate enough to be a complete system on its own. In addition, detailed interaction with the system environment is often not accounted for in lifecycle studies, despite its strong potential effects on the problem domain. To manage such complexity, this thesis suggests a methodology that focuses on integrating existing modeling constructs in a transparent manner, and capturing structural and functional relationships for efficient model reuse. The Systems Modeling Language (OMG SysML™) is used to formally implement the modeling framework. To demonstrate the method, it is applied to a large scale multi-modal transportation network. Analysis of key network parameters such as emissions output, well-to-wheel energy use, and system capacity are presented in a case study of the Atlanta, Georgia metropolitan area.

Results of the case study highlight several areas that differ from more traditional lifecycle analysis research. External influences such as regional electricity generation are found to have extremely large effects on environmental impact of a regional mobility system. The model is used to evaluate various future scenarios and finds that existing policy measures for curbing energy use and emissions are insufficient for reducing impact in a growing urban region.

CHAPTER 1

INTRODUCTION

1.1. Motivation and Problem Definition

As cities grow and the global demand for modern amenities increases, the design of sustainable urban systems has become an increasingly important topic. Currently, over half of the world's population resides in urban areas, with that proportion expected to increase to 70% by 2050 (United Nations 2005). Within these population centers, accessibility to goods, services, and places of employment is crucial for economic growth and quality of life.

In much of the developed world and the United States in particular, infrastructure has grown around the private automobile and related forms of travel. Roadways handle 80% of global motorized traffic volume, with automobiles contributing over 50%. As population continues to centralize, road capacity cannot cope with subsequent demand. In the U.S. alone, 4.2 billion hours and 2.9 billion gallons of fuel were wasted in 2007 because of congestion in urban regions, almost double the totals from a decade earlier (Schrank and Lomax 2009). Figure 1 shows the growth in both of these indicators over a 20 year period.

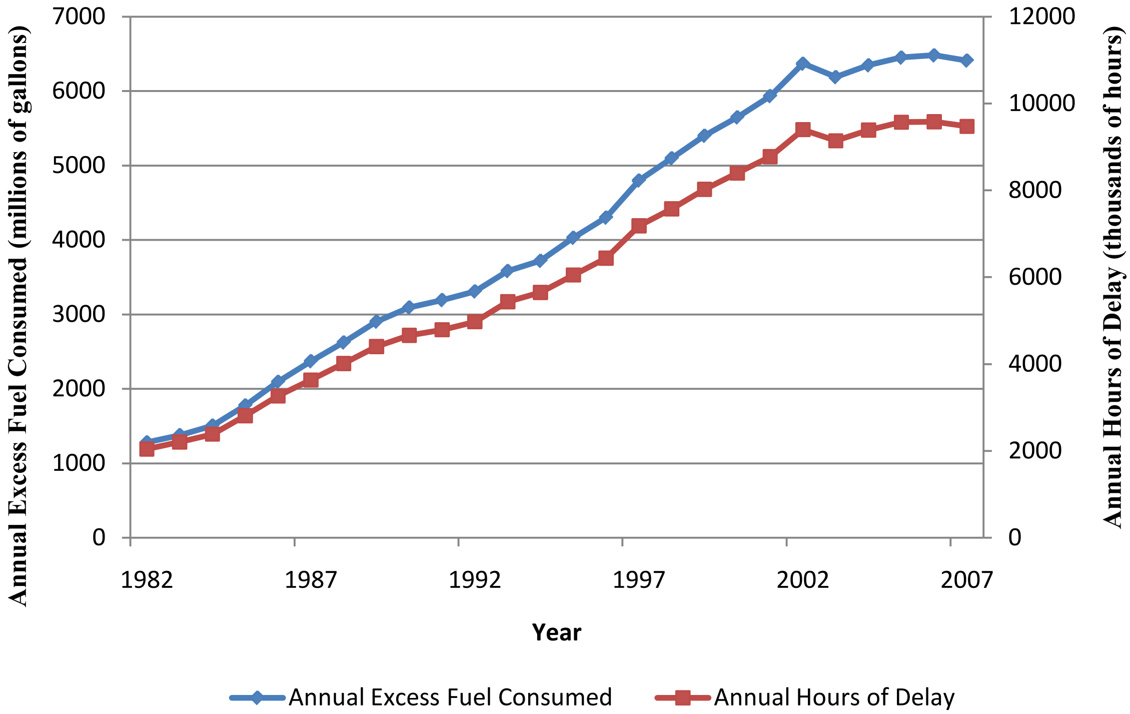

Figure 1: Average congestion indicators in United States urban areas (Schrank and Lomax 2009)

Even disregarding capacity problems, motor vehicle use presents serious issues for energy consumption and the environment. Transportation uses 39% of all energy consumed in the United States, and is the largest and fastest growing consumption sector. It is responsible for 32% of all U.S. greenhouse gas emissions, 97% of which are from the use of petroleum. These contributions are expected to increase another 20% and 24% respectively by 2035 (Schafer 1998). Amid growing evidence of global warming and eventual petroleum shortages, a departure is needed from the current state of affairs.

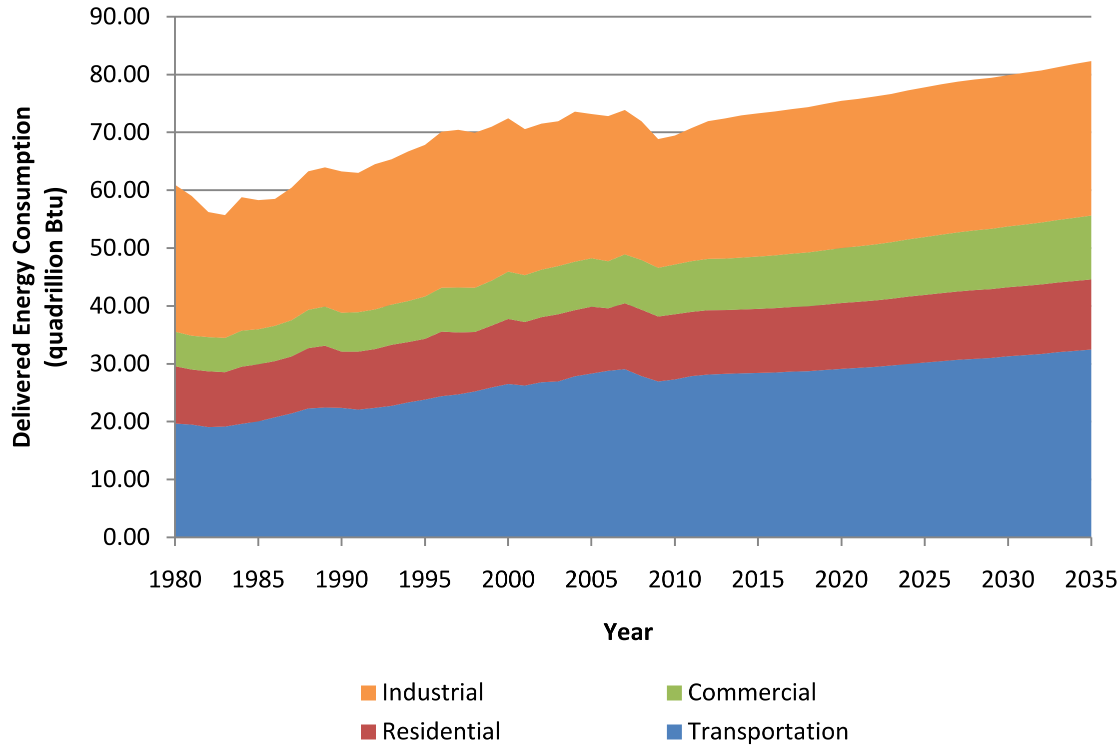

Figure 2: Delivered U.S. energy consumption by sector (U.S. Energy Information Administration 2009)

With so much urban growth and a clear body of evidence suggesting transportation is a serious environmental problem, intracity transit has been increasingly pushed into the spotlight. A wide body of literature exists on the topic of urban design, urban transportation and the sustainability of each. Approaches differ widely, and no wonder; the topic spans technical, social, economic, and environmental landscapes, all with distinct goals. Many authors emphasize the concept of "new mobility" (Goldman and Gorham 2006; Luca Bertolini and Dijst 2003; Zielinksi 2006), which utilizes a combination of location-based planning, virtualization, and integrated transport to solve the mobility dilemma.

Since physical movement between locations is likely to remain important for the foreseeable future, the latter of these three approaches provides an interesting look at how to increase sustainability within short time scales. Linking transportation modes effectively within an integrated system has the potential to maximize multiple other investments, including transportation infrastructure, public transit systems, and adoption of new vehicle technologies such as hybrid or battery electric powertrains.

However, difficulties arise when attempting to evaluate the sustainability of such integrated solutions. What metrics should be used as the overall design goals? Where should system boundaries be drawn? Traditional problems in lifecycle analysis become compounded when dealing with complex systems-of-systems, composed of numerous interacting layers that have wide ranges of temporal and spatial resolution. Taking a holistic view of these systems and understanding the functional relationships between them allows for solutions not apparent when examining a single system or component.

1.2. Defining "Sustainable Urban Mobility"

Although agreed upon as an admirable goal, sustainability is difficult to define, and current literature demonstrates a range of different interpretations and research angles. The 1987 Brundtland Commission report (Brundtland 1987) is widely credited with formally defining the overall concept of 'sustainable development', as 'development that meets the needs of the present without compromising the ability of future generations to meet their own needs'. Generally, it is accepted that these 'needs' are not merely those of survival, but stem from economic, social, and environmental goals (Goldman and Gorham 2006). These three pillars of sustainability are more colloquially known as the "triple bottom line". From an environmental perspective, preserving the ability to meet these needs depends on using resources so that they are renewable or replaceable as time goes on.

To apply this to the field of mobility, Black (Black 1996) suggests a simple restructuring of the Brundtland statement, defining 'sustainable transportation' as meeting current transport and mobility requirements without sacrificing future ability to do the same. The difficulty in assessing sustainability now revolves around which resources need to be preserved: the choices include energy, land use, and time, amongst others. Optimizing one may have adverse effects on the rest. Choice of evaluation metrics is another source of variation. Some advocate quantifiable measures of performance such as fuel consumption or total vehicle miles traveled (VMT) (Black 1996; Small and Van Dender 2005), while others use broader concepts such as safety, congestion, and access (Richardson 2005). In an effort to reduce sources of uncertainty, this thesis focuses primarily on the former category of concrete, measurable metrics. Energy consumption, VMT, and various types of emissions are used as primary indicators of sustainability within a given system.

Further, a distinction should be made between transport and mobility. While transport involves the movement of any object, mobility deals specifically with people. The freight industry is influenced by a unique set of factors when compared to personal transportation. Though there is a great deal of overlap, the differences are large enough that it is useful to treat them as separate entities. The primary focus of this thesis is on mobility, but conclusions that can be made about transportation as a whole are discussed in Chapter 6.

Finally, the definition of a mobility 'network' needs to be refined. Bertolini and Djist (Luca Bertolini and Dijst 2003) discuss mobility 'environments' that are both temporal and spatial entities, with their function defined by not only their location, but how their purpose and demographics change throughout the day, month, or year. These environments form hubs that provide access to one or more forms of transportation. A comprehensive 'mobility network' includes these hubs and the flow of both people and information between them.

Combining these concepts results in a departure from traditional urban transportation. Existing approaches to transit within cities has been ad-hoc at the network level: roads, bus systems, rail systems, etc, are added on an as-needed basis to wherever there is maximum demand. Although each mode of transportation may be implemented in a way that optimizes its own routing and service level, multi-modal interaction has not been examined closely. More recently, urban and regional planning commissions have begun to examine the effects of this symbiosis, but have only scratched the surface in terms of potential system connectivity.

The concept of connectivity is central to urban mobility design. The established goal of transportation is to connect people from their current location to wherever they need to be, preferably as quickly as possible. Research has shown that proximity of location and trip time are paramount when providing a mobility service (Cervero and Kockelman 1997). Therefore, mobility goals should be centered on reducing these variables in the most economical way possible. In many cases, this means maximizing the impact of pre-existing transportation resources, through IT solutions, new routing possibilities, policy changes, and hub network design. In order to evaluate such interconnected scenarios, new modeling and simulation approaches are needed to manage consistency, complexity, and reduce modeling effort across the entire system domain.

1.3. Research Questions and Hypotheses

The evidence above suggests that despite recent focus on the integrated mobility network approach, holistic systems modeling seems to be a somewhat neglected aspect of sustainable transportation. Current work in lifecycle analysis and sustainability evaluation tends to sacrifice system breadth in return for increased depth. Energy inputs and outputs of a particular cycle are exhaustively catalogued, but studies often fail to note the effect such energy consumption has in a larger context, or even what research question is being answered by the evaluation (Delucchi 2004; Graham and Marvin 1996). The central goal of this thesis is to develop tools that allow for integration of multiple model scales without a loss of resolution or clarity. This motivation leads to the central research question:

How can high level environmental impacts of a transportation system be examined while maintaining high spatial and component granularity?

Improving the design of transportation systems for sustainability requires considering each interacting subsystem in detail, but managing the resulting complexity in such a way that still allows for overarching system metrics and optimization criteria. In order to accomplish this, one must carefully consider the chosen methodology, tools to implement the methodology, and finally whether both tools and process can be expanded or improved to improve the desired multi-scale accuracy and performance.

Each of these three elements leads to necessary sub-questions that must be answered in the course of proposing a hypothesis for the central problem. The first element, methodology, involves consideration of how to organize and represent the various disciplines, stakeholders, objectives, and information within an urban transportation system. It is clear that an ad hoc method is not sufficient for such tasks. This leads to the first sub-question:

What methodology should be used to model a transportation system in order to effectively evaluate it at multiple scales?

A formalization of mobility network parameters, interactions, and subsequent outcomes could improve anticipation of the effects of infrastructure changes before they occur. Planning of new networks in developing countries could also be improved. With a formal 'template' for modeling an integrated mobility network, the task of evaluation and optimization requires less setup and less manual manipulation. Concepts applied to mobility are largely transferrable to sustainable systems in general. Therefore, this thesis proposes a hypothesis in answer to sub-question 1:

Model-based systems engineering (MBSE) can increase evaluation consistency, reduce modeling effort, and integrate analysis tools when evaluating and designing sustainable mobility networks.

In order to prove this, a specification and associated tools must be used to carry out the chosen methodology. The Systems Modeling Language (SysML) is one possibility for implementing this formalization, when combined with existing lifecycle, resource, and emissions models. It will be used here to demonstrate the modeling and analysis techniques necessary to provide an integrated multi-scale view of sustainable networks.

Once a flexible modeling framework is in place, it may used to examine various mobility scenarios that are of interest to city planners, sustainability experts, and other stakeholders. By lowering modeling effort to the point where many result sets may be gained easily by various parties, possibilities for system-of-systems optimization are created. In order to do this, the domain specific model must be tied to various executable analysis tools that simulate system conditions and make computations. The next research question stems from this goal:

How can a created modeling framework be used to integrate multiple executable models, in order to evaluate complex system designs and scenarios?

The established engineering approach to creating sustainable systems is fundamentally reactive. Systems are designed, and then evaluated for environmental and social impact using certain chosen metrics. However, the use of MBSE and SysML for mobility networks opens up new possibilities for scenario analysis and optimization. With proper integration of input and output models, major changes can be evaluated well before implementation, transforming the design process into a proactive procedure. In this case, SysML can act as a central point of consistency between different types of engineering analysis models, defining system structure and constraints which are then translated into the necessary analysis domains. Therefore, it is proposed that:

Through the use of model transformations and input/output mappings, SysML and MBSE can integrate executable models and provide traceable consistency within the framework.

1.4. Research Strategy and Organization

The questions outlined in section 1.3 are first investigated with a review of relevant literature in urban mobility and related modeling and simulation. The review begins with work on urban mobility and transit, discusses multi-modal integration, vehicle impact assessment, and integration of sustainability efforts in urban planning. Complex systems modeling is addressed, particularly with regard to environmental impact. Problems with transportation lifecycle analysis and other assessments of sustainability are highlighted. Finally, links are drawn between these issues and the chosen research questions, in order to provide context for the following methods, results, and conclusions.

Chapter 3 discusses the chosen methodology for answering the proposed research questions. Section 3.1 demonstrates the benefits of using MBSE for managing complexity, and section 3.2 discusses the advantages of model capture and reuse for complex system life-cycle inventories. SysML is introduced as a model-based tool in section 3.3, and section 3.4 covers implementing MBSE within SysML. Once model information is captured, further functionality is obtained by making the SysML model executable, then linking it with other analysis models, as shown in sections 3.5 and 3.6.

In order to implement the methodology described in Chapter 3, a specific approach is needed. Chapter 4 details the series of steps taken to create a formal systems model and use it to evaluate sustainability. First, a mobility system model and associated hierarchy is defined within SysML, including reusable part and model libraries and captured system parametrics. Then, this model is linked to numerous external data sources and analysis tools. Finally, a transformation is implemented that maps SysML model elements to an analysis language in order to run simulations and calculations on various system scenarios.

Chapter 5 evaluates the environmental impact of several urban mobility implementations using the developed framework. Case studies of several cities are presented, including Atlanta and Washington DC. Several scenarios for each city are discussed, along with implications for urban planning and mode split decisions. Due to the ease of system evaluation using the MBSE framework, it is possible to investigate alternative objectives with a minimum of additional effort.

Finally, Chapter 6 discusses the case study results and draws conclusions about their implication for transit policy as well as the adopted modeling methodology. It is found that using SysML does help to manage model complexity, although analysis is still heavily dependent on the quality and quantity of large amounts of input data. For the Atlanta case study, results suggest that current transportation policy will be ineffective for curbing growth in energy use and emissions output. Several factors are presented as key drivers of this growth, including electricity generation methods, vehicle occupancy, and trip length. Although Atlanta is extreme in several of these drivers, the results may imply a similar outcome for other U.S. cities. Future work is suggested to improve the model and apply it to a larger domain.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1. Urban Mobility and Transit Networks

While discussing urban environments, Bertolini notes that "the ability to provide opportunities for human interaction is an - if not the - essential reason for cities to exist" (Luca Bertolini and Dijst 2003). These opportunities may be survival-based, structured around better access to food, goods, or safety in numbers, or they may be to serve higher level needs, such as companionship or work. The central purpose of any area with high population density is to allow better access to places where these needs can be met. Upon examining this premise, it becomes clear that the most attractive cities are ones that minimize the costs associated with such interaction; thus placing a premium on the ability to get from one interaction to the next. Normally, people consider moving from interaction to interaction in spatial terms, placing emphasis on mobility between locations. Graham and Marvin demonstrate that this is embodied in the development of many historical urban areas, which grew to be dense in order to minimize distance constraints (Graham and Marvin 1996).

However, mobility from one interaction to the next can also happen on a temporal scale. Many locations transfer their purpose or interaction potential over the course of the day, for example, a street that is busy with workers during the day may also house restaurants and bars that attract a different demographic at night. In fact, with the advent of new communications technologies, mobility is even less tied to specific locations, as cell phones, videoconferencing, and the internet increase our access to interaction from almost anywhere in the world. Because of this abstraction from movement through space, “mobility environments” are defined as a combination of “accessibility and proximity features” (Luca Bertolini and Dijst 2003).

In recent decades, the focus has shifted from minimizing distance constraints to minimizing time constraints. Litman and Laube find that the rapid motorization of transit, increasing volume of roadways, and increased average speed of vehicles has led to less of a focus on distance due to its lessening impact on the overall cost of mobility (L. Bertolini et al. 2005; Litman and Felix Laube 2002).

Addressing mobility constraints along one particular dimension over another is made more complicated by the complex feedback relationship between mobility, transportation, and temporal and spatial dynamics. Priemus et al. provide an introduction to many of the issues associated with interactions. They point out that as access to mobility within an area increases, so does the surrounding land value, changing development patterns. Resulting effects are multiple-order and influence population behavior, density, and subsequent usage of the transportation system. The authors argue that much closer cooperation is necessary between policy-making entities that govern transit and land-use development, in order to increase overall accessibility and align development with policy goals (Priemus et al. 2001).

As urban areas swell in size, motorized transit can no longer overcome distance constraints with such ease. The annual Urban Mobility Report by Schrank and Lomax provides clear evidence of growing congestion effects in the U.S. (Schrank and Lomax 2009). Tracking road-based congestion indicators in the U.S. for the better part of a decade, the report shows rising commute times, larger VMT, lower roadway speeds, and longer peak periods for travel. Though international cities have arguably managed growth in mobility demand more effectively than many locations in the United States, there are countless publications attesting to the universality of the problem (Black 1996; Kenworthy and Townsend 2002; Litman and Felix Laube 2002).

2.2. Multimodal Integration

To deal with demand for rapid location-based mobility, one established response is to provide such mobility in alternate forms. Improving vehicle efficiency is certainly a valuable resource for increasing environmental impact (Turton 2006), but does not address the congestion problems that affect overall sustainability. To combat the environmental, social, and economic aspects of congestion, strategies must be explored to reduce automobile dependence, or more generally, dependence on a single mode of transit. The World Business Council for Sustainable Development recommends a two-pronged approach, by increasing motorized transit options, and where possible, decreasing demand for motorized transit entirely (World Business Council for Sustainable Development 2001).

In order to effectively increase transit options, and just as importantly, usage of those options, alternative modes of transit must be integrated effectively with both each other and the existing transportation infrastructure. The European Commission applies the term "intermodality" to describe such integration: "Intermodality is characteristic of a transport system that allows at least two different modes to be used in an integrated manner in a `door-to-door' transport chain. In addition, it is a quality indicator of the level of integration between different transport modes. In that respect more intermodality means more integration and complementarity [sic] between modes, which provides scope for a more efficient use of transport systems" (European Commission 1997).

Research on multimodal integration with regard to logistics is extensive, but definitive studies discussing passenger transport are less common. Bailey et al. highlight a significant negative correlation between transit accessibility and automobile travel, regardless of actual transit usage numbers in a given area (Bailey et al. 2008). Other studies establish a similar correlation between urban density and mixed transit use (Kenworthy and F Laube 2001). The pair of findings makes sense given that in a high density city, more of the population will have good access to transit given a fixed public transit system or number of facilities. Janic points out that data concerning the impact of multimodal integration legislation in the EU is limited, despite numerous policy changes designed to encourage linked trips and increase ridership on transit modes other than the private automobile (Janic 2001).

Litman and Laube suggest that reliance on motorized travel in general over a certain threshold produces a negative economic effect, as transport costs begin to outweigh the benefits. Figure 3 demonstrates this lack of correlation between higher vehicle travel and overall wealth.

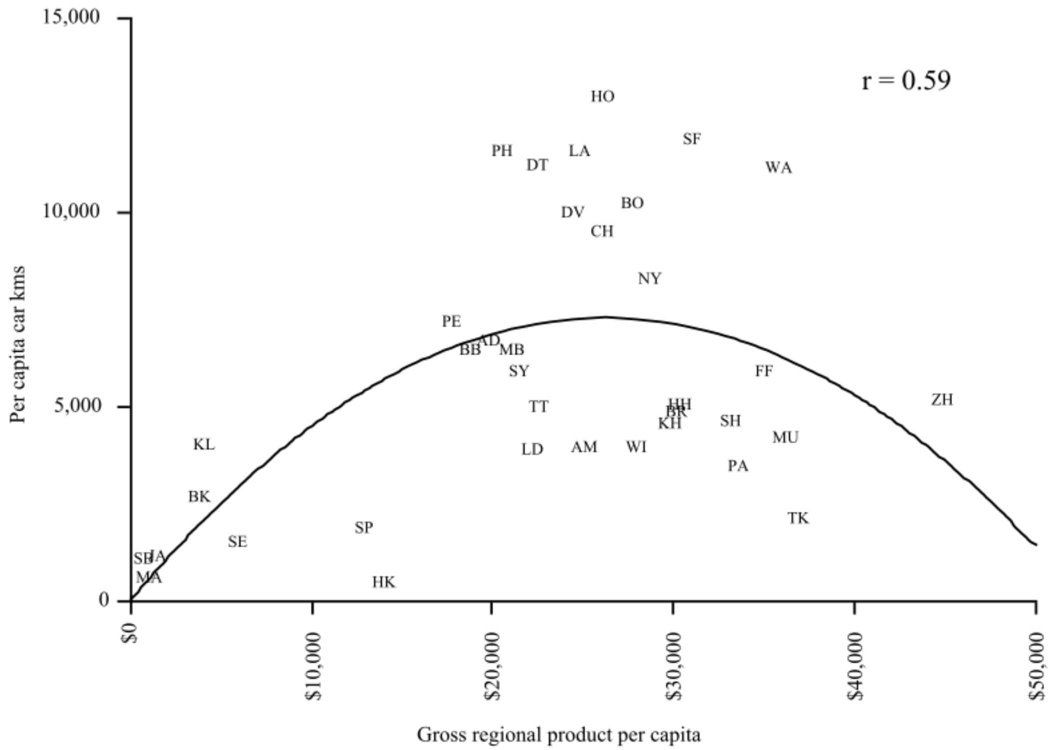

Figure 3: Vehicle-Kms versus gross regional product in 37 cities, 1990 (Litman and Felix Laube 2002)

However, no matter the overall level of transport use, the authors point out that total transportation costs tend to decline as transit use becomes increasingly multimodal. This is demonstrated in Figure 4. Additionally, they find that since automobile expenditures are capital intensive and often imported, in most cases they provide less regional economic benefit than public transit expenditures.

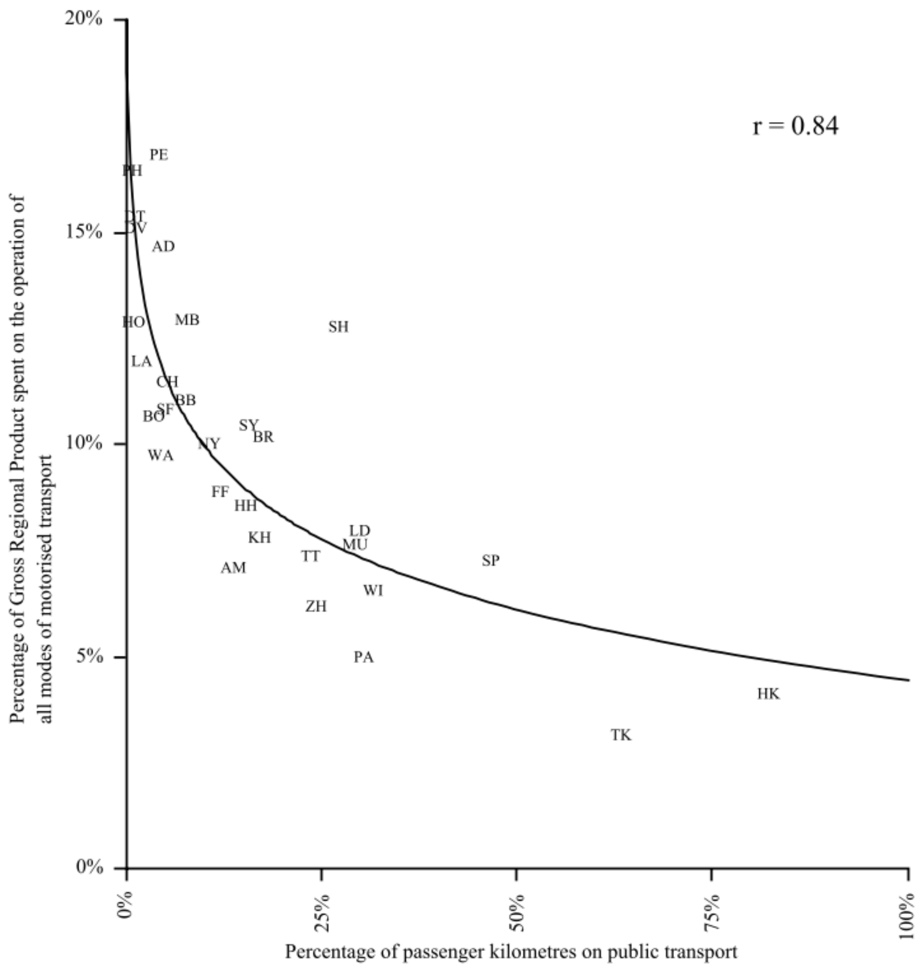

Figure 4: Transport expenditures versus transit use (Litman and Felix Laube 2002)

The Millennium Cities Database is a collection of data from over 100 cities, compiled by the International Association of Public Transport (UITP). The database compiles 69 indicators of population, growth, transit use, transportation efficiency, and number of vehicles. Evidence from the Millennium Cities Database supports this claim, but also suggests that it may not be a causal relationship. Population density likely also plays a large role, and data taken from numerous cities shows that as density increases, transit mode share increases and overall cost of transport drops (Vivier and Mezghani 2001).

Table 1: Density, modal choice, and cost of urban transport in selected cities (Vivier and Mezghani 2001)

Cities	Density (inhab/ha)	Modal split (walking +cycling +PT)	Cost of urban transport (% GDP)
Houston	9	4.5 %	14.0 %
New York	18	25 %	9.4 %
Paris	48	56 %	6.8 %
Munich	56	60 %	5.8 %
Singapore	94	47 %	4.7 %
Hong Kong	320	82 %	5.0 %

Of course, overall data on the subject of multimodality is not always conclusive, and some authors disagree that the expenditure necessary to achieve a multimodal system is worth it. Stopher examines the effects of congestion policy using recent publications and argues that congestion in U.S. cities is not likely to decrease no matter what policy measures are taken. He proposes that policy would be better served focusing on potential advantages of congestion, and finds that even doubling current transit ridership levels has a minimal impact on travel demand and traffic.

2.3. Transportation Life Cycle Analysis

Now that the need for integrated systems has been established, tools are necessary to evaluate their environmental impact. Life cycle analysis, alternatively referred to as life cycle assessment (both abbreviated LCA), "stands as the pre-eminent tool for estimating environmental effects caused by products and processes from 'cradle to grave' or 'cradle to cradle'" (Reap et al. 2008).

A product, defined by the International Organization for Standardization as "any goods or service", can be catalogued from the perspective of raw material production, manufacturing, distribution, and disposal, as well as transportation between each of these activities (International Organization for Standardization 2006). The life cycle assessment itself is divided by the ISO into four main phases: goal and scope definition, inventory analysis, impact assessment, and interpretation.

Phases 1-3 must occur linearly; i.e. the goal and scope of the LCA must be defined before conducting an inventory analysis, which must be completed before assessing impact. However, each of these three phases is subject to their own interpretation, including overall analysis, sensitivity analysis, and other metrics. The results of each phase can have large effects on the execution of the remaining phases, and may dictate revisions to an earlier phase if necessary.

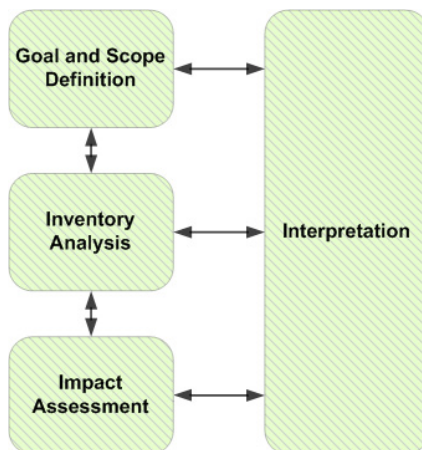

Figure 5: Illustration of LCA phases in ISO 14040 series standards.

One of the central problems with any sustainability analysis involves boundary selection. When performing a study, limitations on time and resources dictate that choices must be made as to the components, systems, and domains included. This in itself is an influential assumption, with potentially large effects on both results and the confidence of the decision maker that uses them (Delucchi 2004; Reap et al. 2008). The final impact is difficult to quantify, due to the fact that anything outside the modeling boundary is inherently precluded from detailed examination. To make matters worse, since certain boundary assumptions occur during definition of the problem itself, they may not be immediately apparent when examining a chosen methodology.

Also, current lifecycle and sustainability analyses often differ in the metrics they use to value one process over another. Decisions on whether to account for different energy qualities, assignment of weights for equivalent greenhouse gas emissions, and even the definition of sustainability itself give rise to non-quantitative uncertainty (Greene and Wegener 1997; Lee et al. 1995; Pezzey and Toman 2002). Choice of indicators and the importance they are given upon evaluation can have major effects on results, but this is often not addressed.

Other efforts to compare life cycle costs of transportation systems include Fels, who examines the energy consumption of various modes of transport based on use-phase and manufacturing costs of both the vehicle and its required guideway. The work contrasts each transit mode using direct comparison per passenger mile, but does not include factors related to travel demand, real-world use cases, or interlinking systems (Fels 1975). The authors conclude that a vehicle's use phase is by far the most dominant factor in lifecycle energy use. Their findings suggest a general trend that manufacture of infrastructure to support a given vehicle type contributes an order of magnitude less energy consumption than vehicle manufacture, and vehicle manufacture contributes an order of magnitude less than vehicle use over the vehicle's lifetime.

A notable effort in life-cycle analysis as it relates to transportation is the Argonne National Laboratory Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) Model. GREET is composed of two models, the GREET 1 Series, which considers vehicle fuel life cycles from well to wheels, and the GREET 2

Series, which considers the life cycle of vehicles from manufacturing to disposal and material recovery (M. Q Wang 2001).

The fuel-cycle portion of the GREET model covers several stages of activities, shown in Figure 6. The well-to-pump stages are also known as the *upstream* portion of the cycle, while the pump-to-wheel stages comprise the *downstream* portion.

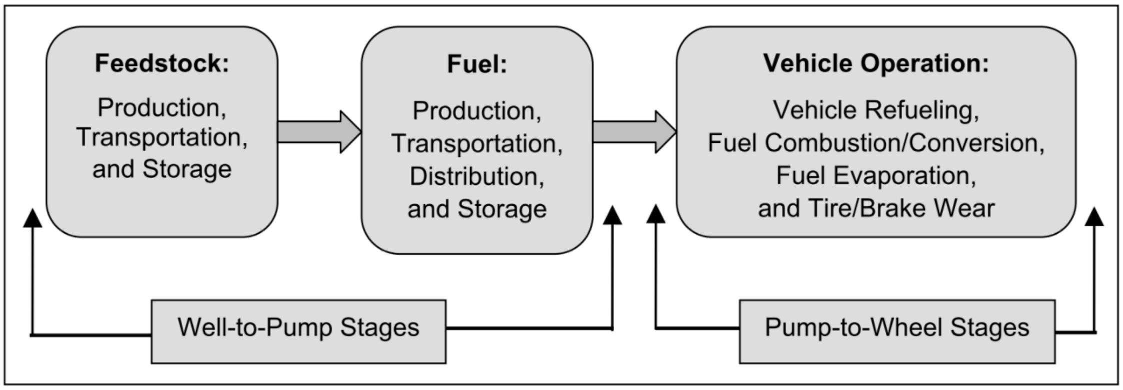

Figure 6: Stages covered in GREET fuel-cycle analysis (M. Q Wang 2001)

The model incorporates many conventional and alternative fuel pathways, including gasoline, diesel, natural gas, methanol, ethanol and various bio-fuels, hydrogen, and electric vehicles. Each pathway incorporates the same set of stages, to ensure a consistent comparison across fuels and vehicle platforms wherever possible. Figure 7 demonstrates the fuel pathway hierarchy.

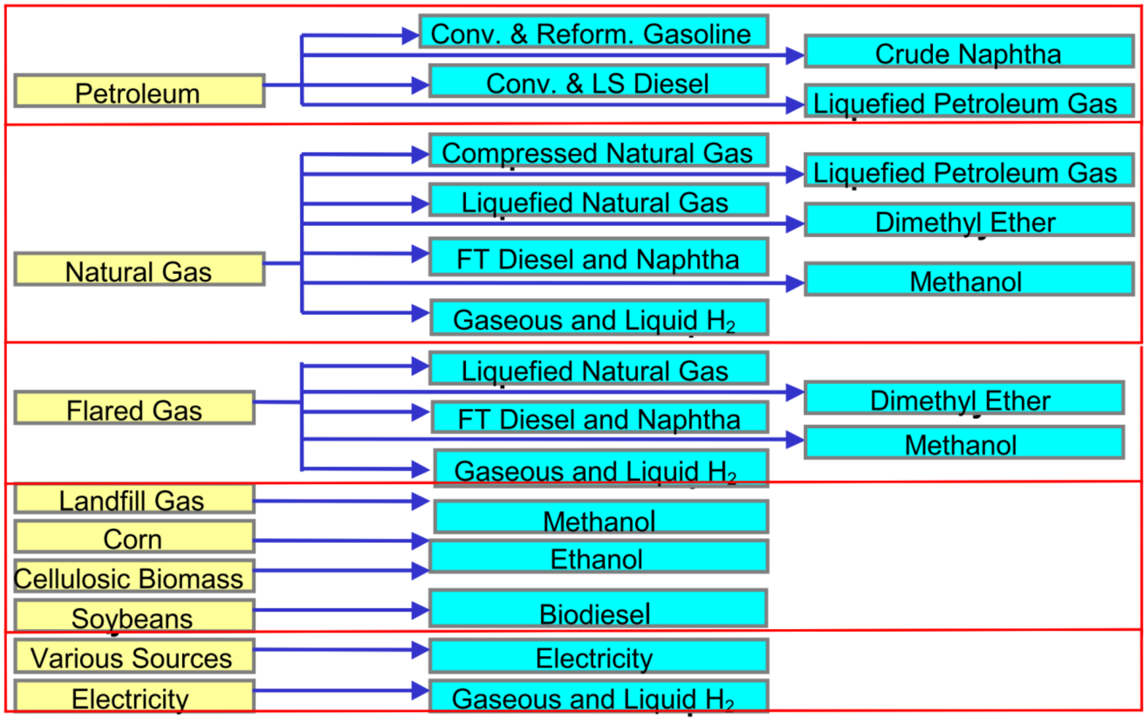

Figure 7: Fuel pathways included in GREET as of version 1.7 (M. Q Wang 2001)

The GREET model has become a standard in fuel cycle evaluation, and is used by many government agencies and corporations. However, it is designed to compare fuels and vehicles on an individual level. To examine the aggregate effect of multiple vehicle types interacting within an urban environment, further calculations are needed.

This thesis uses the GREET model as input data for individual passenger transport vehicles, and integrates it with other data sources to create a comprehensive picture of urban transportation energy use and emissions. Any regional model must incorporate higher level modeling techniques to account for demographics and changing market shares of conventional and alternative vehicle technologies.

High level energy and emissions models are common among the literature, with varying scales and focus. MARKAL, developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency, and its successor, TIMES, are high level energy system modeling tools, represent energy and emissions evolvement "top down" from a worldwide, national, or regional level (Seebregts et al. 2001).

More specific to transportation, the Argonne National Laboratory VISION model is designed to estimate energy use and emissions output of highway vehicles at an aggregate market level. It is intended to be a user-friendly, rapid-response alternative to the Energy Information Agency's National Energy Modeling System (NEMS), which itself is similar to MARKAL in that it simulates energy use across the entire U.S. economy, with subcomponents for industry, transportation, etc. (Singh et al. 2004). VISION is used as a data source for vehicle market shares within the regions specified in the case studies in Chapter 4.

2.4. Integration with Urban Planning

Transportation modeling is often closely combined with more general urban planning and land use studies. Reasons for such a partnership stem from the simple fact that transportation is designed to move people or goods from where they are to where they need or would like to be, whereas urban planning decides where these current and desired locations are and how they interact with one another. As mentioned in Section 2.1, the two fields impact each other in complex ways.

Many urban planners put a premium on fixed transportation infrastructure, such as rail transit systems or dedicated bus rapid-transit (BRT) lanes. Access to mobility within station areas increases, and dedicated/reserved transit rights-of-way are more likely to be clearly routed and on more precise schedules. Additionally, the high capital investment and physical permanence of rail lines (and to a lesser degree, dedicated lanes or guideways) makes the local population more likely to invest long-term capital of their own to benefit from improved access. Bollinger and Ihlanfeldt study the effects of the Metropolitan Atlanta Rapid Transit Authority rail system, after reviewing literature concerning other U.S. heavy rail transportation lines. They find that MARTA had little effect on employment and population near station areas at the time of the study.

Other authors have reported mixed views on the same subject. Nagurney highlights that complex networks do not always react as expected to changes in infrastructure. She points out three common paradoxes within urban mobility networks, including emissions increases despite decreased travel demand, increased emissions when a road is added to a network, and increased emissions due to decreased transportation costs, despite no increase in demand. She highlights the need to take into account network topology, cost structure, and travel demand structure when evaluating urban policies (Nagurney 2000).

Richardson studies analysis frameworks for transport sustainability, and finds that indicators of sustainability are influenced by very different factors between freight and passenger transit. For passenger transport, physical, psychological, and social needs primarily influence sustainability, while freight sustainability is dominated by market forces and government policy (Richardson 2005). A framework showing feedback loops of various metrics is shown in Figure 8.

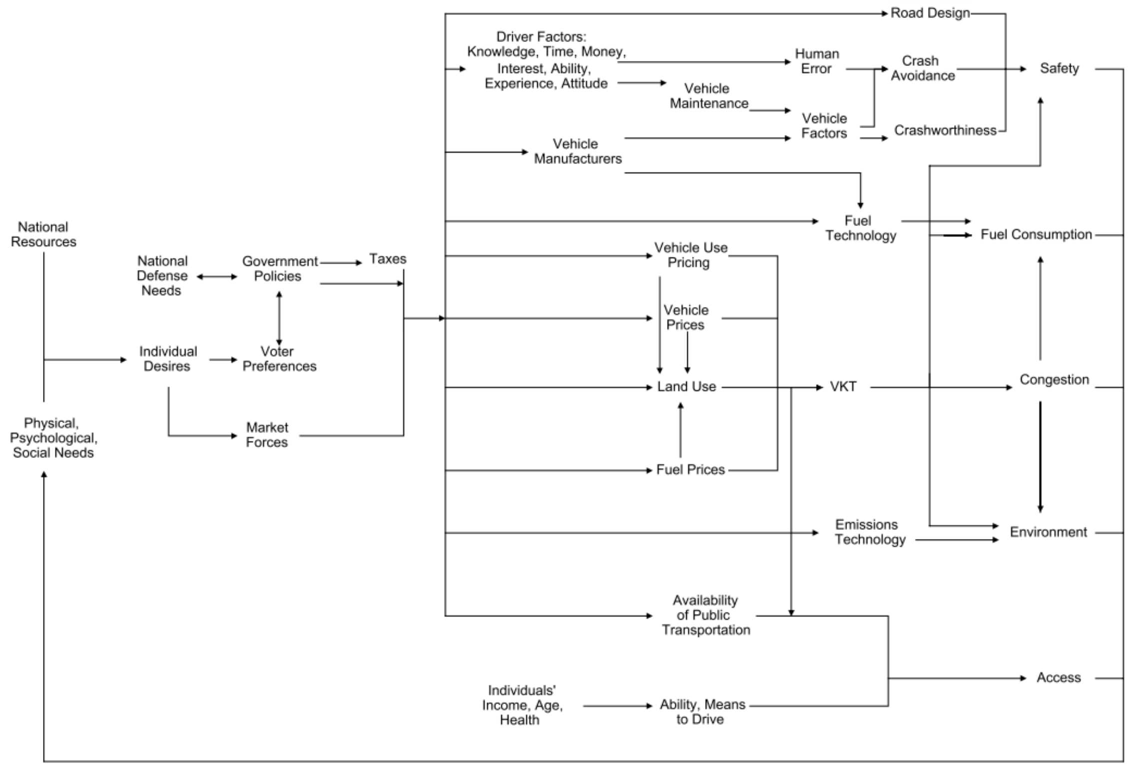

Figure 8: Passenger factors affecting sustainability of a transportation system (Richardson 2005)

Other researchers integrate vehicle life cycle analysis with urban growth modeling. Stone et al. study the effectiveness of "smart growth" policies and aggressive vehicle fleet hybridization in several Midwestern cities (Stone et al.). They find that aggressive technology policies could reduce 50 year increases in emissions by 34%, and drastic increases in urban density could provide even larger emissions offsets.

2.5. Complex Systems Modeling and Optimization

In order to implement the MBSE process in a sustainability assessment, this thesis expands on previous work performed with the Systems Modeling Language, or OMG SysML™. Using an open source profile of the Unified Modeling Language (UML), SysML eliminates the software-centric focus of UML and adds new functionality (Object Modeling Group 2008).

Jobe et al. (Jobe 2008) describe the use of multi-aspect component models (MAsCoMs) within SysML. MAsCoMs enable connections between multiple analysis viewpoints of a particular component or structure within a system. This approach allows for stakeholders to clearly identify analysis pathways, domain assumptions, and structural organization methods chosen by the system designers.

Additional work has been performed on providing an interface between SysML and other existing modeling solutions. For example, Johnson et al. (Johnson et al. 2007) demonstrate integration of continuous dynamic simulations into a larger SysML framework. Using triple graph grammars, they provide a bidirectional mapping between existing SysML constructs and the Modelica simulation language, extending the functionality of both languages.

More generally, models meant to facilitate the design of complex systems are common among the literature. Bonabeau (Bonabeau 2002) discusses agent-based modeling, where systems are depicted as collections of independent decision-making entities. He outlines four general areas of application, and emphasizes that being able to model interactions between components is key to flexibility and complexity management. Smith et al. (Smith et al. 1995) examine an agent-based modeling approach for transit using TRANSIMS, which simulates individual travelers and freight quantities as they travel throughout a network. Barth discusses the topic of transportation modeling as it relates to sustainability several times, notably with Norbeck (Barth and Norbeck 1994) while focusing on Intelligent Transportation Systems, and later with Todd (Barth and Todd 1999) on the subject of shared vehicles.

Other efforts at complex system optimization rely on carefully identifying relationships and feedback loops between different system elements. System dynamics is one such methodology, which relies on causal loops and stock and flow modeling to understand the behavior of a target domain (Taylor 1999). Actively growing since its invention in the 1950's by Dr. Jay Forrester, it has been used more recently within the context of complex transportation systems and associated policy decisions (Jifeng Wang et al. 2008).

Keating et al. (Keating et al. 2008) discuss underlying concepts of multi-level complex systems, and identify prevalent themes and problems to facilitate organization of future research. The authors define "metasystems" as a system that "exists beyond, or transcends, the multiple complex systems it is intended to integrate". This thesis uses the principles of metasystems outlined there in an attempt to bring clarity to the problem of sustainability on multiple scales.

2.6. Urban Systems Sustainability

Efforts to comprehensively model sustainability in complex systems are limited, though several exist. Many of these efforts focus on an urban area at an aggregate level, incorporating feedback from land use, migration, and other interactions at various levels of resolution. In order to understand how urban systems work and their interactions with environmental systems, Alberti proposes a framework consisting of three parts:

1. Key variables to describe urban and environmental systems and their interrelationships;
2. Measurable objectives and criteria that enable us to assess these inter-relationships;

3. Feedback mechanisms that enable the signals of system performance to generate behavioral responses from the urban community at both individual and institutional levels.

Alberti specifies that the metrics and criteria chosen for the framework is dependent on how urban sustainability is defined (Alberti 1996). Definitions are varied, and there is no consensus among the scientific community on which are superior, or what characteristics make a given urban ecosystem more sustainable than another. He defines the "urban ecological space" as " the total natural capital and flows on which a city depends to meet the long-term needs of its inhabitants", and proposes that urban sustainability cannot truly be addressed until links are established between the urban ecosystem of interest and the surrounding natural resource base.

The flows established between the urban ecosystem and surrounding natural ecosystems govern the amounts of resource capital available to support human activities. There is a large amount of debate over how manufactured capital can replace natural capital; some researchers suggest a one-to-one relationship, while others argue that adequate substitution of certain non-renewable resources is unlikely or even impossible (Rees and Wackernagel 2008). The only common conclusion is that living well below the surrounding ecosystems carrying capacity and disturbing natural capital as little as possible generally contributes to making an urban ecosystem more sustainable.

When dealing specifically with transportation within an urban area, one must consider the types of vehicles used, their size and number, their manufacturing origin, what type of resources they consume, and the distance traversed and utility achieved by each vehicle.

In addition, tools for applying sustainability metrics to planning and policy of complex systems are not adaptable. While numerous examples of multi-criteria decision making exist in transportation publications (Turton 2006), many of these deal with a unique situation where the author has applied a general optimization approach to a singular vision of the problem. The application of decision making to each topic allows for variable manipulation within a system, but has little or no universal component that allows comparisons across separate systems. Furthermore, the prevailing strategy for appraising the effectiveness of transportation policy involves making a change, then evaluating data collected after the fact (Bollinger and Ihlanfeldt 1997).

Existing sustainability modeling and simulation efforts focus heavily on extremes of scale. Considerations of the life cycle of an individual product may take into account energy, material inputs, and costs for that product. However, they may not account for other processes occurring at the place of manufacturing, market forces, future changes in technology, or many other factors. Broader analyses of regions or ecosystems sacrifice detail in order to achieve the overall scope they intend.

Including all of these factors is desirable, but attempting to append additional considerations to existing models quickly becomes cumbersome. For example, the Lifecycle Emissions Model, or LEM, deals with fuels, transportation, heating and electricity use. It encompasses over 1200 pages of documentation and data, developed and refined across a period of more than 20 years (Delucchi 2003). Certainly, this body of work is an extremely valuable contribution to lifecycle emissions research. However, LEM inputs and outputs are predefined. Adapting the chosen methodology to new geographical areas or system configurations would require extensive understanding of all model documentation before deciding what inputs and constraints to modify. Other LCA and energy models demonstrate similar characteristics.

To remedy these problems, this thesis uses a MBSE methodology to integrate several existing models and use them to complement a central life-cycle inventory model of an urban transportation network.

2.7. Summary

A survey of the literature on urban transportation networks suggests that there is a great deal of optimism for integrated mobility systems, but investigation on potential benefits of such systems is lacking. Authors have proposed that the key to more sustainable accessibility to goods, people, and places involves minimizing time and distance constraints through any methods available.

Integrated multimodal systems are one such method for improving mobility. In general, the literature finds positive impact in cities that have more transit modes readily available to the public. However, some studies differ over some of the external benefits of extensive multimodal infrastructure and its effects on land use and population habits. In particular, the findings of

Research on the lifecycles of transportation fuels and individual vehicle types is abundant. Existing work supports the relative efficiency of large occupancy vehicles and alternative renewable fuels, finding that in most cases, the impact of fuel consumption vastly outweighs fuel and vehicle production over product lifetimes.

Though exceptions exist, lifecycle analysis which takes into account regional and network-based context is notably lacking. Existing environmental modeling efforts trend towards the individual vehicle level or a much higher scale. Regional transportation research is common with respect to traffic and congestion, but relies on complex static models. Chapters 3 and 4 discuss this gap and how it may be addressed with model-based techniques discussed by Peak, Johnson, and others. Chapter 5 demonstrates the approach and provides an example of the information that can be made through a regional, system-based approach.

CHAPTER 3

APPROACH AND METHODOLOGY

When modeling a complex urban transportation system, there are several issues that must be addressed. First, information transfer between multiple stakeholders must be taken into account. Various interacting parties such as transit agencies, municipalities, and end users mean that there is more information to sift through. Once sorted, the important facts and design constraints must be propagated throughout the system, as well as communicated to all vested parties.

Next, multiple stakeholder objectives must be dealt with effectively. Due to the presence of multiple interacting systems, stakeholders involved in each system rarely have the same goals or desires when moving through the design process. Improving one area of a system may adversely impact another area, or even have an impact on the external environment. For example, transit users are likely to have spatial and temporal transit availability as their primary objectives, while operating agencies are likely to prioritize operating cost. The modeler needs to be careful to address these impacts and minimize exclusion of stakeholders during boundary selection. Even with all relevant objectives included, they must be properly weighted and combined into a single multi-attribute objective function in order to produce meaningful results.

Finally, boundaries between various interacting domains must be defined. In a transportation system, there are sources of goods, including manufacturing pathways for vehicles and infrastructure, sources of energy, including fossil fuels, electricity, and various methods of producing electricity, as well as the vehicles themselves and the area and infrastructure they reside in. A modeler must take care to ensure that functional units for each domain are equivalent and converted effectively when crossing domain boundaries.

3.1. Model Based Systems Engineering

The use of models to represent system components already takes steps towards mitigating the difficulties in representing a complex transportation system. Traditional system engineering is normally characterized as being document-centric, using a systematic process to record objectives and requirements, then transform them into an overall system description. Such approaches include the Pahl and Beitz method, which uses transformations to convert requirements and stakeholder objectives into a system description (Pahl and Beitz 1988), or the VEE Model, used to structure the system development lifecycle (K. Forsberg et al. 1998). Although such requirements may contain quantitative information, they are normally conveyed in a qualitative way, using natural language. This leads to ambiguity, obscuring and amplifying the problems discussed in Sections 2.3 and 2.6.

To attempt to remedy these issues, large system-of-systems can be analyzed using formal techniques to document links between various structural components, as well as relationships among different interaction levels and scales. One method to accomplish this is through an application of model-based systems engineering (MBSE). MBSE uses modeling to support analysis, design, specification, and verification of a system (Friedenthal et al. 2008). By developing a coherent system model and corresponding model repository, necessary information can be captured in a way that improves traceability of flows and requirements, as well as the ability to share knowledge. This mitigates the difficulty of moving between multiple scales and subdomains of a large system.

Once properly described, system relationships have extremely high potential for reuse (Jobe et al. 2008). Most complex systems have subsystems that satisfy similar objectives; this is especially true in domains for which sustainability is a focus, such as manufacturing and transportation. For example, the well-to-wheel energy pathway for a light-duty internal combustion engine (ICE) automobile powered by conventional gasoline is extremely similar to that of a heavy-duty gasoline-fueled truck. It can even be compared relatively directly to a well-to-wheel petroleum diesel pathway, if differences in refining and processing efficiencies are properly accounted for. When abstracted to universal building blocks and energy flows, a lifecycle inventory process can be standardized and used as a template for multiple scenarios. Functional relationships are left intact, leaving only application-specific details to be modified.

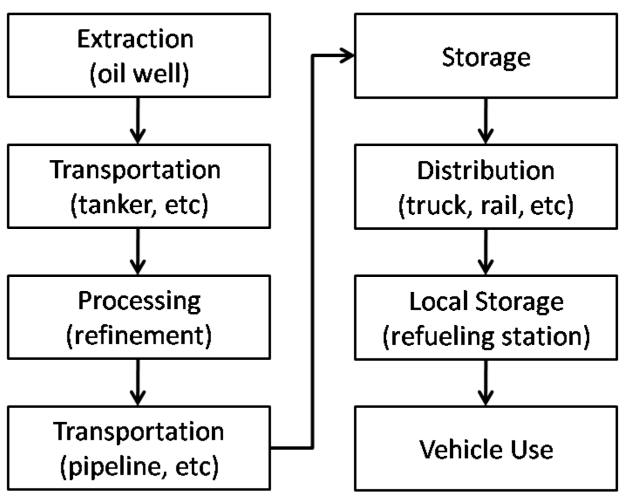

Figure 9: Typical life cycle pathway for petroleum-based fuels.

This examination suggests that one approach to effectively analyzing a complex system is by first breaking down energy inventory techniques into smaller, modular components, rather than immediately broadening scope to include additional modes. Once this is accomplished, an integrated analysis using MBSE is less daunting and more clearly defined than formulating a single "meta-system" model.

3.2. Model Capture and Reuse

With MBSE as a basis for an approach to the problem, one can outline a method for developing a reusable system model:

- Define the desired system boundaries and surrounding domain
- Define a hierarchical model structure that corresponds to a central viewpoint and includes all necessary scales
- Identify relevant system constraints and associated object variables
- Use analysis tools to automatically build system parametrics based on model structure and specified constraints
- Map SysML object variables to appropriate variables in the analysis tool
- Execute system parametrics to obtain calculation results at each level of the system hierarchy
- Define other system viewpoints and analyses as needed

The first step, defining system boundaries, is extremely important because of interactions between a complex system and its environment as mentioned in Chapter 2. Due to time and effort limitations, a modeler cannot depict the surrounding environment and domain at the same level of detail as the entire system, but must take care to clearly define connections, transfers of energy and mass between the system and its external environment, and where modeling resolution changes.

The model structure contains information on design, specification, requirements, analysis, and verification. Elements are organized by their relationship to the parent system. SysML provides diagram types for specific model viewpoints deemed important, such as system structure, behavior, requirements, and parametrics (governing equations).

Parametrics form a set of constraints that govern how the system behaves as well as mathematical relationships between various model elements. In this thesis, parametrics are often used to conform to first principles of thermodynamics during energy and mass transfer calculations. Parametrics are key differentiator between SysML and UML, and are a large part of why SysML is capable of modeling physical systems.

In order to formalize a useful set of parametrics within a model, the modeler must decide which variables are most relevant to the system's behavior and the desired modeling viewpoints. There are an infinite number of value properties that may be represented within a SysML model, but the model may become unmanageable without significant paring and careful selection of design parameters. Once these properties are modeled, the constraints imposed by parametric diagrams support other viewpoints specific to engineering analysis. These constraints can be applied to each alternative within a particular design space in order to perform optimization and trade studies.

Also, the addition of parametrics enables the use of external analysis tools in conjunction with the user's SysML modeling environment.

3.3. Introduction to SysML

The Systems Modeling Language (OMG SysML™) is a general purpose modeling language built upon the base of the Unified Modeling Language (UML). UML is also a general purpose modeling language, but is designed specifically for the field of object-oriented software engineering. The UML standard is managed and updated by the Object Management Group, with inputs from many other working groups.

UML and other graphical modeling languages of its kind are not development methods by themselves, but rather are tools designed to facilitate leading object-oriented design methods (Hunt 2000). The current UML specification has 14 diagram types used to formally represent system artifacts. Seven of these types represent structural information about a system, while the other seven are used to represent various types of behavior and interactions either within the system or between the system and its domain.

SysML uses a subset of the UML 2.1 specification, and extends it in the following ways:

- Support for parametric and requirements modeling
- Flexible allocation tables
- Management constructs to support models, viewpoints, and views
- Additional systems-related semantics
- Flow ports

Figure 10 shows the SysML diagram taxonomy, which uses a subset of existing UML diagram types and adds two new types in support of parametric and requirements modeling as mentioned above.

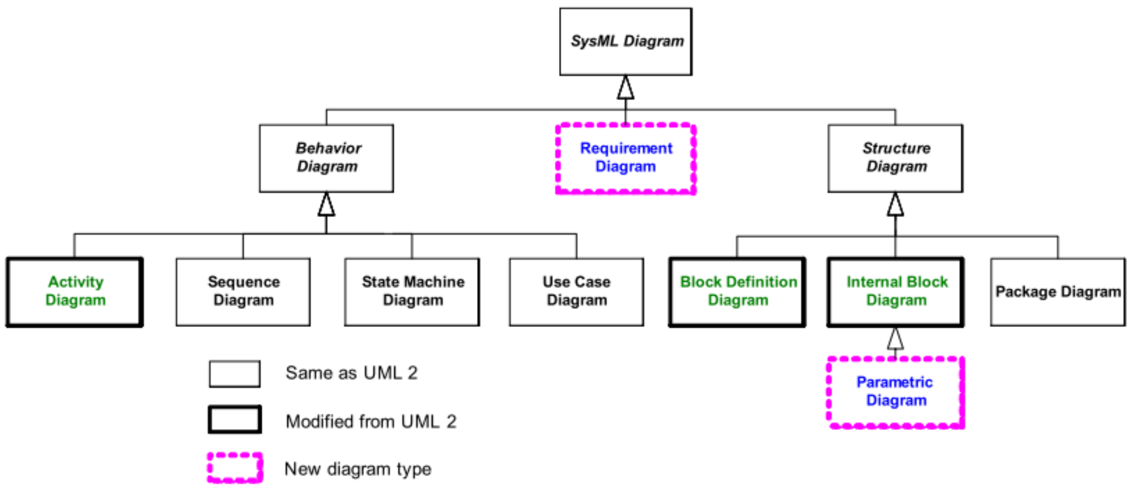

Figure 10: The SysML diagram taxonomy (Object Modeling Group 2008)

In general, SysML semantics tend to be more flexible and expressive, although in practice this can contribute to a lack of formalism that some authors claim as a limitation (Herzog et al. 2005).

The universal structural unit in SysML is the *block*. Blocks can be used to model physical objects, hardware, software, or any number of abstract entities that describe a system (Friedenthal et al. 2008). Each block describes a set of *instances*, or individual objects that exhibit the features of their defining block but also have an explicit and unique identity within the model. Blocks may be composed of other blocks, or be associated with them in a variety of ways. Within each block, quantitative characteristics are stored by *value properties*. These properties must conform to a *value type*, which defines the relevant units, dimension, and a range of possible values.

Relationships between blocks are captured and displayed by a *block definition diagram* (BDD). BDDs can visually represent a composition hierarchy between a set of blocks, or a classification hierarchy that defines generalization and specialization pathways.

Behavior and interaction between blocks is defined through the use of *ports*. Standard ports specify behaviors that are required or provided, while flow ports specify an item that can enter or leave a block. Ports with similar specification can be connected to each other to model interaction or indicate transfer of energy or material. *Internal block diagrams* show ports and connections between blocks, rather than structural associations such as those found in a block definition diagram. Other behaviors that govern how a block responds to external stimuli are handled by several SysML language facilities, including *activities*, *interactions*, and *state machines*. Each of these is associated with a diagram type used to properly represent the behavior being modeled.

Capturing system equations is accomplished through *constraint blocks* that define equations and the parameters within them. Constraint blocks are included in a *parametric diagram* to show connections between constraint parameters as well as value properties from various parts of the model.

3.4. Implementing MBSE in SysML

Strategies for explicitly defining analysis viewpoints are extremely applicable to sustainable lifecycle assessment. In particular, the use of MBSE in SysML serves to mitigate LCA boundary selection problems. Including multiple viewpoints of the model that formally define the modeling domain, goals, assumptions, and constraints reduces uncertainty where assumptions of boundary and scope occur. If these boundaries are refined during the design process, the refinements can be formally documented by keeping a history of SysML iterations, clearly showing the evolution of an LCA model and further reducing questions about the design decision process.

SysML also provides a unique method of mapping existing LCA tools to a system-of-systems model such as a transportation system. By acting as an interface between various existing tools, SysML allows system designers to significantly expand the scope of their system domain with little increase in associated costs. It should be noted that this does negate some of the benefits of formally modeling every component of interest within SysML, but in some cases this may be undesirable or even impossible.

3.5. SysML analysis models

While one approach to defining system parametrics involves specifying constraints within the SysML block that they operate on, this is not required, and sometimes not the optimal approach. For example, many analysis viewpoints may require properties of multiple blocks to be used as constraint inputs, or multiple constraints may be applied to a block or set of blocks. For a multi-scale model, the ability to decouple analyses from the system structure is invaluable, since the desired resolution of an analysis may change depending on the system or subsystem to which it is applied. An *analysis model* is composed of constraint blocks that are separate from structural elements of the system. Much like other elements intended for model reuse, they may be kept in pre-existing libraries so as to avoid modeling repetition when dealing with common constraints.

The power of analysis models lies in their ability to act as a bridge between the SysML modeling environment and external analysis tools. Although SysML has the ability to define system parametrics, the created parametric structure must be interpreted and solved. By decoupling constraints from the structural model, these constraints may be passed to any number of specialized software packages or solvers, such as MATLAB, Mathematica, or others.

By using a consistent transformation protocol between the SysML analysis model and a solver, the analysis model can be made executable to automate calculations. The transformation takes system structure and parametrics stored in SysML and translates them into semantics native to the tool of choice. This assumes that SysML and the chosen external tools have equivalent language functions, or at least close approximations.

3.6. Linking to other analysis models

Another strength of SysML comes from an objective stated within the SysML language specification: "SysML is intended to unify the diverse modeling languages currently used by systems engineers" (Object Modeling Group 2008). Because complex systems involve multiple analysis domains, it is often difficult to integrate models and simulations from each domain, many of which rely on proprietary, non-exchangeable languages and tools.

Just as SysML can act as an interface between various LCI data inputs as mentioned previously, it also provides a neutral exchange format to interface between analysis models. Flexibility in semantics allows stereotypes to be created for various data input and output types. When linked with a parser and execution engine, the overarching system model created in SysML can provide a bridge between data from CAD/FEA models, statistical simulation modeling packages, and other engineering software programs.

The SysML specification stores model information using Extensible Markup Language, or XML, which is an open source standard for electronic document encoding. Since XML is widely used and openly maintained, storing SysML information using XML formatting increases interoperability. Several authors have discussed the merits of XML-based information exchange for creating engineering models. Since UML also relies on XML standards and is a much older specification, it has a large body of literature dedicated to model transformations and code generation using XML exchange.

Overall, MBSE implementation using SysML appears to offer several major advantages over more traditional modeling and systems design methods. Model capture leads to reusable components and an object-oriented modeling environment, reducing the amount of complexity that is presented to a modeler. Organizing this information into diagrams using formal relationships and semantics reduces complexity for end users and stakeholders. Using captured model information to generate analysis models provides a way to automate simulations and trade studies, and also provides a method and format for integrating external analyses and exchanging input and output data. The end result is that a model's domain boundary can be extended well beyond what would be possible with a document-centric or less formal approach.

CHAPTER 4

IMPLEMENTATION

4.1. Description

This chapter demonstrates the use of a SysML model to assist in an LCI of the use-phase of various vehicle types within a regional urban mobility network. An organizational scheme is outlined, and the network structure and parametrics relevant to the model are defined. The model is exported to an external file for use with external analysis tools. Parametrics are analyzed using ParaMagic/Mathematica as well as MATLAB as an external parser and solver. Data for each vehicle type is taken from a lifecycle inventory of fuel pathways commonly used in transportation vehicles. Statistics from the region are used to look at each vehicle type in the context of its use within a larger transportation system.

4.2. SysML Model Structure

The SysML model is divided into several key packages. Broadly, these packages organize the model elements by in two categories: function (such as constraints or value types), and structure (infrastructure, vehicles, etc. of the transportation system being modeled). Together, the packages form a hierarchical structure, as seen in Figure 11.

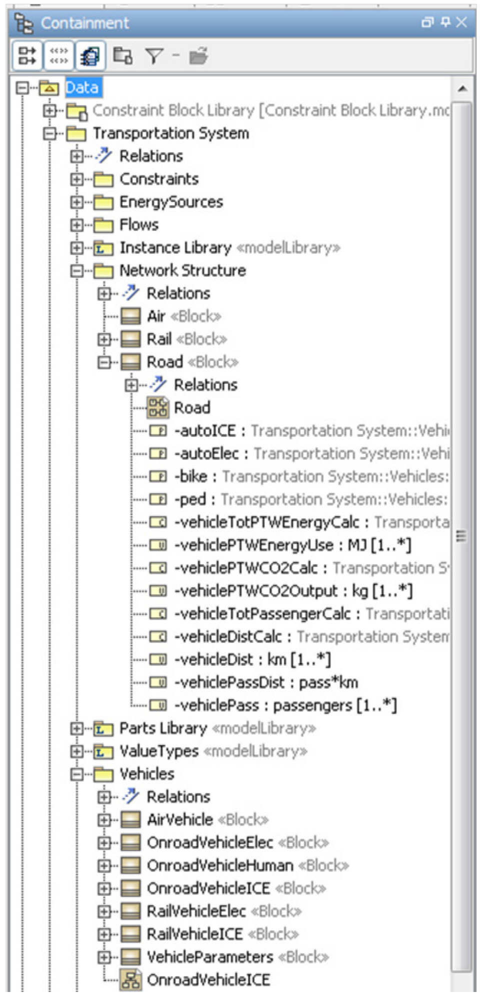

Figure 11: Transportation system package hierarchy.

The top level package is called Transportation System, to signify the overall system in question. Within it, there are several major structural subdivisions. First, the system structure is designated by transportation modes within the network, which are contained within the "Network Structure" package.

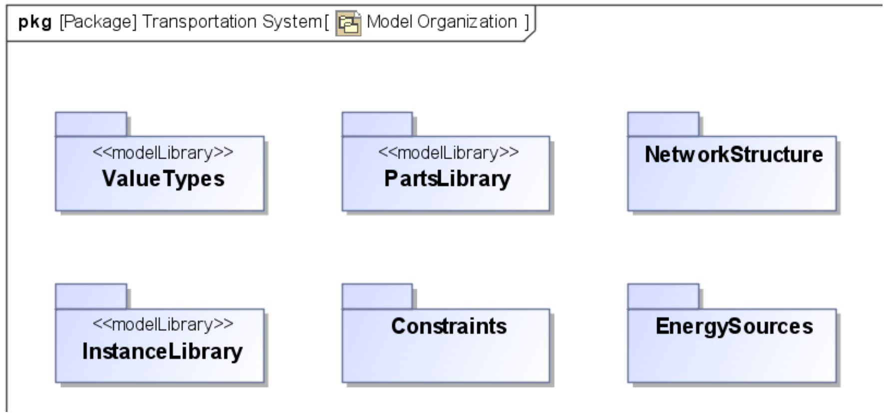

Figure 12: Model organization into various packages within SysML

In this case, the major modes to be examined are air, road, and rail. To make the system abstract and applicable to multiple domains, other modes such as maritime transport are modeled as well. However, since this case study the project was designed to examine Atlanta as the primary system instance, and Atlanta has no maritime passenger transport, the level of maritime detail modeled is lower than in other modes. For the purposes of this analysis, air travel is also not modeled in detail, since it deals with trips between urban regions and not within one.

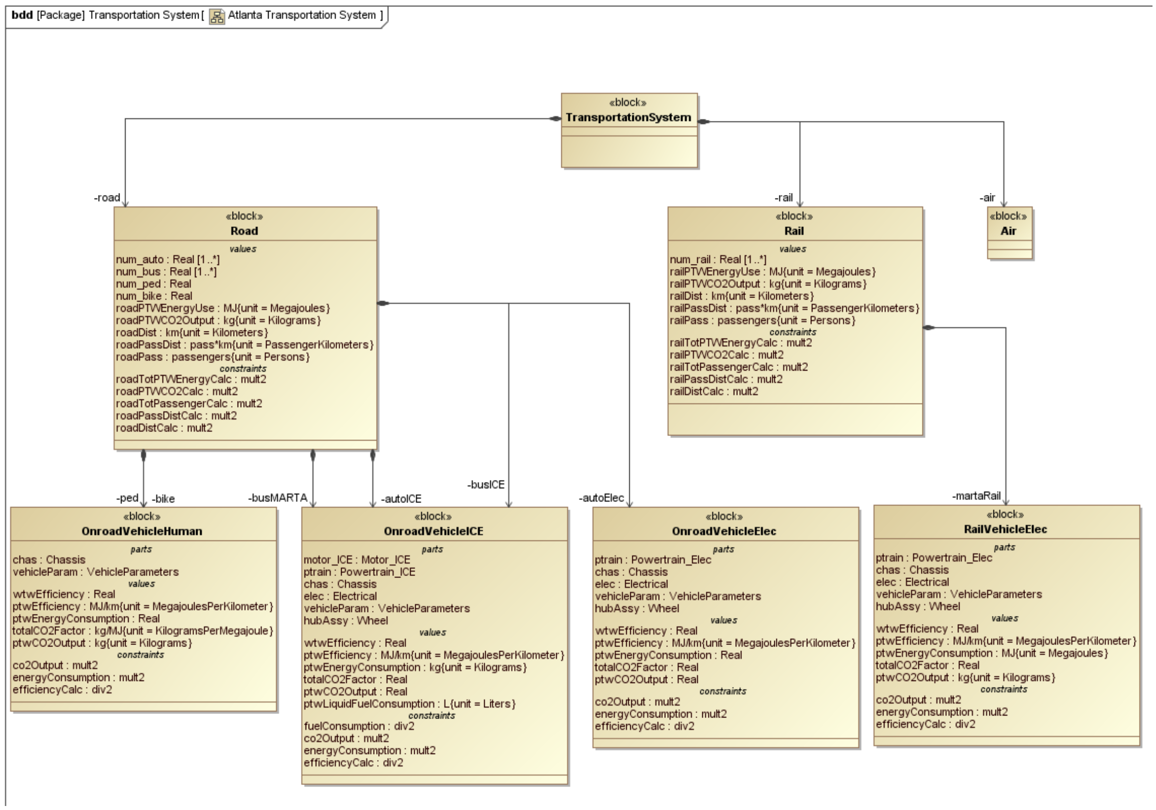

Figure 13: Block definition diagram of the overall transportation system structure.

Figure 13 demonstrates the overall structure of the system. Within each of the applicable travel modes, relevant vehicle types are modeled as part properties. In this case, there are part properties for three general types of vehicle propulsion source: electric vehicles, internal combustion vehicles, and vehicles powered by human-generated mechanical effort. Since each of these propulsion methods deals with energy in a fundamentally different way, it is useful to model them separately for later analysis. Each of the vehicle part properties are an abstraction of multiple real-world vehicle types. Instances are used to provide finer grained specification between vehicles, which will be discussed below.

Each transportation mode has value properties that store how many of each vehicle type exists within that mode. For example, the "Road" block contains an array “num_auto”, which has an element for the multiplicity of each type of automobile instance (number of gasoline automobiles, number of hybrids, number of electric autos, etc) that exist within the road subsystem. The road block also has value properties for total pump-to-wheel (PTW) energy consumed by all road vehicles, as well as total CO2 output, vehicle distance, and passenger distance. Other major modes such as “Rail” have similar corresponding value properties. The calculation of these values will be covered in detail in Section 4.3.

Examining an individual vehicle type shows the general model structure used for various vehicles. Figure 14 demonstrates the structure of an onroad vehicle with an internal combustion powertrain. The vehicle, which can be considered a system in and of itself, is laid out into three main subsystems, the chassis, the powertrain, and the electrical subsystem. The subsystems of interest have individual parts that are specified, such as the motor and in this case, the choice of fuel. Individual parts as well as subassemblies of parts (such as powertrains) are stored in a library called “Part Library”, since many are found in multiple vehicle types and are intended for reuse.

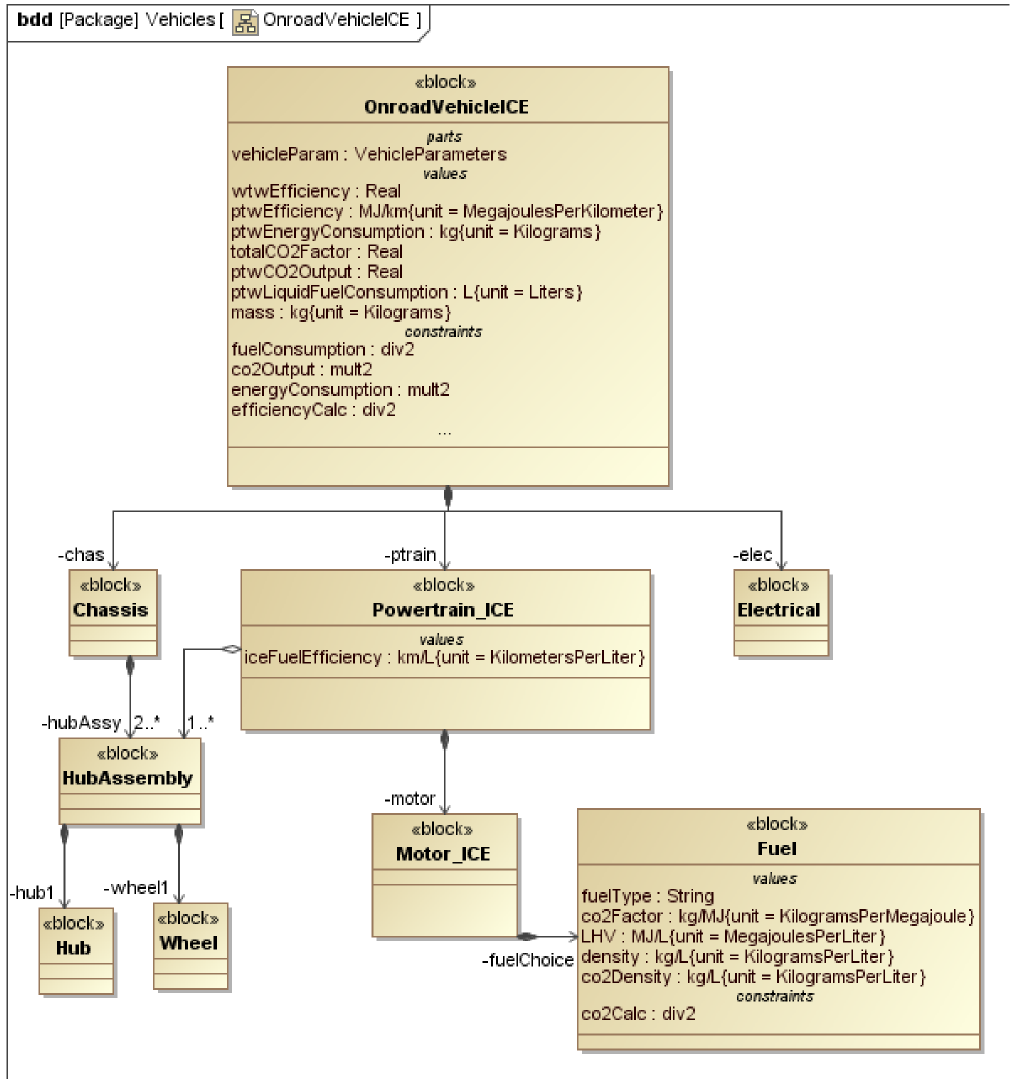

Figure 14: Block definition diagram of an onroad vehicle with an internal combustion powertrain.

Other vehicle types have similar basic structure, but with modifications to reflect fundamental structural differences. For example, an air vehicle has a “Wing” part, and a rail vehicle has different multiplicity for the number of wheels. Details of each vehicle, such as mass, fuel efficiency, and energy consumption, can be specified at the instance level. Using the parts library to facilitate object-oriented creation of vehicle models means that most parts can be reused in multiple vehicle blocks, greatly increasing model utility.

Fuel types for each vehicle are modeled as a generic "Energy Source" at the base level, as in Figure 15. The Energy Source block is used as a generalization of more specific types of fuel, such as liquid or gaseous fuel resources. Universal properties of all energy sources consumed, such as CO2 output from production processes, are included within the generalizing class, while the specific classes contain information unique to their resource type. For example, the "Fuel" block contains part properties for mass density in kilograms per liter, energy density in the form of the fuel's lower heating value (LHV), and CO2 per unit energy density based on carbon content.

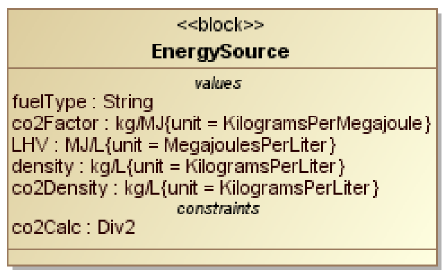

Figure 15: SysML block of vehicle energy source

4.3. Analysis Model

4.3.1 Fuel pathway constraints

The analysis model begins with low level fuel resources consumed by vehicles within the transportation network. Established well-to-pump (WTP) efficiencies for different fuel types are used to provide a basis for estimation of CO_2 production. Although fossil fuel recovery and refining techniques do change over time, their rates of change are slow compared to the vehicles themselves, and certain energy inputs for mining, recovery, and transport remain relatively constant. Multiple assessments of fuel feedstock recovery, transportation, production, and distribution have been carried out and provide a solid basis for model calculations (Michael Wang 2002; M. Q Wang 1999). Table 2 shows input values for a number of common transportation fuels.

Table 2: Fuel specifications within the GREET model (M. Q Wang 1999)

Fuel	LHV	HHV	Density	C ratio (% by wt)	S ratio (ppm by wt)
Liquid Fuels	(Btu/gal)	(Btu/gal)	(g/gal)		
Crude oil	130,000	138,100	3,200	85.0	16,000
Conventional gasoline	115,500	125,000	2,791	85.5	200
Federal reform. gasoline	112,300	121,500	2,795	82.9	30
Calif. Reform. gasoline	113,000	122,200	2,794	83.5	30
Conventional diesel	128,500	138,700	3,240	87.0	250
Reformulated diesel	128,000	138,000	3,240	87.0	050
Residual oil	140,000	149,500	3,630	87.0	5,000
Methanol	57,000	65,000	2,996	37.5	0
Ethanol	76,000	84,500	2,996	52.2	0
Liquefied petroleum gas	84,000	91,300	2,000	82.0	0
Liquefied natural gas	72,900	80,900	1,589	74.0	0
Dimethyl ether	68,180	NA[a]	2,502	52.2	0
Methyl ester (biodiesel)	117,090	128,520	3,346	78.0	0
Fischer-Tropsch diesel	118,800	128,500	2,915	86.0	0
Liquid hydrogen	30,100	35,700	263	0.0	0
NG liquids	81,460	90,500	NA	NA	NA
Still gas	128,590	142,860	NA	NA	NA
Gaseous Fuels	(Btu/scf)	(Btu/scf)	(g/scf)		
Natural gas	928	1,031	20.5	74.0	7
Gaseous hydrogen	274	324	2.4	0.0	0
Solid Fuels	(Btu/ton)	(Btu/ton)			
Coal	18,495,000	20,550,000	NN[b]	60.0	11,100
Coking coal	20,532,600	22,814,000	NN	NA	11,800
Woody biomass	17,000,000	NA	NN	NA	NA
Herbaceous biomass	15,600,000	NA	NN	NA	NA

[a] NA = not available.

[b] NN = not needed.

To perform useful analysis on any given fuel type, first the fuel's energy content is required. In the U.S., this is normally taken to be the fuel's higher heating value (HHV), and therefore HHV will be used in the following calculations. This should be emphasized when reporting results, since some other parts of the world, particularly

Europe, perform calculations using the lower heating value (LHV). GREET uses LHV for calculations by default, but has the option to make calculations using HHV as well, which has been chosen for the following results. HHV refers to a fuel's gross calorific value, and accounts for the amount of heat released by combustion once all reaction products have returned to a standard temperature of 25°C. The resulting measurement takes into account the latent heat of vaporization of water in the fuel's combustion products, whereas LHV assumes that combustion products are returned to 150°C. At this temperature, water content remains in vapor form at the end of combustion, and therefore is not recovered. The difference in the two values for any given fuel depends on the fuel's hydrogen content. The HHV tends to be approximately 6-12% higher than the LHV for common hydrocarbons.

Volumetric energy density (MJ/L) is used to facilitate calculations involving vehicle fuel efficiencies, which are normally given in distance traveled per unit volume of fuel consumed. By multiplying the fuel's energy density by the WTP efficiency factor, the total WTP energy consumption per unit volume of fuel available for end use can be obtained.

$$\boldsymbol{E_{WTP} = HHV * (1 - \eta_{WTP})} \tag{1}$$

CO_2 output per unit energy is calculated using known CO_2 generation per unit mass, based on carbon content and normal combustion conditions, as well as the fuel's energy density.

$$\boldsymbol{CO2_{WTPE} = CO2_{fuel}/HHV} \tag{2}$$

The SysML parametric diagram for a fuel resource is shown in Figure 16. Energy density is imported during GREET model execution, and therefore is not included in the SysML parametric structure.

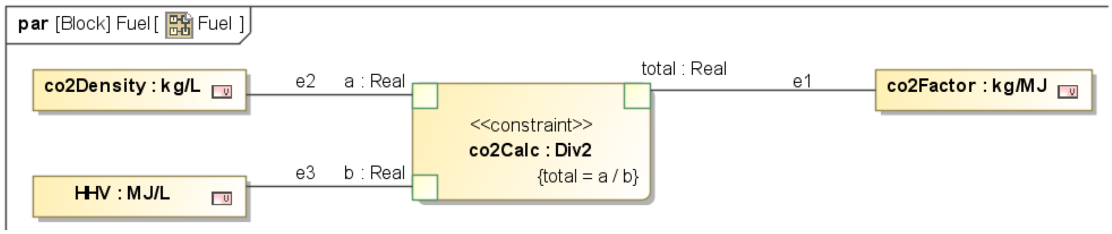

Figure 16: Parametric diagram of a fuel resource in SysML

WTP calculations for common fuels used in most U.S. urban areas are shown in Figure 17. CG denotes conventional gasoline, RFG refers to reformulated gasoline as specified by the U.S. EPA Clean Air Act (Environmental Protection Agency 1994), and EtOH FFV is an 85% ethanol/15% gasoline mixture using corn ethanol (commonly available as "E85" at refueling stations). The results for electricity shown below are for the U.S. average generation mix (Energy Information Administration 2009; Luna-Camara et al. 2009). As opposed to other fuel types, electricity exhibits high CO2 output upon reaching the "pump" (end-use outlet) because combustion of input fuels has already occurred. WTP efficiency, or the ratio of energy expended to energy extracted and produced, varies widely. This is due to differences in production techniques. While fossil fuels such as gasoline and natural gas can be extracted from the earth directly and refined with relatively low energy expenditure, bio-fuels such as corn ethanol must undergo a great deal of energy intensive processing after harvest in order to be used as a transportation fuel. As mentioned before, electricity often must combust another fuel type as input fuel for its production, leading to the lowest WTP production efficiency, but normally a much higher use-phase (PTW) efficiency. Whether well-to-wheel efficiency for an electric propulsion pathway is higher or lower than fossil fuels is highly dependent on electricity generation methods and a vehicle's individual use case. These factors will be discussed further in the following case studies.

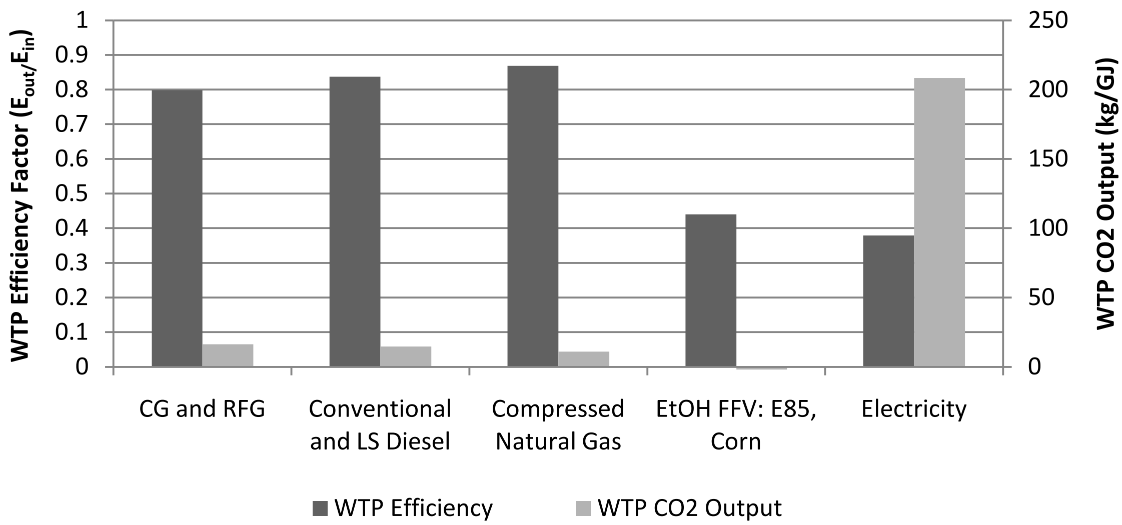

Figure 17: Energy use and greenhouse gas output per GJ of fuel energy available for end use

4.3.2 Vehicle constraints

Moving upwards in the system hierarchy, the analysis model computes statistics for an individual vehicle type. Each vehicle has a defined fuel type, which allows it to inherit the fuel's well-to-pump efficiency factor. Vehicles sold in the U.S. are required to be rated with a standardized fuel economy, based on drive-cycle tests developed by the EPA. This fuel economy is taken as the *pump-to-wheel* (PTW) energy consumption, i.e. accounting solely for the use phase of the fuel. The PTW rating is divided by the WTP efficiency factor to produce numbers for *well-to-wheel* (WTW) energy use.

$$E_{WTW} = E_{PTW}/\eta_{WTP} \tag{3}$$

Carbon content is multiplied by fuel economy and a combustion ratio to produce CO_2 output per kilometer. The proper ratio is given by the atomic weight of CO_2 divided by the atomic weight of standard carbon, resulting in 44/12. Researchers must take care to account for only the fuel that is oxidized during the combustion process, which is approximately 99% for common fuels (Garg and Pulles 2006).

$$\boldsymbol{CO2_{out} = E_{PTW} * m_{fuel} * C_{fuel} * 0.99 * (\frac{44}{12})} \tag{4}$$

This approach also provides a method for seamlessly comparing internal combustion vehicles with those that rely on electric motors or other forms of propulsion: the well-to-wheel energy calculation results in a number that defines distance traveled per unit of energy used, such as km/MJ. This figure is also commonly tested and published for any alternative fuel vehicle (essentially, the "fuel economy" of a battery powered vehicle or similar), which can then be combined with regional data on standard grid electricity production to arrive at the same well-to-wheel energy use and emissions output.

In the case of electric vehicles, it is not possible to do a simple carbon content calculation as is outlined above. Instead, the generation of electricity used for propulsion must be considered. Depending on the source fuels and methods used for generation, this can have an extremely large effect on overall efficiency and emissions. Similar to the pathway shown in Figure 9 for a petroleum fuel lifecycle, power generation has distinct stages, each with their own efficiency ranges. Also, power plants in the U.S. are carefully regulated, and normally are required to record their production totals as well as their emissions output. To determine the average rate of emissions produced by the generation of electricity in an area, the annual CO_2 emissions from each plant are summed during model analysis using the eGRID national database of U.S. powerplants, then divided by the sum of total annual plant energy generation. The result is the amount of CO_2 per unit of electricity produced within the chosen region.

$$\boldsymbol{CO2}_{rate} = \sum \mathbf{CO2}_{\mathbf{annual}} \Big/ \sum \mathbf{P}_{\mathbf{annual}} \tag{5}$$

When determining vehicle inputs, GREET data is used for calculations concerning on-road light-duty cars and trucks. Gasoline equivalent fuel efficiencies for a light-duty fleet vehicle of average size and weight are used to calculate use-phase energy consumption, and molecular composition and relevant combustion reactions leads to average vehicle emissions by fuel type. Average fleet fuel economy of 10.77 km/(L gasoline) is used as a basis for consumption equations (M. Q Wang 2001; Michael Wang 2002). In addition to internal combustion vehicles using the fuels outlined above, gasoline and diesel hybrid vehicles, plug-in hybrids, and pure electric vehicles are included in the light-duty fleet. The resulting well-to-wheel pathways are only a small cross section that are possible with the GREET model, but represent the vast majority of current conditions for the chosen networks. The VISION model incorporated for vehicle market shares uses statistics from U.S. Department of Energy and Office of Transportation Technologies to form a base case of vehicle market penetration, and subsequently project future penetration and energy-related statistics (Singh et al. 2004).

Once constraints are in place for each vehicle type, and specific values defined for each specific vehicle, overall emissions and *vehicle-km-traveled* (VKT) can be computed within each infrastructure subsystem. VKT is currently calculated using a bottom-up approach: the total number of units for each vehicle type is multiplied by that type's average daily travel distance:

$$VKT_{daily} = n * x_{avg} \tag{6}$$

The average travel distance by vehicle type is the largest source of uncertainty within the model. Figures for public transportation such as trains and buses can be calculated with some level of certainty, but trip lengths for nonpublic vehicles can vary widely. However, metropolitan transportation organizations commonly record some type of total mileage data, allowing trip length assumptions to be checked. As discussed in the results section, using an average daily distance provides reasonable results for computing total VKT for the chosen case studies outlined. The SysML parametric diagram for an ICE automobile is shown in Figure 18.

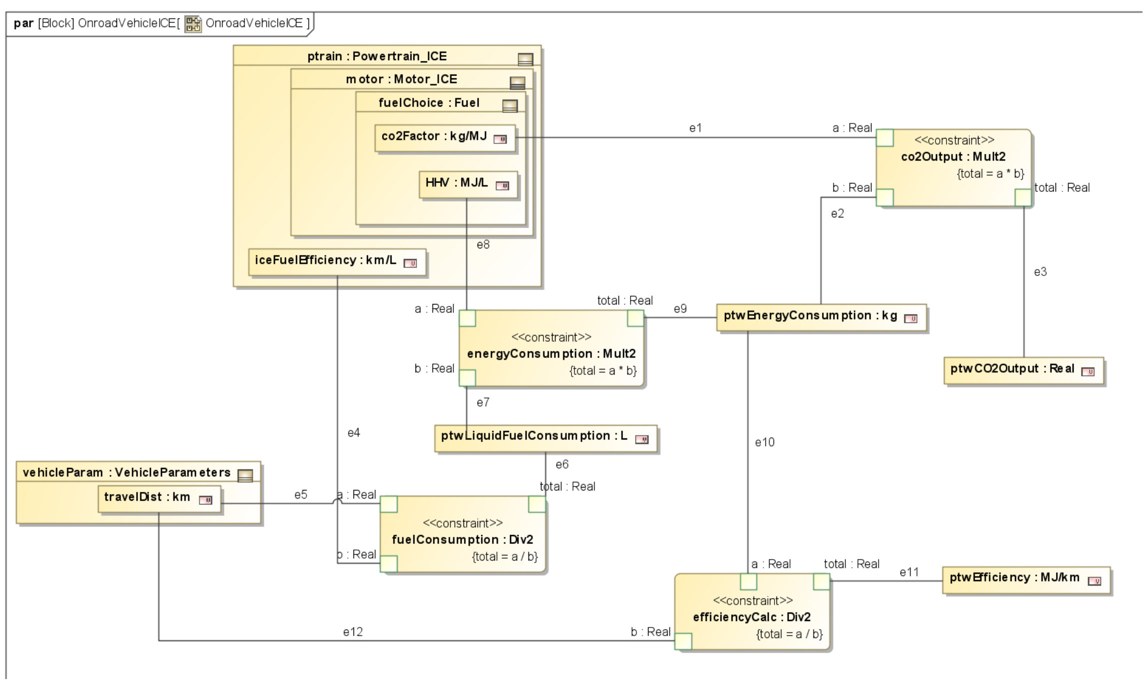

Figure 18: SysML parametric diagram of an ICE automobile

By introducing separate modes of transportation into the analysis, however, new complications arise. Public transit vehicles are larger and heavier than their automobile counterparts, meaning that directly comparing vehicle efficiency is a fruitless exercise. To better determine which mode is best at moving passengers from A to B, energy use per *passenger-distance* is compared. Passenger-distance is defined as a distance traveled multiplied by the number of people that have traveled it. Since the SI system has been used thus far, the passenger-kilometer is a reasonable choice of unit, and is simply defined as one person moved a distance of one kilometer. Calculating VKT and vehicle efficiencies in terms of passenger-km takes each vehicle's occupancy into account, and gives much more insight into the effectiveness of a particular mode.

The relevant equations involving passenger distance are total passenger distance for a vehicle type, seen below.

$$\boldsymbol{PKT_{daily} = VKT_{daily} * Oc_{avg}} \tag{7}$$

Vehicle energy use and CO_2 are also redefined in terms of this parameter.

$$\boldsymbol{E_{PKT} = {E_{WTW}}/{Oc_{avg}}} \tag{8}$$

$$\boldsymbol{CO2_{PKT} = {CO2_{WTW}}/{Oc_{avg}}} \tag{9}$$

Performing these calculations gives energy and CO_2 output statistics for individual vehicle types. The number of each vehicle type is known and used as an input variable, and so calculation results are multiplied by unit number and summed where appropriate to create regional results for the case study area.

In terms of average use characteristics and overall fuel energy efficiency, many public transit vehicles have not been subjected to the same level of research scrutiny as the light-duty fleet. Therefore, empirical data from a variety of sources is used to build comprehensive inputs for case study transit modes.

Small vehicles such as bicycles and motorcycles, as well as pedestrians, are also included in the framework. Their energy and emission contributions are valuable for purposes of further research, but are negligible in the scenario presented here, and as such are not included in all of the presented results.

4.3.3 System constraints

Remaining constraints for the transportation system are derived from system usage data and recorded statistics concerning vehicle distance traveled. Distance and passenger distance for each vehicle type are summed by mode, and then summed with each other to obtain total distance traveled by the entire network. Mode calculations for the road subsystem are shown in Figure 19.

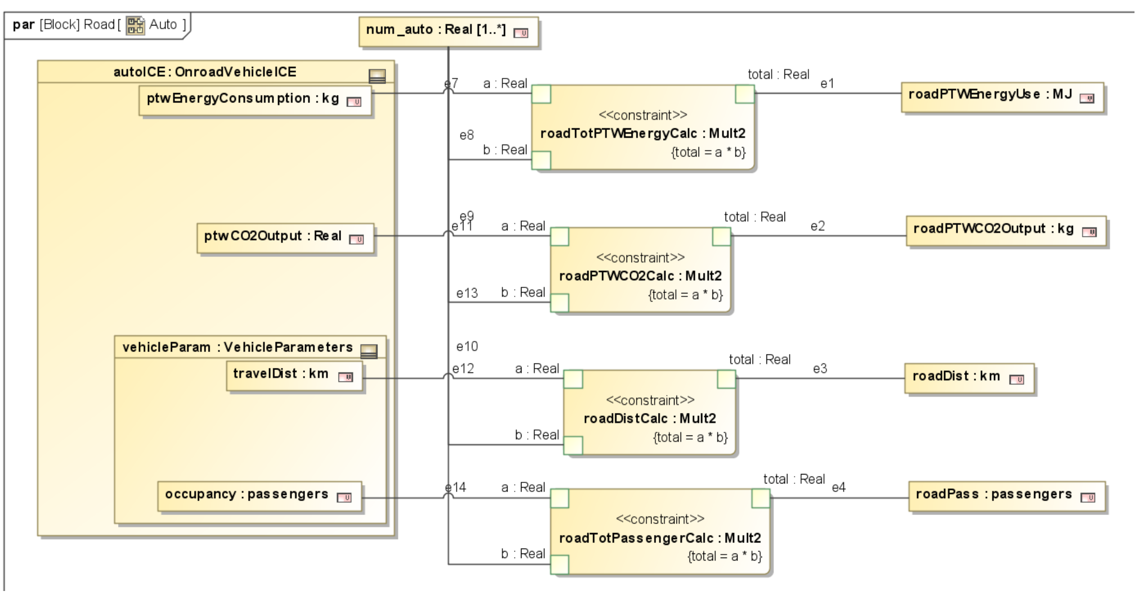

Figure 19: Parametric diagram for all internal combustion automobile types in SysML

4.4. Analysis Execution

Since SysML has no inherent execution capability, external tools must be applied to execute various analyses using parametrics contained within a SysML model. The model in this thesis tested two methods of analysis execution. First, parametrics were executed using the ParaMagic™ plugin, developed by InterCAX, an Atlanta based software company.

4.4.1 **ParaMagic Plugin**

ParaMagic was originally developed from ongoing SysML research by Dr. Russell Peak and others at the Georgia Institute of Technology. It relies on the theory of composable objects (COBs) to parse information from model instances and execute parametrics contained within the model structure.

The tool currently exists as a plugin for MagicDraw, a UML modeling software package developed by No Magic, Inc. MagicDraw has a mature SysML plugin, and is the chosen software package to create the SysML models used in this thesis. Since ParaMagic is tightly integrated with MagicDraw software and also continues to have a close affiliation with Georgia Tech, it was a natural first choice for model execution.

ParaMagic reads instance information and displays it within a separate browser window within MagicDraw. In the browser window, the user can see instance values relevant to parametrics of the top level instance specification. Figure 20 shows the browser and the instance values for the transportation system model.

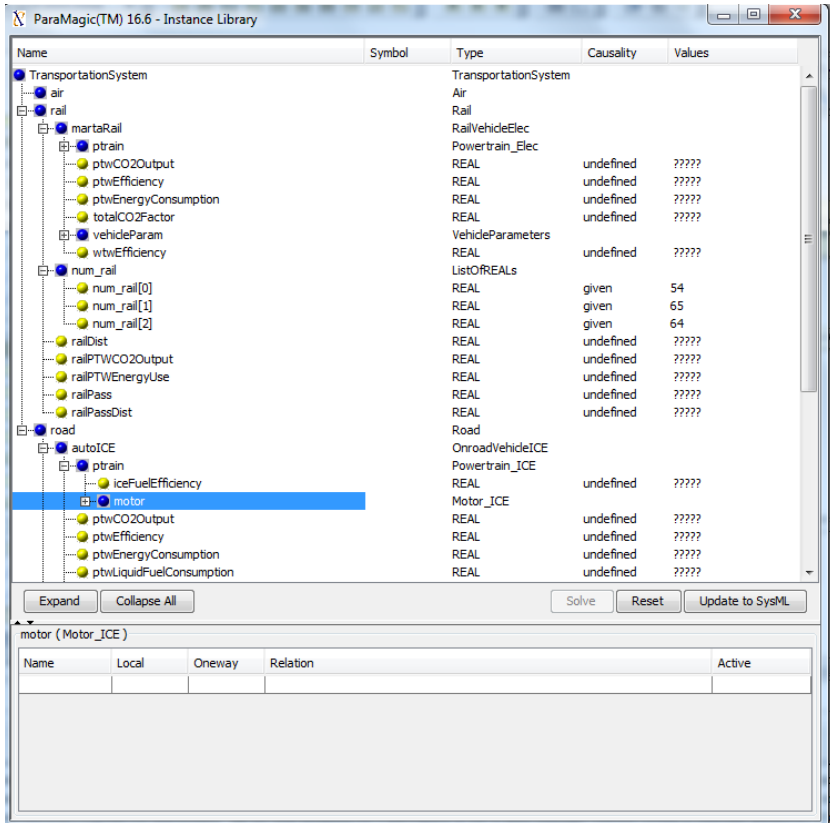

Figure 20: ParaMagic browser showing SysML transportation system model parametrics

Instance values have a causality assigned to them, which signifies whether the ParaMagic solver should treat them as given inputs, ancillary calculation results, or targets of the analysis. When all causality has been properly assigned, the user can choose to solve for designated targets. ParaMagic accomplishes the actual solving by parsing SysML data into a single system of symbolic equations, and passing these equations to Mathematica software by Wolfram Inc., which acts as the actual solution engine.

The ParaMagic plugin offers good integration with the MagicDraw SysML plugin, but is still under heavy development, and hence suffers from a number of maturity issues. It can only handle a subset of Mathematica compatible equation syntax, and can only handle certain types of nested structures, vector and matrix operations, and other structural features. Although development is continuing rapidly, initial analysis results from ParaMagic were mixed, and included a great deal of additional effort tracking down and repairing compatibility problems between the model structure and ParaMagic functionality.

4.4.2 **External Solver Using MATLAB**

To attempt to address difficulties with ParaMagic, an alternate execution method was investigated that relied on the MATLAB programming environment and Java scripting. A custom MATLAB program using Java XML parsing classes was written to read SysML parametric information, then parse instance input values from designated sources using Microsoft Excel spreadsheets. The parametrics are solved within MATLAB and stored as a repeatable symbolic solution, and results are passed back to designated worksheets within Excel for easy formatting and external display, and also to the relevant target instance values within SysML.

The decision to develop a custom MATLAB script to execute SysML parametrics involves several relevant pros and cons. First, using a custom analysis solution eliminates some of the interoperability advantages of SysML modeling. Unless the developer chooses a well-planned, widely inclusive parsing schema, the script may have to be modified to accept certain input sources or modeling elements if they are not included from the beginning. The sheer variety of possible domains and parametric techniques available to SysML modelers means that a single tool is unlikely to encompass them all. This applies to all execution tools; ParaMagic included, and is not unique to a custom executable. However, commercial or open source tools are more likely to include significant collaboration from others knowledgeable in the field.

Computer science is not a particular focus of this author's expertise, and so while others were consulted on how to best construct an analysis tool, there are likely overlooked practices that could improve the current implementation.

Benefits of developing a custom tool include a more integrated end to end package. The MagicDraw/ParaMagic combination, while commercially supported, is not yet mature enough to provide a stable platform for complex model development. A modeler may spend hours finding a workaround for a specific execution or validation problem, only to find that their original method is allowable in the latest software release. End users of a model and associated analysis may be frustrated by lack of functionality or a lack of configuration options. Developing a custom set of scripts means that desired functionality can be included from the beginning, and analysis evaluation for an end user proceeds in a consistent and stable manner.

The overall modeling framework using this method assumes a form demonstrated in Figure 21. Data flow occurs first between stakeholders and modelers when defining system requirements. Requirements are next used to develop formal specification of system behavior, structure, and the resulting parametrics for determining performance as well as simulating desired metrics. In an existing urban transportation system, the general requirements, structure, and behavior of the system is often already specified, although these viewpoints and system objectives may evolve over time.

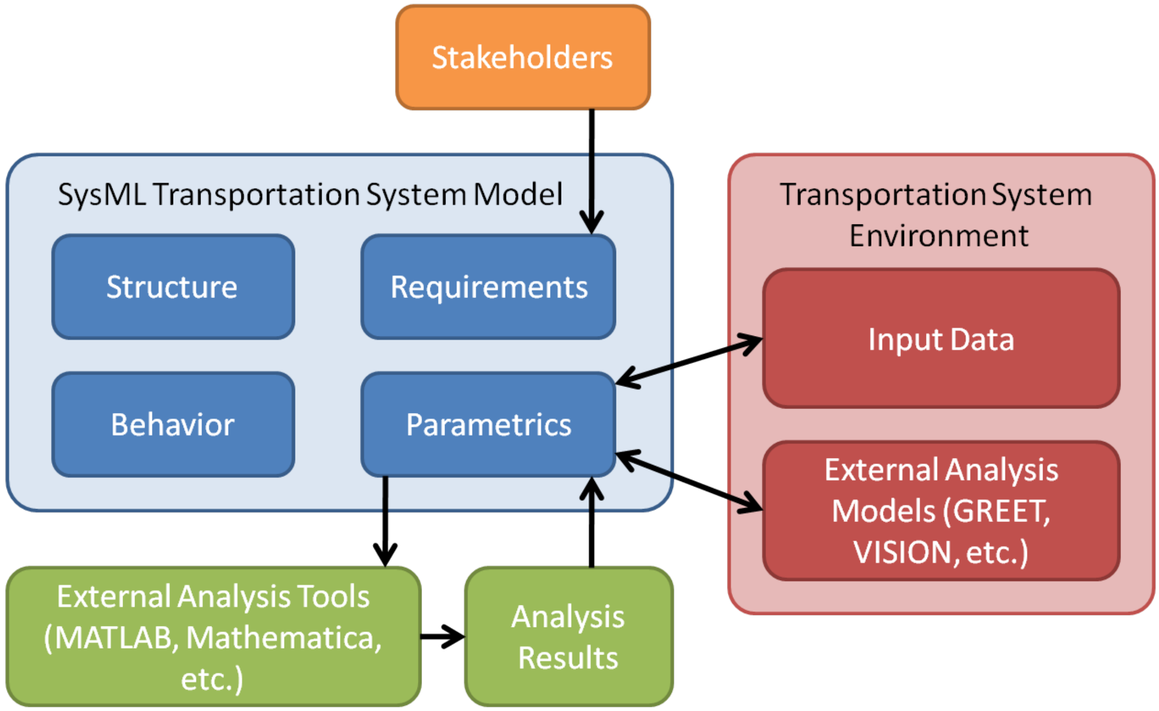

Figure 21: Overview of SysML modeling framework using external analysis tools

Once modeled in SysML, the transportation system model is linked to relevant environment variables, which may include input data necessary to populate SysML instance specifications directly, or applicable external models which do not deal directly with the transportation system itself, but serve to expand the system domain and increase subsequent analysis accuracy. External tools are used to execute the SysML model parametrics (and linked external models simultaneously, if necessary) using specified instance data, then provide analysis results to populate target properties within the SysML instance. These results can be exported either from SysML or from the analysis tool directly into other forms that are convenient for data visualization, optimization, or further analysis.

CHAPTER 5

SCENARIO EVALUATION: ATLANTA CASE STUDY

5.1. Description

5.1.1 Goal

This chapter aims to provide insight into using a created SysML transportation network model to evaluate specific design alternatives and potential future scenarios within a regional system. Several scenarios will be evaluated. Evaluation will occur from a modeling perspective to determine model ease of use and accuracy, and from an environmental design perspective to determine impact and sustainability of the scenarios under consideration.

5.1.2 Scope

The SysML model is used to create an instance specification and fuel pathway LCI results of the Atlanta, GA metropolitan area, shown in Figure 22. With a large population of approximately 5.3 million (U.S. Census Bureau, Population Division 2008), the City of Atlanta provides an interesting boundary for the problem domain. The region supports many commuters, most of whom live in areas of low population density. Urban sprawl contributes to heavy reliance on the road system. Air quality, traffic congestion, and sustainability are major issues that the city is attempting to address (Chapman and Frank 2004).

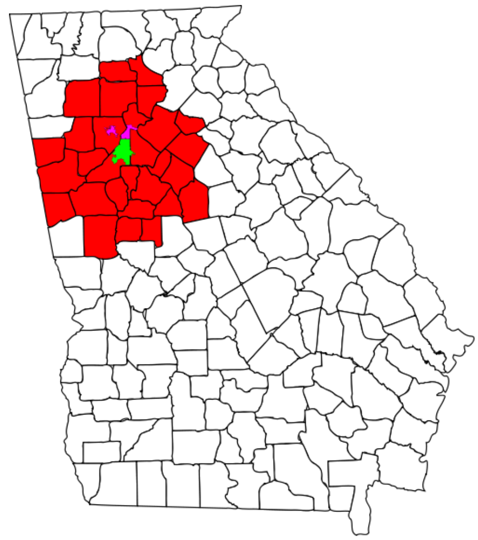

Figure 22: The Atlanta metropolitan area

Inputs to the model include common vehicle types used within the network, their number, and use parameters. Use parameters include metrics describing distance per trip, average occupancy, and average efficiency. Outputs include overall energy use, overall carbon dioxide output, energy use and CO2 output by vehicle type and mode, as well as energy use and CO2 output per unit of passenger distance for each of the three previous categories.

Several sets of input data are examined to determine the utility of using the SysML model to evaluate design and policy alternatives. First, a base case scenario is evaluated. This scenario reflects current conditions in Atlanta (as of 2009). It is compared to known energy use and emissions data to assess the accuracy of the model. Next, several potential future scenarios are modeled, to demonstrate model reuse and assess ease of analysis iteration. A "business as usual" scenario for 2025 is evaluated using current growth rates for population, vehicle travel, and vehicle market share. The 2025 base case is compared to an alternative scenario using assumptions of increased use of renewable energy and hybrid vehicles. These assumptions are designed to reflect conditions similar to the goals laid out in the current U.S. Presidential Administration's "New Energy for America" plan, which identifies a number of policy objectives aimed at increasing energy independence and reducing overall energy use and greenhouse gas emissions. While not a complete evaluation of design alternatives, the two scenarios are designed to evaluate ease of comparison using the SysML model and associated analysis results.

5.2. Inputs

5.2.1 Fuel Pathways

Fuel pathways for the Atlanta system are assumed to use U.S. national averages, taken from the GREET model as described previously. Unlike electricity, petroleum-based fuels used within a region are not necessarily likely to be supplied by geographically nearby entities. Extraction, refinement, and processing occurs far offsite, and thus using data specific to Atlanta or the State of Georgia is inappropriate for such calculations.

5.2.2 Vehicle Types

Most large U.S. cities have a central agency that provides the majority of public transit within the metro region. In Atlanta, the Metropolitan Atlanta Regional Transportation Authority (MARTA) coordinates public transit within the city limits and in Fulton and Dekalb counties. Although other counties within the metro area are served by various independent commuter bus providers, MARTA ridership greatly outweighs the contribution of any other provider in the region. Because of this, heavy-duty vehicles operated by MARTA have been modeled explicitly. These include two types of compressed natural gas buses (Chandler et al. 1999), a low emissions diesel bus, and the three types of heavy rail cars currently in use in the city (Metropolitan Atlanta Rapid Transit Authority 2007; Federal Transit Administration 2007; Ansaldobreda 2007; Dawson 2008). Fuel efficiency for these transit vehicles has been taken from the sources cited about. For transportation providers with lower vehicle usage within metro area limits, such as the Georgia Regional Transit Authority (GRTA), inputs for average fleet vehicles are used (Davis et al. 2008). In the current model iteration, smaller transit providers are grouped together, while MARTA exists as separately calculated instances within each vehicle type.

Table 3 lists input data for the analyzed vehicle types within the Atlanta case study. Fuel efficiencies for private vehicles are assumed to be that of the national fleet average, and are taken from the GREET model (M. Q Wang 2001).

Table 3: Vehicle mode statistics for the Atlanta area, 2010 base case

Vehicle Type	# in Operation, Peak (units)	Capacity (persons)	Avg. Occupancy (persons)	Daily Unit Distance (km)
Avg. Diesel Bus	1948	84	8.8	60.9
MARTA CNG Bus	385	84	8.8	237.5
MARTA Clean Diesel Bus	136	84	8.8	237.5
MARTA Heavy Rail	182	262	21.8	655.7
SI CG/RFG Automobile	766358	5	1.2	57
EV Automobile	8	5	1.2	57
E85 FFV Automobile	87081	5	1.2	57
DI CD/LSD Automobile	29477	5	1.2	57
SI CNG Automobile	195	5	1.2	57
SI HEV Automobile	32375	5	1.2	57
Diesel HEV Automobile	47	5	1.2	57
SI PHEV Automobile	0	5	1.2	57
Diesel PHEV Automobile	0	5	1.2	57
Gaseous H_2 FC Automobile	0	5	1.2	57
Bicycle	3315	1	1	5
Walking	35321	1	1	3

5.2.3 **System Constraints**

The number of commuters in Atlanta and their chosen modes of transportation provide an estimate of overall system capacity (American Community Survey: 2008), under the assumption that workdays represent the busiest periods for the transportation system. MARTA ridership data strongly supports this assumption (Federal Transit Administration 2007). Overall, the Atlanta mobility network experiences approximately three million users and over 57 million vehicle kilometers per day, most of these accounted for by single-occupant or low-occupancy vehicles (American Community Survey: 2008; Georgia Department of Transportation 2007a, b).

5.2.4 **Environment**

Power generation was calculated using data from the Emissions & Generation Resource Integrated Database (eGRID), developed by the EPA. EGRID is a tabulated record of every major electricity producer in the United States at the time of last release (currently incorporating up to year 2005 data). This record was used to sum power production and emissions totals to determine average CO_2 output. Primary fuel type of each plant is accounted to provide a snapshot of the power generation mixture by state or region. Since the model calculates emissions based on transportation energy usage and not on total current production, varying production totals in a given year does not have a significant effect on results. However, recent construction of a new major power plant in a given region could skew the profile distribution. The distribution of generation fuels for the state of Georgia is shown in Table 4, and provided inputs for the initial Atlanta analysis.

Table 4: Power generation by primary fuel source in Georgia

Fuel Type	Total Annual Generation (MWh)	% of Profile
Coal	87235509	63.9%
Nuclear	31534259	23.1%
Oil	1006253	0.7%
Gas	9773531	7.2%
Hydro	3820290	2.8%
Biomass	3196376	2.3%
Other Fossil Fuels	51224	0.0%
Total	136617442	100.0%

Since regional power generation can have a large effect on these outputs, emissions output and efficiency factors are computed separately using emissions by generation method and power generation profiles for the U.S. average and the state of Georgia (Luna-Camara et al. 2009). These differences will be covered further in Section 5.3.

5.3. Results

5.3.1 Case 1: Base Case, 2010 Conditions

5.3.1.1 <u>Fuel Pathways</u>

Figure 23 and Figure 24 show calculation results for energy use and CO2 emissions by vehicle type in Atlanta, respectively. On a total well-to-wheel basis, every alternative light-duty pathway except E85 ethanol is more efficient per passenger-km than conventional gasoline. The majority of ethanol WTW energy use, about 55%, is expended in non use-phase processes, and is by far the least efficient well-to-pump pathway out of any combustion fuel. Other light-duty pathways, such as hybrid and plug-in hybrid vehicles, show significant energy savings (21-73%) over conventional ICEs. Interestingly, out of all primary public transit options in the Atlanta area, only heavy rail provides energy savings over light-duty choices, and it is the most efficient transit choice overall. Diesel buses come close to matching the efficiency of a standard automobile, but MARTA CNG buses are noticeably less efficient. At 1.29 MJ/passenger-km, rail uses 62% less total energy than an average gasoline car. Among private vehicles, gasoline and diesel PHEV automobiles are the two most efficient forms of travel in the Atlanta area, at 1.63 and 1.54 MJ expended for every passenger-kilometer traveled.

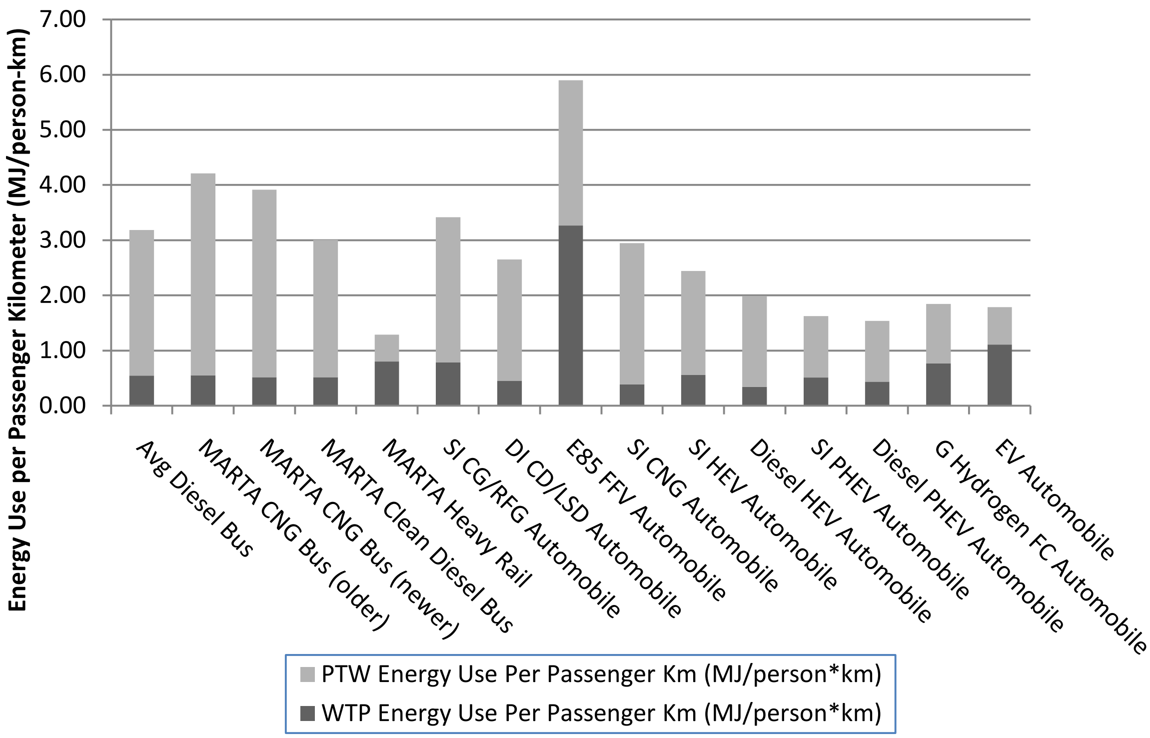

Figure 23: Energy use by vehicle type in Atlanta transportation network –2010 base case

The CO_2 output by vehicle type portrays a slightly different outcome. Again, both variations of PHEV top the list as having the least total CO_2 emissions, at 93.7 and 92.7 g/passenger-km. However, as opposed to the energy use calculations, CO_2 output from E85 ethanol is comparable with other automobile configurations, at approximately 140.9 g of CO_2 per passenger-km. Again, other than heavy rail, public transportation still gives no clear advantages over the alternatives. Compressed natural gas buses show slight (4-11%) improvement over a gasoline automobile, while diesel buses demonstrate slightly (8 and 14%) higher emissions in the same comparison. The large WTP contributions of electric energy pathways stand out, although all have fewer emissions than standard gasoline. Public rail emits 109.1 g/passenger-km, a 51% decrease vs. base case gasoline automobiles.

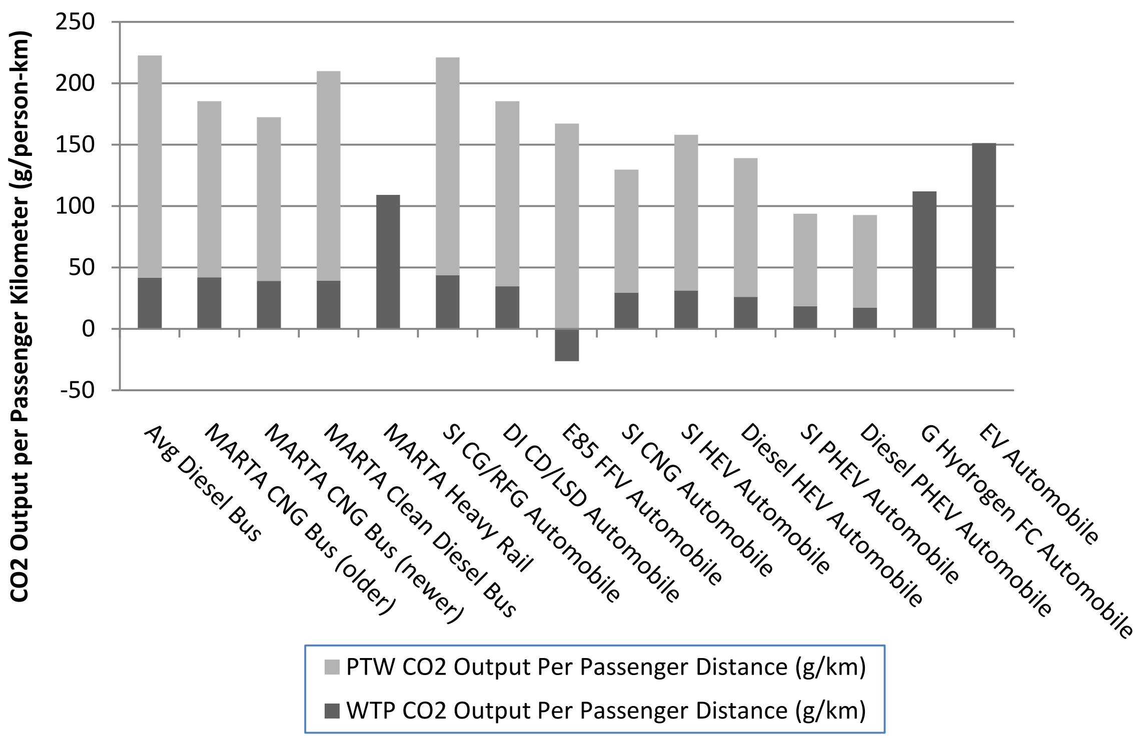

Figure 24: CO_2 output by vehicle type in Atlanta transportation network –2010 base case

5.3.1.2 System Statistics

Table 5: Distance and passenger distance traveled in Atlanta network by vehicle mode – 2010 base case

Vehicle Type	Vehicle Distance (km/day)	% of Total	Vehicle Passenger Distance (p-km/day)	% of Total
Light-duty road	52185894	99.08%	62623073	92.78%
MARTA	243738	0.46%	3704890	5.49%
(MARTA Bus)	(123738)	(0.19%)	(1088890)	(1.61%)
(MARTA Rail)	(120000)	(0.15%)	(2616000)	(3.88%)
Other public transit	118741	0.23%	1044924	1.55%
Pedestrian	105963	0.20%	105963	0.16%
Bicycle	16575	0.03%	16575	0.02%
Total Atlanta System	**52670911**	**100.00%**	**67495424**	**100.00%**

Table 5 shows model results for daily vehicle distance and passenger traveled throughout the system. Light-duty road vehicles represent the vast majority of traffic within the Atlanta mobility network, accounting for over 99% of all vehicle kilometers traveled. MARTA vehicles capture around 0.5% of daily vehicle distance, with buses and heavy rail each accounting for a similar share. All other modes capture less than a quarter of one percent of total system distance. However, public transportation, by nature of its higher average occupancy, accounts for a higher percentage of passenger distance. MARTA is responsible for 5.49% of all passenger-kilometers, about two thirds of that portion from rail travel.

Table 6: System-wide energy use and CO_2 output by vehicle type – 2010 base case

Vehicle Type	System WTW Energy Use (GJ/day)	% of Total	System WTW CO2 Output (kg/day)	% of Total
Light-duty road	224414	95.39%	13188567	94.81%
MARTA	7487	3.18%	488550	3.51%
(MARTA Bus)	(4109)	(1.7%)	(202955)	(1.5%)
(MARTA Rail)	(3377)	(1.4%)	(285594)	(2.1%)
Other public transit	3327	1.41%	232577	1.67%
Pedestrian	35	0.01%	624	0.00%
Bicycle	2	0.00%	49	0.00%
Total Atlanta System	**235265**	**100.00%**	**13910366**	**100.00%**

Examining energy use across the entire transportation system reveals that light-duty vehicles use slightly higher amounts of energy and have a higher carbon footprint in comparison to public transport for the amount of people they move, accounting for 95% of energy use and total CO_2 despite their lower percentage of passenger distance. However, the overall proportional differences are small. This is not surprising considering the similar efficiency of standard automobiles when compared to most public transit in the Atlanta region. Although public transit vehicles have the potential for much higher efficiency, low average occupancy rates lead to higher energy expenditures per passenger mile versus private vehicles.

5.3.2 Case 2: Base Case, 2025 Conditions

Table 7 shows modified vehicle input data to reflect a base case scenario in the year 2025. Vehicle demand is predicted to increase based on population increases. The Atlanta metro area population is assumed to have a 1.6% compound annual growth rate (CAGR), based on census data and analysis from the Atlanta Regional Commission (ARC) (U.S. Census Bureau, Population Division 2008). This CAGR is lower than in previous decades, primarily due to economic recession and declines in the housing market. Even with such assumptions, Atlanta remains one of the fastest growing urban regions in the United States.

Table 7: Vehicle mode statistics for the Atlanta area - 2025 base case

Vehicle Type	# in Operation, Peak (units)	Capacity (persons)	Avg. Occupancy (persons)	Daily Unit Distance (km)	Energy Efficiency (MJ/km)
Avg. Diesel Bus	2468	84	10	61	23.20
MARTA CNG Bus	486	84	10	238	32.17
MARTA Clean Diesel Bus	172	84	10	238	29.91
MARTA Heavy Rail	182	262	27	656	10.70
SI CG/RFG Automobile	643819	5	1.2	68.4	2.94
EV Automobile	1829	5	1.2	68.4	0.81
E85 FFV Automobile	160881	5	1.2	68.4	2.94
DI CD/LSD Automobile	146010	5	1.2	68.4	2.45
SI CNG Automobile	707	5	1.2	68.4	3.10
SI HEV Automobile	191396	5	1.2	68.4	2.10
Diesel HEV Automobile	299	5	1.2	68.4	1.84
SI PHEV Automobile	20042	5	1.2	68.4	1.15
Diesel PHEV Automobile	0	5	1.2	68.4	1.11
Gaseous H_2 FC Automobile	517	5	1.2	68.4	1.28
Bicycle	4205	1	1	5	0.12
Walking	44799	1	1	3	0.33

Daily unit distance traveled for public transit vehicles remains constant in comparison to the 2010 base case, assuming that any expansion in system service frequencies or geographic availability has been handled by additional vehicles. Automobile daily travel distance has increased by 20%, from 57 km/day to 68.4 km/day. This is a key assumption, implying that travelers are making longer or more frequent trips. While trip frequency may stay relatively constant under a variety of input conditions, increasing trip length implies that population growth by geographic location has not reflected existing population density, i.e. the region has experienced significant sprawl or suburbanization. Atlanta has been identified as having one of the highest rates of urban sprawl in the country. Although efforts have been made to reduce rapid land use and geographic expansion, it is reasonable to assume that this will continue to some extent in the next 15 years (Yang and Lo 2003).

Occupancy rates for public transit vehicles have increased to reflect higher area population and subsequent increased demand. Automobile occupancy is assumed to remain constant, in the absence of statistically significant behavior modification by the local population. Significant changes in transportation costs such as rising fuel prices, congestion pricing, or other transportation policy measures could alter this input assumption.

Fuel economy has been altered based on output from the 2009 VISION model, which predicts changes in powertrain energy efficiency based on technological improvements. Also, since the SysML analysis model links to GREET, GREET outputs for the year 2025 are used to obtain WTP fuel data for the new scenario.

5.3.2.1 Fuel Pathways

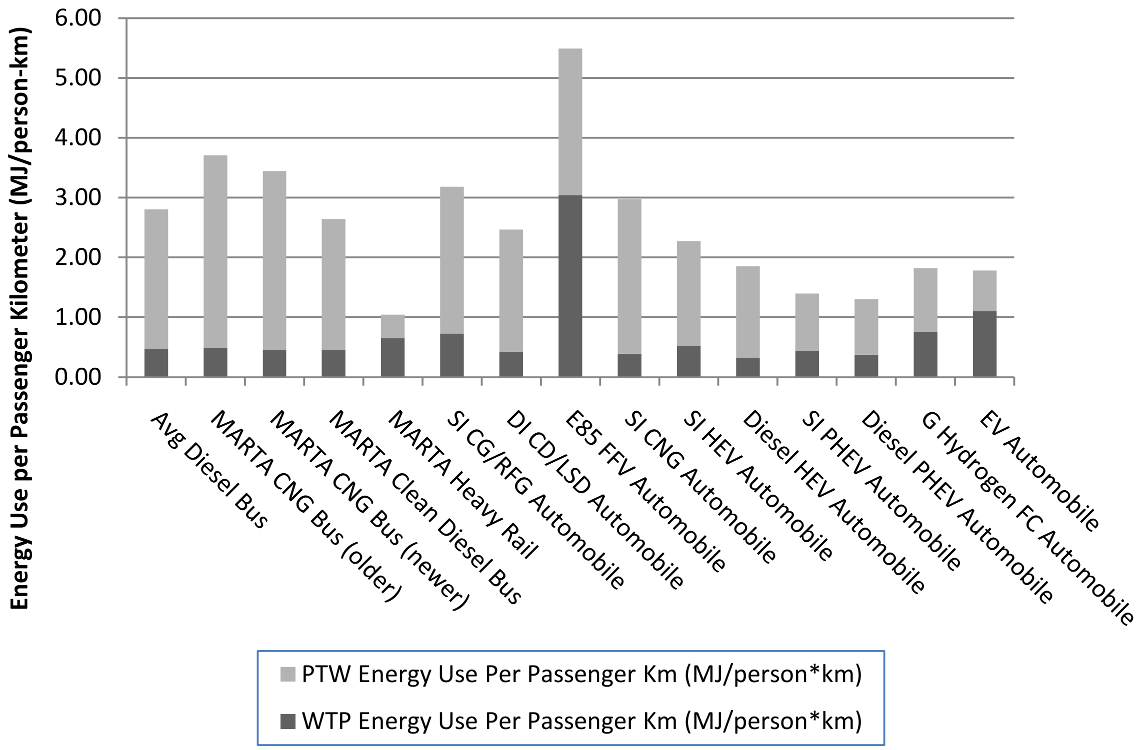

Figure 25: Energy use by vehicle type in Atlanta transportation network – 2025 base case

Figure 25 shows results by vehicle type for the revised set of inputs in the 2025 base case. Under the given input assumptions, fuel pathways do not change significantly vs. the 2010 scenario. PTW efficiency across all vehicles has increased slightly, although this is somewhat offset by higher WTP energy costs due to resource scarcity. Public transit fuel pathways exhibit noticeably lower energy consumption in comparison to the 2010 case, approximately 26% for heavy rail and 12% for buses. The decrease is due to increased demand and higher average occupancy rates.

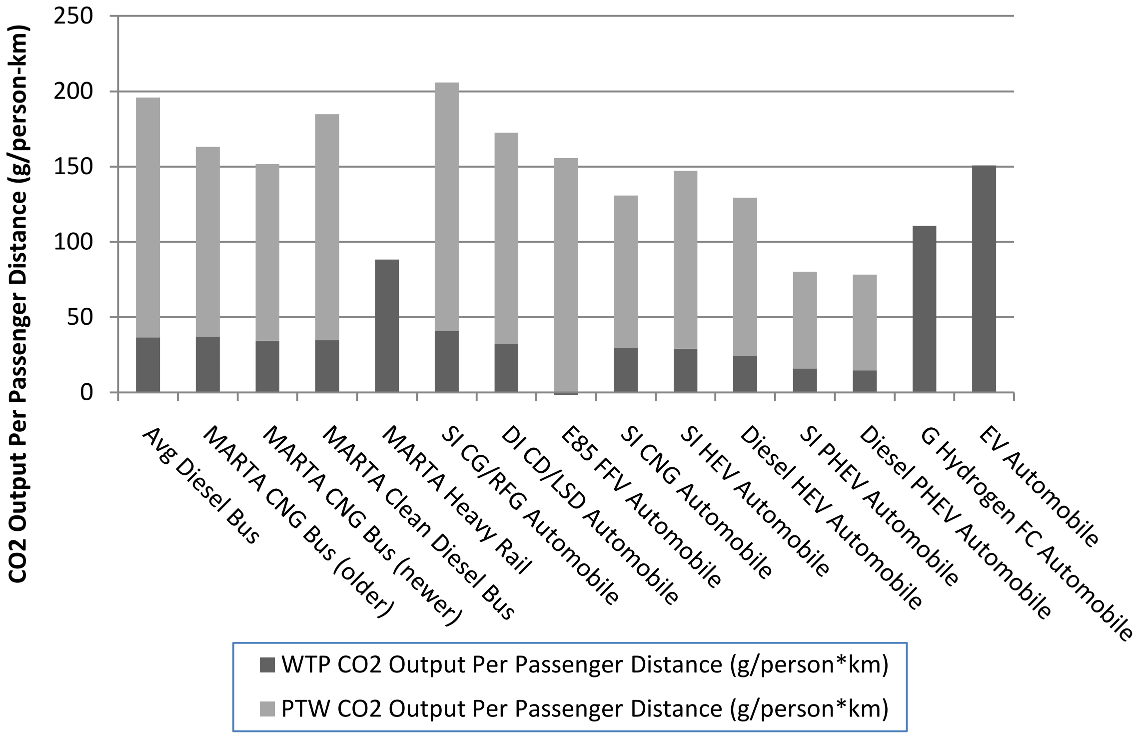

Figure 26: CO_2 output by vehicle type in Atlanta transportation network – 2025 base case

Figure 26 shows CO_2 output calculation results from the new scenario. Results and trends show similar changes as the energy use calculations when compared to the 2010 base case.

5.3.2.2 System Statistics

Table 8: Distance and passenger distance traveled in Atlanta network by vehicle mode – 2025 base case

Vehicle Type	Vehicle Distance (km/day)	% of Total	Vehicle Passenger Distance (p-km/day)	% of Total
Light-duty road	79720200	99.32%	95664240	93.70%
MARTA	276275.00	0.34%	4802750	4.70%
(MARTA Bus)	(156275)	(0.19%)	(1562750)	(1.53%)
(MARTA Rail)	(120000)	(0.15%)	(3240000)	(3.17%)
Other public transit	150438.17	0.19%	1504381.74	1.47%
Pedestrian	105963	0.13%	105963	0.10%
Bicycle	16575	0.02%	16575	0.02%
Total Atlanta System	**80269451**	**100.00%**	**102093910**	**100.00%**

Table 8 shows system level analysis results for vehicle and passenger distance traveled, organized by mode and vehicle type. Within the public transit sector, the proportion of transit passenger distance in relation to the Atlanta transportation system has gone down. However, the percentage of bus transit has gone up in relation to public transit as a whole, from 36% of all transit passenger distance in 2010 to 42% in 2025. The primary factor for this shift is assumed system capacity and service levels. Bus and rail ridership both increase due to rising trip demand. However, while buses have been added to the system to keep pace with population growth, no increase in rail infrastructure has been assumed. This may change, particularly due to several development plans such as the Atlanta Beltline project (Garvin 2006). Such changes in fixed transit infrastructure would affect the available transit service and subsequent proportions of transit mode choice within the metro area.

Table 9: System-wide energy use and CO_2 output by vehicle type – 2025 base case

Vehicle Type	System WTW Energy Use (GJ/day)	% of Total	System WTW CO2 Output (kg/day)	% of Total
Light-duty road	308712	96.01%	17161756	95.35%
MARTA	8557	2.66%	541826	3.01%
(MARTA Bus)	(5173)	(1.61%)	(255687)	(1.42%)
(MARTA Rail)	(3384)	(1.05%)	(286139)	(1.59%)
Other public transit	4213	1.31%	294691	1.64%
Bicycle	3	0.00%	62	0.00%
Pedestrian	44	0.01%	791	0.00%
Total Atlanta System	**321529**	**100.00%**	**17999126**	**100.00%**

Table 9 demonstrates system energy use and CO_2 calculations from the analysis model with year 2025 inputs. The effects of increased population, trip distance, and transportation demand are immediately apparent. Overall system energy use increases by 36.6%, from 235,265 GJ/day to 321,529 GJ/day. CO_2 output also increases from 13.9 million kg to 18.0 million kg per day, or 29.5%. Light-duty road vehicles are the primary source of these increases. This suggests that under the baseline conditions and given assumptions, continuing sprawl and increasing population will lead to further reliance on personal motorized transport. Self-propelled transportation, including bicycles and pedestrian traffic, also increase, but their effect is negligible on system energy use and emissions impact.

5.3.3 **Case 3: Alternative Technology Pathways, 2025 Conditions**

Next, a third case was examined to evaluate the Atlanta transportation system under a set of alternate, more environmentally sustainable conditions for the year 2025. Population growth estimates remain the same, as do density, land-use, and trip length assumptions that are included in the model.

Input values for vehicle choice among the private sector are changed significantly. Market share assumptions used in the VISION model inputs are modified to reflect national transportation policy that encourages adoption of alternative vehicle powertrains, particularly PHEV and fully electric (EV) automobiles. Using the U.S. government's stated goal of 1 million PHEVs and EVs on U.S. roads by 2015, the sales and overall ownership percentages needed to reach this target were extrapolated to 2025 using the VISION model. Average ownership percentage of each vehicle type was then applied to the existing Atlanta transportation demand to result in new vehicle type percentages throughout the Atlanta system.

Although vehicle market share conditions in Atlanta may not match national averages, the input assumptions serve as a reasonable approximation of a future scenario where aggressive vehicle electrification policies have been adopted and enforced. These policies may be enacted in a number of different ways, whether through higher petroleum based fuel taxes and other negative reinforcements, or electric vehicle tax incentives and various positive measures. The resulting vehicle choice inputs are shown in Table 10 below.

Table 10: Vehicle mode statistics for the Atlanta area - 2025 alternative scenario

Vehicle Type	# in Operation, Peak (units)	Capacity (persons)	Avg. Occupancy (persons)	Daily Unit Distance (km)	Energy Efficiency (MJ/km)
Avg. Diesel Bus	2468	84	10	60.9	23.20
MARTA CNG Bus	486	84	10	237.5	32.17
MARTA Clean Diesel Bus	172	84	10	237.5	29.91
MARTA Heavy Rail	182	262	27	655.7	10.70
SI CG/RFG LV	602489	5	1.2	68.4	2.94
EV LV	8321	5	1.2	68.4	0.81
E85 FFV LV	160881	5	1.2	68.4	2.94
DI CD/LSD LV	146010	5	1.2	68.4	2.45
SI CNG LV	707	5	1.2	68.4	3.10
SI HEV LV	191396	5	1.2	68.4	2.10
Diesel HEV LV	299	5	1.2	68.4	1.84
SI PHEV LV	54881	5	1.2	68.4	1.15
Diesel PHEV LV	0	5	1.2	68.4	1.11
Gaseous H_2 FC LV	517	5	1.2	68.4	1.28
Bicycle	4205	1	1	5	0.12
Walking	44799	1	1	3	0.33

When compared to the 2025 base case, PHEV and EV units in operation have increased significantly, at the expense of traditional petroleum pathways such as conventional gasoline and diesel-powered vehicles. In terms of percentages, Case 3 assumes that 6% of automobiles and 3% of light trucks within the Atlanta area are PHEVs, as well as 0.8% and 0.6% EV ownership for the same categories. This is a significant increase from Case 2, where PHEVs constitute only 3% of automobiles and 0.01% of light truck ownership, and EVs make up only 0.2% and 0.1% of the two vehicle types.

Note that only private vehicle mode choice has been modified, while transit mode share stays the same as in the 2025 base case. In reality, policy measures designed to encourage alternative technology adoption may also affect general transportation mode choice, particularly in low income population segments where upgrading their vehicle or purchasing a new vehicle is not an option. However, predicting mode choice based on economic factors involves detailed choice modeling and analysis that has not yet been implemented into the existing framework, and therefore it will not be included here. The addition of further choice-based trip modeling capacity is discussed in Section 6.3 as a promising area of future work.

5.3.3.1 Fuel Pathways

Since only vehicle ownership shares have been modified from Case 2 to Case 3, the analysis results for fuel pathways remain the same. Refer to Figure 25 and Figure 26 for WTP energy use and CO_2 output for various fuel pathways used in the Case 3 analysis.

5.3.3.2 System Statistics

Table 11 contains analysis results for vehicle and passenger distance of the Atlanta system for the 2025 alternative scenario. As stated previously, the input assumptions for this case do not assume changes in travel demand or mode choice, and thus the VKT and PKT for each mode type remain the same as in Case 2.

Table 11: Distance and passenger distance traveled in Atlanta network by vehicle mode – 2025 alternative scenario

Vehicle Type	Vehicle Distance (km/day)	% of Total	Vehicle Passenger Distance (p-km/day)	% of Total
Light-duty road	79720200	99.28%	95664240	93.67%
MARTA	276275.00	0.34%	4802750	4.70%
(MARTA Bus)	(156275)	(0.19%)	(1562750)	(1.53%)
(MARTA Rail)	(120000)	(0.15%)	(3240000)	(3.17%)
Other public transit	150438	0.19%	1504382	1.47%
Pedestrian	134397	0.17%	134397	0.13%
Bicycle	21025	0.03%	21025	0.02%
Total Atlanta System	**80302335**	**100.00%**	**102126794**	**100.00%**

Moving to energy use and CO_2 output, the results portray only a slightly modified environmental picture despite aggressive market share assumptions. System energy use has dropped by approximately 1.8%, from 321,529 to 315,684 GJ per day. CO_2 output drops 2.3%, from 18.0 million to 17.6 million kg per day.

Table 12: System-wide energy use and CO2 output by vehicle type – 2025 alternative scenario

Vehicle Type	System WTW Energy Use (GJ/day)	% of Total	System WTW CO2 Output (kg/day)	% of Total
Light-duty road	302867	95.94%	16772807	95.24%
MARTA	8557	2.71%	541826	3.08%
(MARTA Bus)	(5173)	(1.6%)	(255687)	(1.5%)
(MARTA Rail)	(3384)	(1.1%)	(286139)	(1.6%)
Other public transit	4213	1.33%	294691	1.67%
Bicycle	3	0.00%	62	0.00%
Pedestrian	44	0.01%	791	0.00%
Total Atlanta System	**315684**	**100.00%**	**17610177**	**100.00%**

Compared to the 2010 base case, the calculated alternative 2025 figures still represent large increases in both energy use and emissions. Energy use by the Atlanta system is up by 34% over 2010 conditions. CO_2 output has climbed by 27%. These numbers suggest that aggressive adoption policies for alternative vehicle technology are not enough to offset rising mobility demand.

5.3.4 **Case 4 – Sensitivity Analysis, Electricity Generation**

As stated in previous case studies, vehicles reliant on electricity for their primary PTW energy source exhibit large WTW energy use and emissions when compared to other energy pathways. To examine the effects that electricity generation has on the characteristics of each transportation mode, the WTW calculations were repeated using alternate input data for electricity generation. Since Georgia is heavily reliant on coal and petroleum as primary generation fuel sources, generation characteristics from Washington State were used to provide a significant contrast. Washington produces 71% of its electricity using hydroelectric sources, so the choice is a good hypothetical scenario to simulate conditions in a city of Atlanta's size with increased (but realistic) access to "renewable" energy. For the purposes of these calculations, renewable energy sources such as wind, water and solar are assumed to be 100% efficient, since any energy within spent fuel that is not captured is not "wasted" in the same sense that combustion of fossil fuels lead to unrecoverable thermal energy. Also, the use of these fuels produces no emissions during the generation phase, making it unnecessary to consider conversion efficiency. In practice, issues such as land use, plant lifecycles, and cost lead to efficiency concerns for every generation type, but such considerations are beyond the scope of the model in its current form. A graph of the power profile used for the new calculations is shown below.

Table 13: Power generation by primary fuel source in Washington State

Fuel Type	Total Annual Generation (MWh)	% of Profile
Coal	10506174	10.3%
Nuclear	8242273	8.1%
Oil	102038	0.1%
Gas	8581295	8.4%
Hydro	72080734	70.7%
Biomass	1586837	1.6%
Wind	498470	0.5%
Other	377765	0.4%
Total	101975587	100.0%

5.3.4.1 Fuel Pathways

Figure 27 and Figure 28 provide results of energy use and CO_2 emissions for each vehicle type using the new power generation input assumptions.

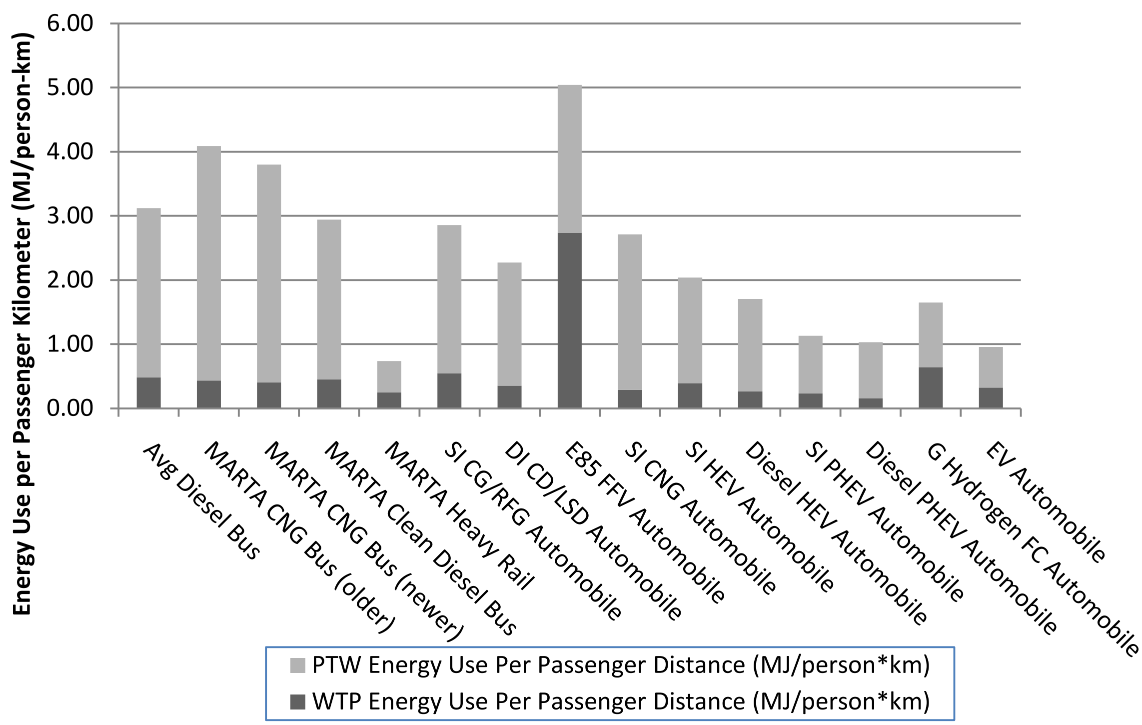

Figure 27: Energy use by vehicle type in Atlanta transportation network –2010, Washington State electricity generation

The differences are immediately apparent. Well-to-pump energy use drops slightly for every vehicle type considered, based on increased efficiency of fuel production processes that involve electricity. The largest changes are seen in vehicles that rely heavily on electricity during their use phase. MARTA heavy rail remains the most efficient way to get around Atlanta under these conditions, at 0.74 MJ/passenger-km. Perhaps most strikingly, battery powered electric automobiles move to the second most efficient spot, at 0.96 MJ/passenger-km.

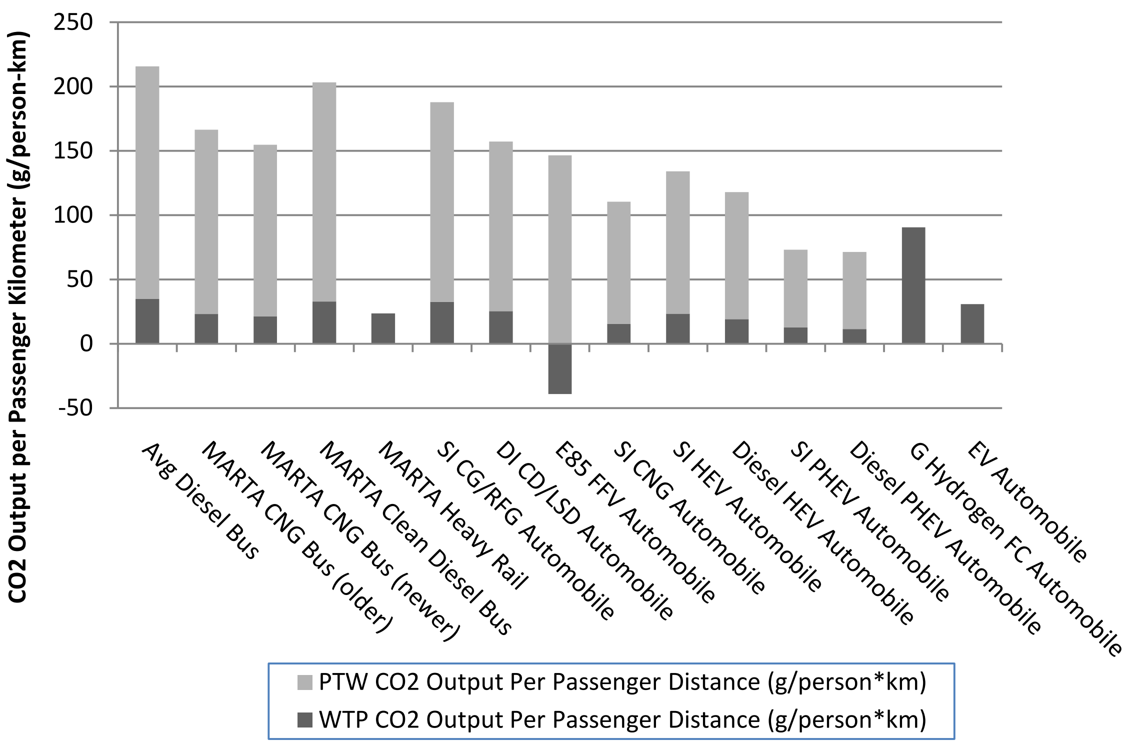

Figure 28: CO2 output by vehicle type in Atlanta transportation network –2010, Washington State electricity generation

CO_2 output calculations demonstrate similar changes, with electric vehicles showing marked improvements. The heavy emissions reductions from using hydroelectricity give rail and electric autos even larger advantages in terms of emissions than in energy consumption. Overall CO_2 output falls by at least a small amount for all vehicles, again due to changes in fuel lifecycle processes.

5.3.4.2 <u>System Statistics</u>

Table 14: System-wide energy use and CO_2 output by vehicle type – 2010, Washington State electricity generation

Vehicle Type	System WTW Energy Use (GJ/day)	% of Total	System WTW CO2 Output (kg/day)	% of Total
Light-duty road	207996	95.75%	12686929	89.56%
MARTA	5929	2.73%	258287	1.82%
(MARTA Bus)	(3997)	(1.8%)	(196317)	(1.4%)
(MARTA Rail)	(1932)	(0.9%)	(61970)	(0.4%)
Other public transit	3260	1.50%	206412	1.46%
Pedestrian	35	0.02%	624	0.00%
Bicycle	2	0.00%	49	0.00%
Total Atlanta System	**217222**	**100.00%**	**14166307**	**92.84%**

The improvements seen in vehicle WTW environmental metrics propagate predictably throughout the system. Since transit supply and demand assumptions have not changed, reductions in system-wide energy use and emissions are relatively linear with respect to changes in WTP performance of electric vehicles. A small amount of additional improvement is afforded by decreased energy consumption and emissions for fossil fuel extraction, processing, and transportation.

5.3.5 **Case 5 – Sensitivity Analysis, Vehicle Occupancy**

Another prominent characteristic of previous case studies was the poor overall performance of public transit vehicle types in comparison to private transportation within the Atlanta region. Public transit is designed to increase access and connectivity within a region at reduced cost to stakeholders, but normally has secondary objectives of reducing congestion, emissions, and overall resource use. Primary factors affecting the efficiency of public transit are trip length and vehicle occupancy. While trip length is difficult to effectively analyze without incorporating extremely complex GIS and ridership data, occupancy is an input variable that can be quickly analyzed using the SysML framework. Results were calculated using a range of average occupancy values for several types of typical system vehicles.

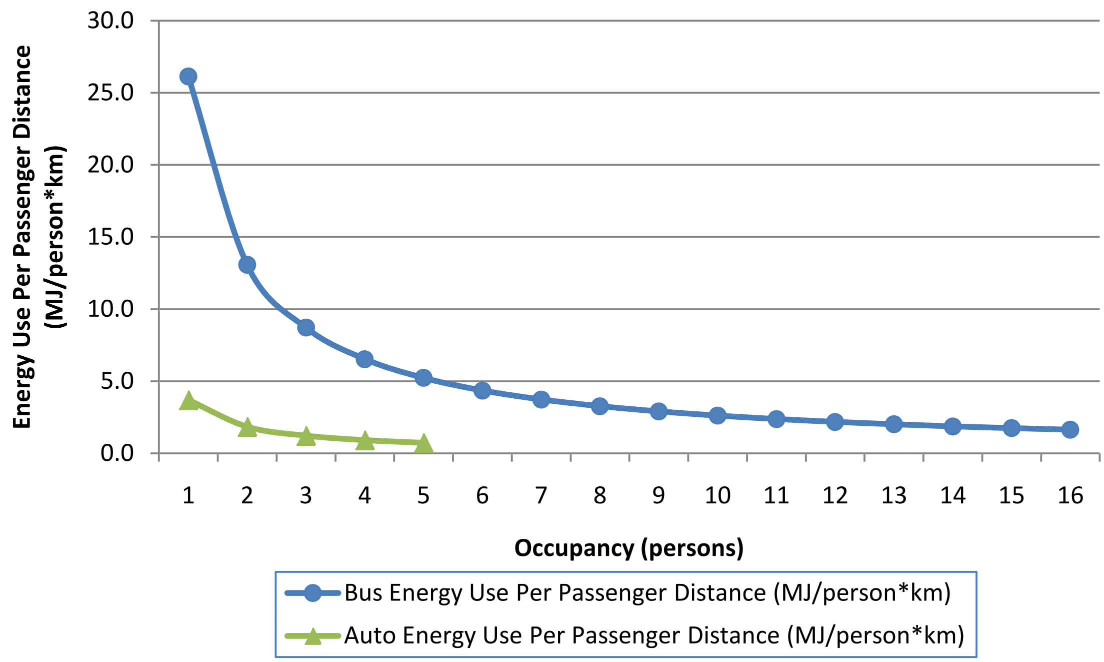

Figure 29: Energy use per passenger distance vs. average occupancy for a typical MARTA diesel bus and ICE automobile

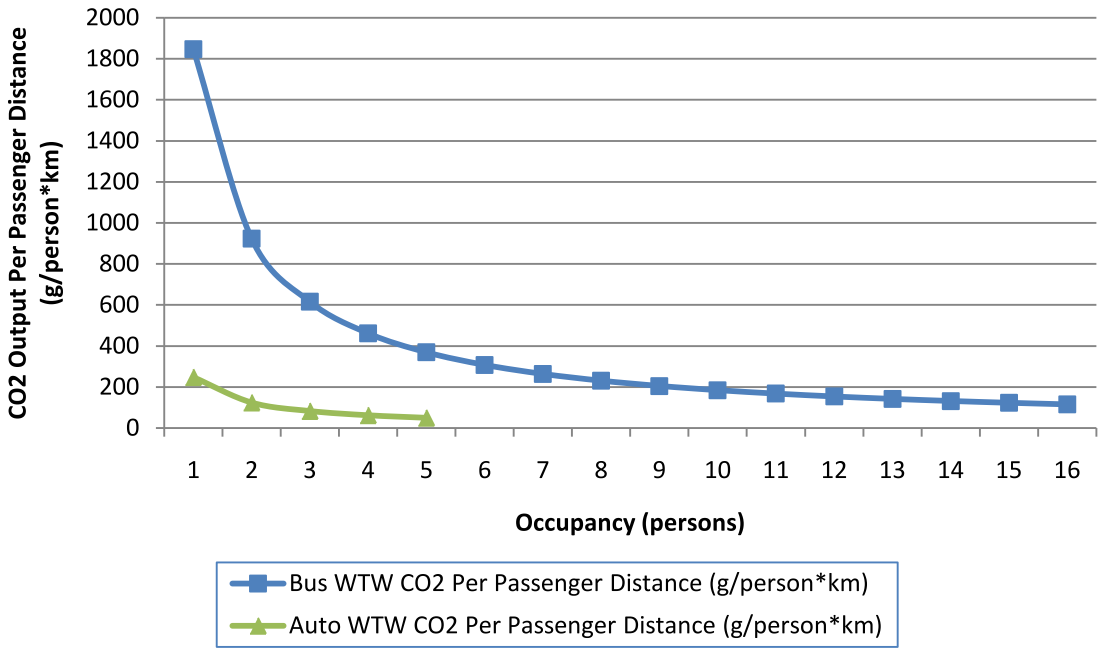

Figure 30: CO_2 output per passenger distance vs. average occupancy for a typical MARTA diesel bus and ICE automobile

Figure 29 and Figure 30 show the effects of occupancy on WTW results for a standard ICE automobile and a MARTA low-sulfur diesel bus. The amount of people each vehicle carries has a large effect on whether they are efficient transportation solutions. Although there are diminishing returns as occupancy rises, getting more people into each vehicle drastically increases transportation effectiveness, even when accounting for increased vehicle mass.

To evaluate the effectiveness of increased occupancy on the entire transportation system, an analysis was run using 10% higher average occupancies for each vehicle type. It is assumed that the current transit infrastructure remains the same, and therefore increased vehicle occupancy primarily affects automobile trips.

Table 15: System-wide vehicle distance and passenger distance - 2010 increased occupancy

Vehicle Type	Vehicle Distance (km/day)	% of Total	Vehicle Passenger Distance (p-km/day)	% of Total
Light-duty road	43836151	98.91%	48435073	90.06%
MARTA	243738	0.55%	4075379	7.58%
(MARTA Bus)	(123738)	(0.28%)	(1197779)	(2.23%)
(MARTA Rail)	(120000)	(0.27%)	(2877600)	(5.35%)
Other public transit	118741	0.27%	1149416	2.14%
Pedestrian	105963	0.24%	105963	0.20%
Bicycle	16575	0.04%	16575	0.03%
Total Atlanta System	**44321168**	**100.00%**	**53782406**	**100.00%**

In Table 15, the decrease in automobile VKT is clearly apparent, decreasing from 52.1 million to 43.8 million km/day, a 15.9% drop. Automobile passenger distance is down from 62.6 million to 48.4 million p-km/day, a difference of 22.6%.

Table 16: System-wide energy use and CO_2 output – 2010 increased occupancy

Vehicle Type	Systemwide WTW Energy Use (GJ/day)	% of Total	Systemwide WTW CO2 Output (kg/day)	% of Total
Light-duty road	192573	94.67%	11255587	93.97%
MARTA	7487	3.68%	488550	4.08%
(MARTA Bus)	(4109)	(2.0%)	(202955)	(1.7%)
(MARTA Rail)	(3377)	(1.7%)	(285594)	(2.4%)
Other public transit	3327	1.64%	232577	1.94%
Pedestrian	35	0.02%	624	0.01%
Bicycle	2	0.00%	49	0.00%
Total Atlanta System	**203424**	**100.00%**	**11977387**	**100.00%**

Occupancy also has a remarkable effect on system energy use and CO_2 output. System-wide WTW energy consumption drops by 13.5%, from 235,265 to 203,424 GJ/day. CO_2 output undergoes a similar decrease of 13.7%, from 13.9 million to 12.0 million kg/day.

5.4. Validation

5.4.1 Model Calibration and General Validation

In order to check the validity of the analysis results, the values obtained in the 2010 base case (Case 1) were checked for accuracy against several published figures concerning the Atlanta transportation system.

The analysis model predicts a system capacity of 2.953 million persons during peak travel demand, which is assumed to be during rush hour on weekdays. According to the 2008 American Communities Survey, peak demand is approximately 2.819 million persons, a difference of 4.7% over the actual figure. This is an acceptable error range, especially when growth is taken into account. The model has been calibrated to reflect current conditions, while the most recent available commuter data for the Atlanta metro region is from 2008. The metro area has seen 2.6% average annual growth since 2000, so current peak travel demand may actually be extremely close to the model's determined result (U.S. Census Bureau 2007).

Concerning vehicle distance traveled, the Georgia Department of Transportation reports average daily VMT for Fulton County to be 31.29 million miles, or 52.15 million kilometers (Georgia Department of Transportation 2007a). The model predicts daily VMT of 52.43 million kilometers, a difference of 0.43%. This is likely low for 2010 conditions, given the established growth rate in travel demand. However, it shows that the model is closely aligned to established data concerning the mobility network.

5.4.2 Validation of Specific Calculations and Data Sources

To ensure that all parametric elements of the model are performing adequately, it is necessary to provide examples of model calculations throughout the automated analysis process. The following paragraphs demonstrate a single calculation iteration for a single vehicle type, highlighting all equations used and all sources of data input.

For the purposes of this example, a MARTA heavy rail train car is highlighted, within the "Rail" subsystem of the top level "Transportation System" block. MARTA heavy rail trains are propelled by electric motors which receive their electricity via a third rail on the track.

MARTA currently has three types of married-pair rail cars in service: 118 CQ310 class cars, built by Société Franco-Belge, 120 CQ311 class cars, built by Hitachi, and 100 CQ312 class, built by AnsaldoBreda (Metropolitan Atlanta Rapid Transit Authority 2007). The CQ312 class cars are the newest to enter service (2001-2005), though the CQ310 and CQ311 units were rebuilt from 2006 to 2009 to allow them to meet modern specifications (Metropolitan Atlanta Rapid Transit Authority 2009). The three types of cars are modeled separately, but they are assumed to be broadly similar in terms of operating characteristics.

The AnsaldoBreda Atlanta Heavy Rail Vehicle (HRV) has a tare weight of 80,200 lbs (36,768 kg) and a maximum rated capacity of 262 persons. It operates on a nominal voltage of 750 VDC, and utilizes 2 AC traction motors per wheel truck for a 560 kW continuous power rating per car (Ansaldobreda 2007).

MARTA's 2007 annual operating report lists average weekday rail ridership of 230,000. MARTA trains travel 15,000 miles on average each weekday, with 72,000 car miles (an average of 4.8 cars per train) and 1,560,000 total passenger miles (Metropolitan Atlanta Rapid Transit Authority 2007). Dividing average passenger miles by average car miles traveled results in an average weekday occupancy of 21.6 riders per car. This number is used as default input for the SysML model. Although MARTA owns 338 rail vehicles in total, the 2007 National Transit Database (NTD) states that a maximum of 182 cars are operated simultaneously during peak service (Federal Transit Administration 2007). An estimate of daily VKT per rail vehicle is obtained by dividing this operating number by total daily vehicle kilometers, which results in 659.0 km/day. This is also used as a default SysML input.

Data from the 2007 NTD specifies that the MARTA heavy rail system consumes 1,983 BTU (2.09 MJ) per passenger mile (O'Toole 2008). Multiplying this figure by total passenger miles per day (1,560,000) results in $3.260*10^6$ MJ WTW daily energy consumption. Dividing total daily energy consumption by daily train car miles gives an estimate of train car WTW energy consumption per VMT (45.28 MJ/mi) which is then converted to energy consumption per VKT (28.13 MJ/km). Note that this is energy consumption per car assuming average occupancy. Since an average passenger of 177 lbs is only 0.22% of the Atlanta HRV's unloaded weight, it is assumed for the purposes of this case study that the additional energy needed to propel one additional passenger is negligible. Therefore, energy consumption is held constant across the range of occupancies tested in each scenario. However, for further accuracy, future work for the model should include modifications to account for the effects of changing vehicle weight, particularly if calculations are performed at the extremes of the potential occupancy range (either at capacity or completely unloaded).

For clarity, the model's calculations will be followed starting with the energy source and moving upwards in the model hierarchy, although during an actual analysis the equations are solved as a system except external model executions that must be performed first.

Beginning with the source energy, the model takes input on the mix of generation fuels used during electricity production from the U.S. EPA's eGRID database. The database aggregates plant specific data from the EPA, EIA, and Federal Energy Regulatory Commission (FERC) in order to compile a comprehensive listing of environmental attributes for U.S. electric power systems. The model assumes that the electricity consumed by system vehicles is produced within the local region, and therefore uses an aggregate mix of all regional power plants to determine net percentages of input fuels. This region is set as a model input. For the Atlanta case study, the State of Georgia is used as the input region. On execution, the model passes this region to a simple Excel spreadsheet which sums all Georgia powerplants in the eGRID database and divides the portion of each fuel type by total Georgia electricity generation. These values are seen within section 5.2.4, in Table 4. They are read into the SysML model as value properties of the Electricity instance specification. Since the most recent version of eGRID at the time of writing utilizes data from 2005, Georgia's generation profile may have changed since then. Rothschild et al. discuss eGRID, its development, and suggested usage in further detail (Rothschild et al. 2009).

The imported electricity profile is then passed from SysML into the attached GREET model as inputs into GREET's own electricity WTP calculations. The imported generation mix and GREET assumptions for combustion technology and power plant energy conversion efficiencies are shown in Table 17.

Table 17: GREET electricity generation mixes, combustion technology shares, and power plant energy conversion efficiencies

	Generation Mix for EVs, Grid-Connected PHEVs, and Electrolysis H2	Generation Mix for Stationary Applications	Combustion Technology Shares for A Given Plant Fuel Type: EVs, GC PHEVs, and Electrolysis	Combustion Technology Shares for A Given Plant Fuel Type (Stationary)	Power Plant Energy Conversion Efficiency (Transportation)	Power Plant Energy Conversion Efficiency (Stationary)	Urban Emission Share
Residual Oil-Fired Power Plants	0.7%	0.7%			34.8%	34.8%	39.0%
Utility boiler			100.0%	100.0%	34.8%	34.8%	
Natural Gas-Fired Power Plants	7.2%	7.2%			42.8%	42.8%	43.0%
Utility boiler			14.0%	14.0%	34.8%	34.8%	
Simple-cycle gas turbine			38.0%	38.0%	33.5%	33.5%	
Combined-cycle gas turbine			48.0%	48.0%	60.0%	60.0%	
Coal-Fired Power Plants	63.9%	63.9%			34.7%	34.7%	16.0%
Utility boiler			97.0%	97.0%	34.4%	34.4%	
IGCC			3.0%	3.0%	50.0%	50.0%	
Biomass Power Plants	2.3%	2.3%			32.7%	32.7%	0.0%
Utility boiler			97.0%	97.0%	32.4%	32.4%	
IGCC			3.0%	3.0%	45.0%	45.0%	
Nuclear Power Plants	23.1%	23.1%			100.0%	100.0%	11.0%
Other Power Plants (hydro, wind, geothermal, etc.)	2.8%	2.8%			100.0%	100.0%	

GREET methodology involves summing the energy use and emissions of each upstream stage in a fuel cycle to determine total WTP characteristics. These stages involve production and transportation of feedstock fuels, and production and distribution of product fuels for any given fuel pathway, which includes electricity. In general terms, emissions generated by these process fuels are calculated as

$$\boldsymbol{EM_{cm,i}} = \left(\sum_{\mathbf{j}} \sum_{\mathbf{k}} \mathbf{EF_{i,j,k}} * \mathbf{EC_{j,k}} \right) \Big/ \mathbf{1,000,000} \tag{10}$$

Where,

$\mathbf{EM_{cm,i}}$ = Combustion emissions of pollutant i in g/10^6 Btu of fuel throughput,

$\mathbf{EF_{i,j,k}}$ = Emission factor of pollutant i for process fuel j with combustion technology k (g/10^6 Btu of fuel burned), and

$\mathbf{EC_{j,k}}$ = Consumption of process fuel j with combustion technology k (Btu/10^6 Btu of fuel throughput).

During production, process fuels may be consumed, meaning that the production and transportation of those fuels must be considered, creating an iterative calculation model. Calculation of total energy use or emissions for a given upstream stage is given by the equation below.

$$\boldsymbol{EM_i} = \left(\sum_{\mathbf{j}} \left(\mathbf{EM_{cm,i,j}} + \mathbf{EF_{up,i,j}} \right) * \mathbf{EC_j} \right) \Big/ \mathbf{1,000,000} \tag{11}$$

In this case,

$\mathbf{EM_i}$ = Emissions of pollutant I in g/10^6 Btu of fuel throughput from a given stage;

$\mathbf{EM_{cm,i,j}}$ = Combustion emissions of pollutant i in g/10^6 Btu of process fuel j burned

$\mathbf{EF_{up,i,j}}$ = Upstream emissions of pollutant i in g/10^6 Btu of process fuel j to produce and distribute the process fuel to the stage (considered within GREET through circular calculation programming); and

$\mathbf{EC_j}$ = Energy consumption of fuel j during the stage.

GREET uses EPA default emissions factors for various combustion and transportation technologies. More information on these factors and their origins is given in (M. Q Wang 1999), particularly in Section 4: Parametric Assumptions and Their Data Sources.

After summing all upstream stages and assuming additional losses of 8% from distribution, GREET arrives at a net WTP efficiency factor (net energy out/net energy in) and measures of energy consumption and various emissions outputs per unit of energy made available for end use.

Table 18: Well-to-Pump energy consumption and emissions: Btu or grams per mmBtu of fuel available at fuel station pumps

	Electricity (transportation)
Total Energy	1,630,268
WTP Efficiency	38.0%
Fossil Fuels	1,405,986
Coal	1,248,020
Natural Gas	123,641
Petroleum	34,325
CO2 (w/ C in VOC & CO)	234,573
CH4	277.339
N2O	3.585
GHGs	242,575
VOC: Total	19.313
CO: Total	56.326
NOx: Total	219.289
PM10: Total	356.381
PM2.5: Total	92.905
SOx: Total	482.809
VOC: Urban	0.771
CO: Urban	8.844
NOx: Urban	33.726
PM10: Urban	2.630
PM2.5: Urban	1.415
SOx: Urban	77.822

Table 18 demonstrates these measures for electricity consumed by transportation, which includes the electricity that is consumed by MARTA rail vehicles during propulsion. GREET results give WTP energy consumption of 1.63 million Btu and 234,573 grams of CO_2 per 1 million Btu electricity produced, equivalent to 1.63 MJ and 222.4 grams CO_2 per MJ produced. This output allows us to determine PTW energy consumption per VKT and PKT by MARTA HRVs, by multiplying WTW values by WTP efficiency, 0.380. The result is 10.70 MJ/km and 0.49 MJ/pers*km for each vehicle.

Note that in this example case involving rail transit, a large amount of preliminary calculation must be performed to obtain necessary SysML model inputs. For most vehicles types, there exists a larger variety of input data sources. These sources often provide figures such as average vehicle distance and average occupancy directly, making instance specification easier than shown here. The Atlanta HRV calculations are shown to highlight the maximum amount of preparatory work necessary to setup the model.

From this point onwards, further calculations are handled within the SysML parametric structure as outlined in the Analysis Model, Section 4.3. Following them upwards from the energy source begins with WTP CO_2 and energy calculations based on the derived GREET data. As opposed to fossil fuel calculations, there are no energy density conversions required for electricity, so the GREET WTP energy use and CO_2 output figures can be used directly.

$$\boldsymbol{E_{WTP} = 1,630,268\frac{BTU_{WTP}}{10^6 BTU_{PTW}} = 1.630\frac{MJ_{WTP}}{MJ_{PTW}}} \tag{12}$$

$$\boldsymbol{CO2_{WTPE} = 234,573\frac{\mathrm{g}}{10^6\mathrm{BTU}} = 222.3\frac{\mathrm{g}}{\mathrm{MJ}}} \tag{13}$$

Next, net energy consumption and CO_2 output per unit distance are calculated.

$$\boldsymbol{E_{WTW} = \frac{E_{PTW}}{\eta_{WTP}} = \frac{10.70\,\frac{\mathrm{MJ}}{\mathrm{km}}}{.38} = 28.13\frac{\mathrm{MJ}}{\mathrm{km}}} \tag{14}$$

$$\boldsymbol{CO2_{WTW} = CO2_{WTPE} * \mathrm{E_{WTP}} = 222.3\frac{\mathrm{g}}{\mathrm{MJ}} *\ 10.70\,\frac{\mathrm{MJ}}{\mathrm{km}} = 2379\frac{\mathrm{g}}{\mathrm{km}}} \tag{15}$$

For the Atlanta HRV vehicle type, average daily distance is computed using the number of units during peak operation, multiplied by average distance for each rail car.

$$\boldsymbol{VKT_{daily} = 182\ vehicles * 659.0\frac{km}{day/vehicle} = 1.200 * 10^5\frac{km}{day}} \tag{16}$$

As expected, this matches MARTA's published value of daily train car miles, cited above. Daily PKT is calculated by multiplying this by the cited average occupancy.

$$PKT_{daily} = 1.20 * 10^5 \frac{km}{day} * 21.8 \frac{\text{persons}}{\text{vehicle}} = 2.62 * 10^6 \frac{person*km}{day} \tag{17}$$

Energy and CO_2 per unit of passenger distance are calculated by dividing vehicle energy consumption and CO_2 output by occupancy, respectively.

$$E_{PKT} = {}^{28.13 \frac{\text{MJ}}{\text{vehicle*km}}} \Big/ {21.8 \frac{\text{persons}}{\text{vehicle}}} = 1.29 \frac{\text{MJ}}{\text{person*km}} \tag{18}$$

$$CO2_{PKT} = {}^{2379 \frac{\text{g}}{\text{vehicle*km}}} \Big/ {21.8 \frac{\text{persons}}{\text{vehicle}}} = 109 \frac{\text{g}}{\text{person*km}} \tag{19}$$

Finally, total energy use and CO_2 production by vehicle type are determined by multiplying per-unit-distance figures by vehicle type daily VKT.

$$E_{daily} = 28.13 \frac{\text{MJ}}{\text{km}} * 1.20 * 10^5 \frac{\text{km}}{\text{day}} = 3.376 * 10^6 \frac{\text{MJ}}{\text{day}} \tag{20}$$

$$CO2_{daily} = 2379 \frac{\text{g}}{\text{km}} * 1.20 * 10^5 \frac{\text{km}}{\text{day}} = 2.855 * 10^8 \frac{\text{g}}{\text{day}} \tag{21}$$

The values obtained here match the model outputs for MARTA heavy rail in the 2010 base case, demonstrating the validity of SysML parametric results.

Additionally, in certain cases, vehicle type results may be compared against existing studies perform a general validity check. For example, the SysML calculations for private vehicles have analogues using the GREET model. Although this thesis uses GREET results solely for fuel pathway assumptions, many authors have done full WTW analyses using GREET results for standard U.S. fleet conditions.

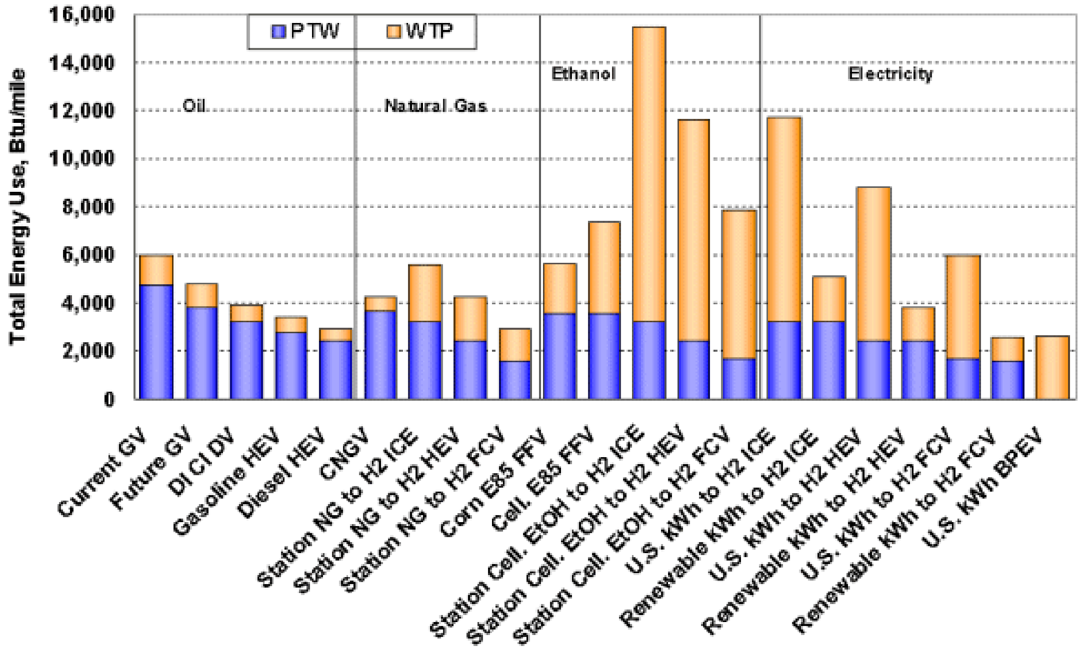

Figure 31: GREET sample WTW energy results using default U.S. input assumptions (M. Q Wang 2001)

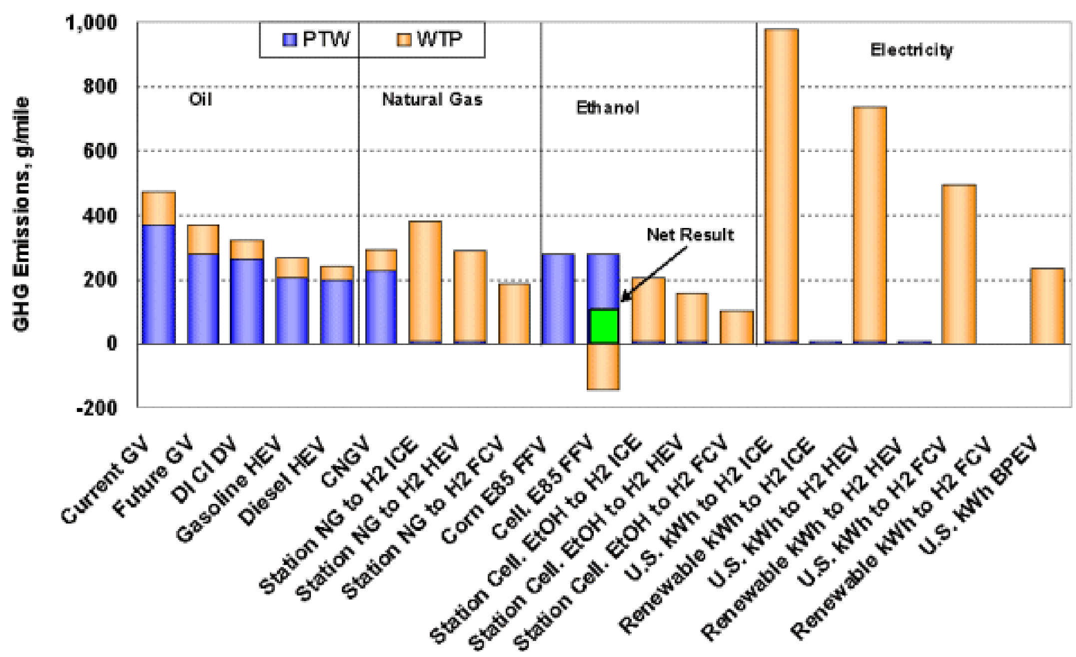

Figure 32: GREET sample WTW GHG emission results using default U.S. input assumptions (M. Q Wang 2001)

Figure 31 and Figure 32 show GREET energy use and GHG emission results using default U.S. input assumptions. They can be compared most directly with Figure

23 and Figure 24, which show the same outputs for the SysML model in the Atlanta 2010 base case. Although net results differ slightly due to differences in the Atlanta input data, there is a great deal of similarity in fuel pathway trends between the two models. For example, the 6,000 BTU/mile WTW energy consumption of current SI gasoline vehicles translates to 3.93 MJ/km, whereas the SysML model predicts WTW consumption of 4.10 MJ/km for the same vehicle type within the Atlanta region. Trends between different fuel technologies also remain intact: the relatively high energy use by ethanol and poor energy and emissions performance by electricity pathways are easily identified in both sets of results.

5.5. Discussion

5.5.1 Transportation System Evaluation

The series of case studies on the Atlanta mobility network give insight into what factors are most important in achieving sustainable mobility. The initial case study results show an extremely automobile dominated environment, in terms of vehicle numbers, use percentage, and energy/emissions footprint. It is well established that Atlanta suffers from sprawl and other issues preventing widespread use of public transport, but similar prevalence of light-duty vehicles can be found to some extent in urban areas all over the country. This dominance by private vehicles suggests that any strategy to reduce impact must directly address automobile use to achieve meaningful results. Possible solutions include reducing distance traveled (land use), reducing users or increasing vehicle occupancy (improved public transit, car sharing, etc), or changing automobile technology and its adoption.

Vehicle occupancy in particular has a huge effect on environmental impact across the entire system. Convincing automobile drivers to take on a single passenger 50% of the time would produce emissions reductions equal to or better than many highly touted alternative energy solutions, at no additional cost. Increasing occupancy of public transit vehicles during operating hours would have similar drastic effect. Bus and rail transit are potentially many times more efficient than light-duty vehicles, but this potential is not even close to being realized. MARTA buses have an 84 person capacity, and each MARTA rail car can hold 264 passengers. In practice, average occupancy of these vehicles is 8.8 and 22 passengers, resulting in 10.5% and 8.3% of capacity, respectively. Obviously, operating at 100% capacity at all hours of the day is not a realistic goal, but the margin for improvement is large.

5.5.2 Impact on Research Questions

Based on the results seen here, the framework demonstrates clear potential for model reuse during evaluation of complex multi-scale transportation systems. The three case studies analyzed here were completed without any changes to the model structure or model parametrics. Only input data was modified between each case. Once proper inputs are inserted as an instance specification, the analysis model was executed to perform necessary calculations.

Eliminating model creation and verification does not mean that analyses become truly inexpensive in terms of time or effort. A large amount of input data is necessary to perform each case study. Many of the assumption calculations for the 2025 cases were automated, and relied on either a single set of base data or external model inputs that predicted future conditions. Overall, however, the amount of inputs required to perform a full analysis is still a limiting factor for turnaround time and scenario evaluation. Each set of inputs (vehicle efficiency, travel demand, average VKT, etc) requires extensive research and verification before insertion into a case study. Many inputs come from different sources, requiring conversion to a common data format or different methods of verification. Modeling effort is reduced, but instance specification remains a burden that the SysML framework can only partially address.

CHAPTER 6

CONCLUSIONS

6.1. Summary

The results obtained from this research show potential for effective model reuse in evaluation of complex multi-scale transportation systems. Through the use of formal modeling constructs and SysML, problems arising from complexity management within a large, multi-layered mobility network are partially addressed and mitigated.

The Atlanta case study demonstrates the ability to interface between existing modeling systems to obtain more complete results. The Argonne National Laboratory GREET model and VISION model were synchronized with relevant inputs from the SysML instance specification, executed, and their results used as inputs for SysML model parametrics. Also, the Atlanta study demonstrated significant model reuse. The model structure remained unchanged throughout each of the examined cases, with only model inputs undergoing modification. SysML provided an effective way to visualize and organize model and parametric structure, which is similar to the results of previous research discussed in the literature review.

The framework presented here shows potential for simulating and understanding sustainable system behavior. The included calculations concerning well-to-wheel energy use are similar to those found in other studies, but they serve as an example of reduced modeling effort and provide system specific measures of energy use and emissions output. Also, they address the identified lack of sustainable transportation research at a regional level. Since broad calculations of energy use can suffer from extreme variability, integration of models with regional, local, and unit scales can be extremely beneficial to researchers and policy makers alike. The flexible analysis domain afforded by SysML modeling allows system inputs to be as specific or global as desired.

6.2. Research Questions

6.2.1 **Transportation Modeling Methodology**

The first research sub-question concerned what methodology would be effective for modeling complex transportation systems at multiple scales. A hypothesis was proposed that suggests using MBSE to increase consistency, reduce modeling effort, and integrate analysis tools when evaluating transportation and mobility networks.

Results obtained during the course of research confirm this hypothesis. MBSE has been proven as an effective method to build and maintain a transportation model, using a variety of viewpoints. Multiple scales are handled relatively well, depending on the level of modeling detail and the accuracy of parametric relations. Although not without problems and room for improvement, SysML is effective as an MBSE language, and existing SysML tools provide flexible capability for creating an extensive and usable model.

6.2.2 **Executable Modeling Framework**

The next research sub-question asked how a modeling framework can be used to integrate multiple executable models, in order to properly evaluate complex systems and their potential environmental impact. The following hypothesis proposed using the MBSE SysML model as the basis for an executable and integrated analysis platform.

This hypothesis was also successfully confirmed, although on a more limited basis than the first. The created SysML transportation model and associated parametric structure was integrated with other models with various transformations and input/output mappings. The resulting overall analysis was executed using external tools to obtain quantifiable information about different instance specifications within the model.

Executing complex analyses on the SysML model proved to be a relatively difficult task. The first method employed, the ParaMagic MagicDraw plugin, was usable for analyses, but its feature set and performance was not robust enough to successfully achieve all modeling objectives. The time and effort required to run full system analyses using ParaMagic required structural workarounds in some cases. The changes also negated certain prior MBSE advantages such as reduced modeling effort, consistent model reuse, and ease of optimization and scenario analysis. In addition, ParaMagic provided little to no functionality for linking the SysML parametric structure to other pre-existing models. All of these reasons prompted a search for alternate methods of making the model executable.

The next attempt at executing analyses was more successful, though not without reservations. A custom MATLAB script was written to parse parametric and instance data from the SysML model, link it to any specified external inputs, then solve the resulting system of equations. The MATLAB script was successful in executing SysML model parametrics, but at the expense of usability and ease of reuse. The script can be used for other models with relatively small modifications, but has not been rigorously tested or debugged under varied operating conditions.

A central difficulty to creating an accurate multi-scale analysis model relies on the quantity and accuracy of input data at the desired levels of resolution. Although the SysML framework reduces effort in integrating multiple sources, it is still time consuming for the modeler to collect, track, and verify all sources of input during instance specification. For this task, MBSE does not provide significant advantages over other systems engineering methods.

It should be stated that SysML is still a relatively new language, and is thus undergoing significant changes, as are the tools that utilize it. While ParaMagic was not ideal for this particular application, the stated development goals of InterCAX have similarities with those of this thesis, and may lead to better compatibility in the future.

6.2.3 **High Level Transportation System Impacts**

The model tested in this thesis was able to provide several insights about a regional transportation system when supplied with inputs for the Atlanta, GA metropolitan area. Atlanta was found to have an extremely high percentage of automobile travel with respect to overall vehicle distance and passenger distance. Also, WTW LCI analysis of common fuel pathways revealed that electric vehicles in the Atlanta area are particularly unattractive with regards to overall energy use and emissions output.

In Section 0, these results were used to identify likely barriers to creating a more environmentally sustainable transportation system. Automobile dominance and the low occupancy of private vehicles suggest that significant transit mode shifts are needed to reduce the network's environmental footprint.

Primary energy sources also require further investigation. Georgia's strong reliance on coal for electricity generation is the likely cause of large CO_2 emissions by electric vehicles. Renewable energy infrastructure is a valuable and perhaps necessary step in reducing Atlanta's transportation footprint.

The results of case study scenarios for 2025 suggest that urban growth is an alarming problem with regards to transportation demand. Under the given set of assumptions, even aggressive policy measures to encourage alternative transportation technology adoption would be vastly insufficient to curb sharp increases in energy demand and emissions output. Given that the region is already portrayed as one of the worst in the nation in terms of traffic congestion and air quality, drastic changes are necessary to prevent these problems from worsening.

6.3. Future Work

In the future, SysML modeling can provide a unique opportunity for optimization within the demonstrated mobility network concept. Developing the model further will allow for evaluation of the impacts of various modes of transportation on other modes, and allow investigation of what system changes would provide maximum benefits to sustainability.

Now that the modeling framework has been proven as an effective method to manage system complexity, it should be expanded to increase analysis accuracy and incorporate more refined algorithms. Currently, the GREET model provides a basis for fuel LCI inputs, and VISION provides vehicle market share inputs. However, the model does not fully account for detailed aspects of transportation supply and demand in the region. Economic considerations of energy and vehicle choice are not addressed, nor are more detailed calculations of trip demand such as choice based models, discussed in Section 2.5. The utility of the model's parametrics would greatly increase if these elements were incorporated. Additionally, the model could be enlarged to account for manufacturing energy and material inputs of vehicles. This would expand LCI capability beyond its current state, which only accounts for the full lifecycle of transportation fuels.

Another benefit of future model expansion concerns the availability of input data. The model currently relies on existing trip data for each vehicle type to estimate distance traveled. This method is relatively accurate for calculations involving current conditions, but when evaluating future scenarios, errors in trip length assumptions are likely to compound, due to unforeseen changes in demographics or land use. Relying on established research concerning trip choice generation would enable the model to use more predictable data as direct inputs, such as population, population density, or databases with spatial information about existing mobility infrastructure.

APPENDIX A

A.1. Scenario Energy Use and CO_2 Full Calculation Results

Table 19: WTW energy use calculation results from SysML analysis model – Case 1, Atlanta 2010 base case

Vehicle Type	WTP Energy Use (MJ/km)	PTW Energy Use (MJ/km)	WTW Energy Use (MJ/km)	Systemwide WTW Energy Use (GJ/day)	WTP Energy Use Per Passenger Km (MJ/km)	PTW Energy Use Per Passenger Km (MJ/km)	Energy Use Per Passenger Km (MJ/km)
Avg Diesel Bus [6]	4.82	23.20	28.02	3327	0.55	2.64	3.18
MARTA CNG Bus [7]	4.88	32.17	37.05	1505	0.55	3.66	4.21
MARTA CNG Bus	4.54	29.91	34.45	1751	0.52	3.40	3.91
MARTA Cl. Diesel Bus	4.54	21.88	26.42	853	0.52	2.49	3.00
MARTA Heavy Rail [2]	17.44	10.70	28.14	3377	0.80	0.49	1.29
MARTA Rail Car	17.44	10.70	28.14	997	0.80	0.49	1.29
MARTA Rail Car	17.44	10.70	28.14	1200	0.80	0.49	1.29
MARTA Rail Car	17.44	10.70	28.14	1181	0.80	0.49	1.29
Autos							
SI CG/RFG	0.94	3.16	4.10	180674	0.78	2.63	3.42
EV	1.33	0.82	2.15	1	1.11	0.68	1.79
E85 FFV	3.92	3.16	7.08	33221	3.27	2.63	5.90
DI CD/LSD	0.55	2.63	3.18	4971	0.46	2.20	2.65
SI CNG	0.47	3.07	3.53	38	0.39	2.56	2.95
SI HEV	0.67	2.26	2.93	5502	0.56	1.88	2.44
Diesel HEV	0.41	1.98	2.39	7	0.34	1.65	1.99
SI PHEV	0.61	1.34	1.95	0	0.51	1.12	1.63
Diesel PHEV	0.53	1.32	1.84	0	0.44	1.10	1.54
G Hydrogen FC	0.92	1.30	2.22	0	0.77	1.08	1.85
Bicycle		0.12	0.12	2	0.00	0.12	0.12
Walking		0.33	0.33	35	0.00	0.33	0.33

Table 20: WTW CO_2 output calculation results from SysML analysis model – Case 1, Atlanta 2010 base case

Vehicle Type	WTP Carbon Output (g/km)	PTW Carbon Output (g/km)	WTW Carbon Output (g/km)	Systemwide WTW Carbon Output (kg/day)	WTP Carbon Output Per Pass-Km (g/km)	PTW Carbon Output Per Pass-Km (g/km)	WTW Carbon Output Per Pass-Km (g/km)
Avg Diesel Bus	366.57	1592.11	1958.68	232577	41.66	180.92	222.58
MARTA CNG Bus	369.50	1261.48	1630.99	66238	41.99	143.35	185.34
MARTA CNG Bus	343.52	1172.78	1516.31	77066	39.04	133.27	172.31
MARTA Clean Diesel Bus	345.63	1501.13	1846.76	59650	39.28	170.58	209.86
MARTA Heavy Rail	2379.95	0.00	2379.95	285594	109.17	0.00	109.17
MARTA Rail Car	2379.95	0.00	2379.95	84274	109.17	0.00	109.17
MARTA Rail Car	2379.95	0.00	2379.95	101441	109.17	0.00	109.17
MARTA Rail Car	2379.95	0.00	2379.95	99880	109.17	0.00	109.17
Autos							
SI CG/RFG	52.60	212.83	265.43	11689392	43.83	177.36	221.19
EV	181.47	0.00	181.47	83	151.23	0.00	151.23
E85 FFV	-31.61	200.72	169.11	793465	-26.34	167.27	140.92
DI CD/LSD	41.62	180.76	222.38	347453	34.68	150.63	185.32
SI CNG	35.25	120.34	155.59	1694	29.37	100.29	129.66
SI HEV	37.57	152.02	189.59	355975	31.31	126.69	157.99
Diesel HEV	31.21	135.57	166.79	504	26.01	112.98	138.99
SI PHEV	22.29	90.21	112.50	0	18.58	75.17	93.75
Diesel PHEV	20.81	90.40	111.21	0	17.34	75.33	92.67
G Hydrogen FC	134.57	0	134.57	0	112.14	0.00	112.14
Bicycle	0.00	2.94	2.94	49	0.00	2.94	2.94
Walking	0.00	5.89	5.89	624	0.00	5.89	5.89

Table 21: WTW energy use calculation results from SysML analysis model – Case 2, Atlanta 2025 base case

Vehicle Type	WTP Energy Use (MJ/km)	PTW Energy Use (MJ/km)	WTW Energy Use (MJ/km)	Systemwide WTW Energy Use (GJ/day)	WTP Energy Use Per Pass-Km (MJ/km)	PTW Energy Use Per Pass-Km (MJ/km)	Energy Use Per Pass-Km (MJ/km)
Avg Diesel Bus	4.80	23.20	28.01	4213	0.48	2.32	2.80
MARTA CNG Bus	4.88	32.17	37.06	1672	0.49	3.22	3.71
MARTA CNG Bus	4.54	29.91	34.45	2422	0.45	2.99	3.45
MARTA Cl. Diesel Bus	4.53	21.88	26.41	1079	0.45	2.19	2.64
MARTA Heavy Rail	17.50	10.70	28.20	3384	0.65	0.40	1.04
MARTA Rail Car	17.50	10.70	28.20	998	0.65	0.40	1.04
MARTA Rail Car	17.50	10.70	28.20	1202	0.65	0.40	1.04
MARTA Rail Car	17.50	10.70	28.20	1183	0.65	0.40	1.04
Autos							
SI CG/RFG	0.87	2.94	3.82	168086	0.73	2.45	3.18
DI CD/LSD	0.51	2.45	2.96	29563	0.42	2.04	2.47
E85 FFV	3.65	2.94	6.59	72510	3.04	2.45	5.49
SI CNG	0.47	3.10	3.57	173	0.39	2.58	2.97
SI HEV	0.62	2.10	2.73	35692	0.52	1.75	2.27
Diesel HEV	0.38	1.84	2.22	45	0.32	1.53	1.85
SI PHEV	0.53	1.15	1.68	2298	0.44	0.95	1.40
Diesel PHEV	0.45	1.11	1.56	0	0.38	0.93	1.30
G Hydrogen FC	0.91	1.28	2.18	77	0.75	1.07	1.82
EV	1.33	0.81	2.14	268	1.11	0.68	1.78
Bicycle			0.12	0.12	3	0.00	0.12
Walking			0.33	0.33	44	0.00	0.33

Table 22: WTW CO_2 output calculation results from SysML analysis model – Case 2, Atlanta 2025 base case

Vehicle Type	WTP Carbon Output (g/km)	PTW Carbon Output (g/km)	WTW Carbon Output (g/km)	Systemwide WTW Carbon Output (kg/day)	WTP Carbon Output Per Passenger Km (g/km)	PTW Carbon Output Per Passenger Km (g/km)	WTW Carbon Output Per Passenger Km (g/km)
Avg Diesel Bus	366.77	1592.11	1958.89	294691	36.68	159.21	
MARTA CNG Bus	369.91	1261.48	1631.39	73616	36.99	126.15	163.14
MARTA CNG Bus	343.90	1172.78	1516.68	106623	34.39	117.28	151.67
MARTA Clean Diesel Bus	345.81	1501.13	1846.95	75448	34.58	150.11	184.69
MARTA Heavy Rail	2384.49	0.00	2384.49	286139	88.31	0.00	
MARTA Rail Car	2384.49	0.00	2384.49	84434	88.31	0.00	88.31
MARTA Rail Car	2384.49	0.00	2384.49	101634	88.31	0.00	88.31
MARTA Rail Car	2384.49	0.00	2384.49	100070	88.31	0.00	88.31
Autos							
SI CG/RFG Automobile	48.97	198.13	247.10	10881570	40.81	165.11	205.92
DI CD/LSD Automobile	38.76	168.27	207.03	2067664	32.30	140.22	172.53
E85 FFV Automobile	-29.46	186.85	157.38	1731902	-24.55	155.71	131.15
SI CNG Automobile	35.62	121.46	157.08	7596	29.68	101.22	130.90
SI HEV Automobile	34.98	141.52	176.50	2310642	29.15	117.93	147.08
Diesel HEV Automobile	29.07	126.20	155.28	3176	24.23	105.17	129.40
SI PHEV Automobile	19.07	77.14	96.20	131884	15.89	64.28	80.17
Diesel PHEV Automobile	17.59	76.35	93.94	0	14.66	63.62	78.28
G Hydrogen FC Automobile	132.58	0.00	132.58	4689	110.49	0.00	110.49
EV Automobile	180.92	0.00	180.92	22634	150.77	0.00	150.77
Bicycle		2.94	2.94	62	0.00	2.94	2.94
Walking		5.89	5.89	791	0.00	5.89	5.89

Table 23: WTW energy use calculation results from SysML analysis model – Case 3, Atlanta 2025 alternative scenario

Vehicle Type	WTP Energy Use (MJ/km)	PTW Energy Use (MJ/km)	WTW Energy Use (MJ/km)	Systemwide WTW Energy Use (GJ/day)	WTP Energy Use Per Passenger Km (MJ/km)	PTW Energy Use Per Passenger Km (MJ/km)	Energy Use Per Passenger Km (MJ/km)
Avg Diesel Bus	4.80	23.20	28.01	4213	0.48	2.32	2.80
MARTA CNG Bus	4.88	32.17	37.06	1672	0.49	3.22	3.71
MARTA CNG Bus	4.54	29.91	34.45	2422	0.45	2.99	3.45
MARTA Clean Diesel Bus	4.53	21.88	26.41	1079	0.45	2.19	2.64
MARTA Heavy Rail	17.50	10.70	28.20	3384	0.65	0.40	1.04
MARTA Rail Car	17.50	10.70	28.20	998	0.65	0.40	1.04
MARTA Rail Car	17.50	10.70	28.20	1202	0.65	0.40	1.04
MARTA Rail Car	17.50	10.70	28.20	1183	0.65	0.40	1.04
Autos							
SI CG/RFG	0.87	2.94	3.82	157295	0.73	2.45	3.18
DI CD/LSD	0.51	2.45	2.96	29563	0.42	2.04	2.47
E85 FFV	3.65	2.94	6.59	72510	3.04	2.45	5.49
SI CNG	0.47	3.10	3.57	173	0.39	2.58	2.97
SI HEV	0.62	2.10	2.73	35692	0.52	1.75	2.27
Diesel HEV	0.38	1.84	2.22	45	0.32	1.53	1.85
SI PHEV	0.53	1.15	1.68	6294	0.44	0.95	1.40
Diesel PHEV	0.45	1.11	1.56	0	0.38	0.93	1.30
G Hydrogen FC	0.91	1.28	2.18	77	0.75	1.07	1.82
EV Automobile	1.33	0.81	2.14	1218	1.11	0.68	1.78
Bicycle		0.12	0.12	3	0.00	0.12	0.12
Walking		0.33	0.33	44	0.00	0.33	0.33

Table 24: WTW CO_2 output calculation results from SysML analysis model – Case 3, Atlanta 2025 alternative scenario

Vehicle Type	WTP Carbon Output (g/km)	PTW Carbon Output (g/km)	WTW Carbon Output (g/km)	Systemwide WTW Carbon Output (kg/day)	WTP Carbon Output Per Passenger Km (g/km)	PTW Carbon Output Per Passenger Km (g/km)	WTW Carbon Output Per Passenger Km (g/km)
Avg Diesel Bus	366.77	1592.11	1958.89	294691	36.68	159.21	
MARTA CNG Bus	369.91	1261.48	1631.39	73616	36.99	126.15	163.14
MARTA CNG Bus	343.90	1172.78	1516.68	106623	34.39	117.28	151.67
MARTA Clean Diesel Bus	345.81	1501.13	1846.95	75448	34.58	150.11	184.69
MARTA Heavy Rail	2384.49	0.00	2384.49	286139	88.31	0.00	
MARTA Rail Car	2384.49	0.00	2384.49	84434	88.31	0.00	88.31
MARTA Rail Car	2384.49	0.00	2384.49	101634	88.31	0.00	88.31
MARTA Rail Car	2384.49	0.00	2384.49	100070	88.31	0.00	88.31
Autos							
SI CG/RFG	48.97	198.13	247.10	10183027	40.81	165.11	205.92
DI CD/LSD	38.76	168.27	207.03	2067664	32.30	140.22	172.53
E85 FFV	-29.46	186.85	157.38	1731902	-24.55	155.71	131.15
SI CNG	35.62	121.46	157.08	7596	29.68	101.22	130.90
SI HEV	34.98	141.52	176.50	2310642	29.15	117.93	147.08
Diesel HEV	29.07	126.20	155.28	3176	24.23	105.17	129.40
SI PHEV	19.07	77.14	96.20	361139	15.89	64.28	80.17
Diesel PHEV	17.59	76.35	93.94	0	14.66	63.62	78.28
G Hydrogen FC	132.58	0.00	132.58	4689	110.49	0.00	110.49
EV Automobile	180.92	0.00	180.92	102974	150.77	0.00	150.77
Bicycle	0.00	2.94	2.94	62	0.00	2.94	2.94
Walking	0.00	5.89	5.89	791	0.00	5.89	5.89

Table 25: WTW energy use output calculation results from SysML analysis model – Case 4, Sensitivity Analysis – Electricity Generation

Vehicle Type	WTP Energy Use (MJ/km)	PTW Energy Use (MJ/km)	WTW Energy Use (MJ/km)	Systemwide WTW Energy Use (GJ/day)	WTP Energy Use Per Passenger Km (MJ/km)	PTW Energy Use Per Passenger Km (MJ/km)	Energy Use Per Passenger Mile (MJ/km)
Avg Diesel Bus	4.25	23.20	27.45	3260	0.48	2.64	3.12
MARTA CNG Bus	3.80	32.17	35.98	1461	0.43	3.66	4.09
MARTA CNG Bus	3.53	29.91	33.45	1700	0.40	3.40	3.80
MARTA Clean Diesel Bus	4.00	21.88	25.88	836	0.46	2.49	2.94
MARTA Heavy Rail	5.40	10.70	16.10	1932	0.25	0.49	0.74
MARTA Rail Car	5.40	10.70	16.10	570	0.25	0.49	0.74
MARTA Rail Car	5.40	10.70	16.10	686	0.25	0.49	0.74
MARTA Rail Car	5.40	10.70	16.10	676	0.25	0.49	0.74
Autos							
SI CG/RFG	0.66	3.16	3.82	168221	0.55	2.63	3.18
EV	0.42	0.82	1.24	1	0.35	0.68	1.03
E85 FFV	3.28	3.16	6.45	30241	2.74	2.63	5.37
DI CD/LSD	0.34	2.63	2.98	4654	0.29	2.20	2.48
SI CNG	0.47	3.07	3.54	39	0.39	2.56	2.95
SI HEV	0.32	2.26	2.57	4834	0.26	1.88	2.15
Diesel HEV	0.28	1.98	2.26	7	0.23	1.65	1.88
SI PHEV	0.19	1.34	1.53	0	0.16	1.12	1.28
Diesel PHEV	0.77	1.32	2.09	0	0.64	1.10	1.74
G Hydrogen FC	0.39	1.30	1.68	0	0.32	1.08	1.40
Bicycle		0.12	0.12	2	0.00	0.12	0.12
Walking		0.33	0.33	35	0.00	0.33	0.33

Table 26: WTW CO_2 output calculation results from SysML analysis model – Case 4, Sensitivity Analysis – Electricity Generation

Vehicle Type	WTP Carbon Output (g/km)	PTW Carbon Output (g/km)	WTW Carbon Output (g/km)	Systemwide WTW Carbon Output (kg/day)	WTP Carbon Output Per Passenger Km (g/km)	PTW Carbon Output Per Passenger Km (g/km)	WTW Carbon Output Per Passenger Km (g/km)
Avg Diesel Bus	146.22	1592.11	1738.34	206412	16.62	180.92	197.54
MARTA CNG Bus	370.33	1261.48	1631.81	66272	42.08	143.35	185.43
MARTA CNG Bus	344.29	1172.78	1517.07	77105	39.12	133.27	172.39
MARTA Clean Diesel Bus	137.87	1501.13	1639.00	52940	15.67	170.58	186.25
MARTA Heavy Rail	516.42	0.00	516.42	61970	23.69	0.00	23.69
MARTA Rail Car	516.42	0.00	516.42	18286	23.69	0.00	23.69
MARTA Rail Car	516.42	0.00	516.42	22011	23.69	0.00	23.69
MARTA Rail Car	516.42	0.00	516.42	21673	23.69	0.00	23.69
Autos							
SI CG/RFG	44.67	212.83	257.50	11340379	37.23	177.36	214.59
EV	39.38	0.00	39.38	18	32.81	0.00	32.81
E85 FFV	-53.52	200.72	147.20	690678	-44.60	167.27	122.67
DI CD/LSD	16.60	180.76	197.36	308366	13.83	150.63	164.47
SI CNG	35.33	120.34	155.67	1695	29.44	100.29	129.73
SI HEV	31.91	152.02	183.93	345347	26.59	126.69	153.28
Diesel HEV	12.45	135.57	148.02	447	10.38	112.98	123.35
SI PHEV	18.93	90.21	109.14	0	15.78	75.17	90.95
Diesel PHEV	8.30	90.40	98.70	0	6.92	75.33	82.25
G Hydrogen FC	134.57	0	134.57	0	112.14	0.00	112.14
Bicycle	0.00	2.94	2.94	49	0.00	2.94	2.94
Walking	0.00	5.89	5.89	624	0.00	5.89	5.89

A.2. MATLAB Analysis Execution Code

```
tic
clear
% clc

% import java String class so MATLAB can process it as a normal string
import java.lang.String;

% create DOM of Magicdraw XML file
filename = 'C:\Users\Kyle\Documents\SRL\SysML\Thesis results\XML Test
Files\trans329.xml'
xDoc = xmlread(filename);

% find connectors, attributes, and nested connectors within DOM
XMLPackagedElements = xDoc.getElementsByTagName('packagedElement');
XMLRuleNodesConn = xDoc.getElementsByTagName('ownedConnector');
XMLRuleNodesAttr = xDoc.getElementsByTagName('ownedAttribute');
XMLRuleNodesNestedConn =
xDoc.getElementsByTagName('Blocks:NestedConnectorEnd');

% initialize blocks, ports, and properties list
block = cell(XMLPackagedElements.getLength,3);
block{1,1} = 'XMI ID#';
block{1,2} = 'Name';
block{1,3} = 'XMLRuleNodesAttr Item#';

port = cell(XMLRuleNodesAttr.getLength,3);
port{1,1} = 'XMI ID#';
port{1,2} = 'Name';
port{1,3} = 'XMLRuleNodesAttr Item#';

prop = cell(XMLRuleNodesAttr.getLength,5);
prop{1,1} = 'XMI ID#';
prop{1,2} = 'Name';
prop{1,3} = 'XMLRuleNodesAttr Item#';
prop{1,4} = 'Parent Block';
prop{1,5} = 'Type';

inst = cell(XMLRuleNodesAttr.getLength,5);
inst{1,1} = 'XMI ID#';
inst{1,2} = 'Name';
inst{1,3} = 'XMLRuleNodesAttr Item#';
inst{1,4} = 'Parent Element';
inst{1,5} = 'Classifier';

portnum = 2;
propnum = 2;
blocknum = 2;
instnum = 2;

% populate block list
for ind = 0:XMLPackagedElements.getLength - 1
    if
strcmp('uml:Class',char(XMLPackagedElements.item(ind).getAttributes.getNamedIte
m('xmi:type').getValue))
        block{blocknum,1} =
char(XMLPackagedElements.item(ind).getAttributes.getNamedItem('xmi:id').getValu
e);
```

```
        block{blocknum,2} =
char(XMLPackagedElements.item(ind).getAttributes.getNamedItem('name').getValue)
;
        block{blocknum,3} = num2str(ind);
        blocknum = blocknum+1;
    elseif
strcmp('uml:InstanceSpecification',char(XMLPackagedElements.item(ind).getAttrib
ute('xmi:type')))
        inst{instnum,1} =
char(XMLPackagedElements.item(ind).getAttributes.getNamedItem('xmi:id').getValu
e);
        inst{instnum,2} =
char(XMLPackagedElements.item(ind).getAttributes.getNamedItem('name').getValue)
;
        inst{instnum,3} = num2str(ind);
        if XMLPackagedElements.item(ind).hasChildNodes
            inst{instnum,5} =
char(XMLPackagedElements.item(ind).getChildNodes.item(1).getAttribute('xmi:idre
f'));
        end
        instnum = instnum+1;
    end
end

% populate ports and properties list to avoid having to search through ALL
% attributes later
for jnd = 0:XMLRuleNodesAttr.getLength - 1
    if
strcmp('uml:Port',char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('x
mi:type').getValue))
            port{portnum,1} =
char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('xmi:id').getValue);
            port{portnum,2} =
char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('name').getValue);
            port{portnum,3} = num2str(jnd);
            portnum = portnum+1;
    elseif
strcmp('uml:Property',char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedIte
m('xmi:type').getValue)) %&&
strcmp('public',char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('vis
ibility').getValue))
            prop{propnum,1} =
char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('xmi:id').getValue);
            prop{propnum,2} =
char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('name').getValue);
            prop{propnum,3} = num2str(jnd);
            prop{propnum,4} =
char(XMLRuleNodesAttr.item(jnd).getParentNode.getAttributes.getNamedItem('name'
).getValue);
%             prop{propnum,5} =
char(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('type').getValue);
            propnum = propnum+1;
    end
end

% trim unused list rows
while length(block)>blocknum-1
    block(blocknum,:) = [];
end

while length(inst)>instnum-1
    inst(instnum,:) = [];
end
```

```
while length(port)>portnum-1
    port(portnum,:) = [];
end

while length(prop)>propnum-1
    prop(propnum,:) = [];
end

% find instance classifiers and enter their block name in instance list
for ind = 1:length(inst)
    for jnd = 1:length(block)
        if strcmp(inst{ind,5},block{jnd,1})
            inst{ind,4} = block{jnd,2};
        end
    end
end

% populate list of all nested connections
nested = cell(XMLRuleNodesNestedConn.getLength,2);
nested{1,1} = 'base connector end id#';
nested{1,2} = 'property path id#';
num = 2;
for jnd = 0:XMLRuleNodesNestedConn.getLength-1
    nested{num,1} =
char(XMLRuleNodesNestedConn.item(jnd).getAttributes.getNamedItem('base_Connecto
rEnd').getValue);
    nested{num,2} =
char(XMLRuleNodesNestedConn.item(jnd).getAttributes.getNamedItem('propertyPath'
).getValue);
    num = num+1;
end

% initialize connector path lists
bpath = cell(XMLRuleNodesConn.getLength,1);
brole = cell(XMLRuleNodesConn.getLength,1);
cpath = cell(XMLRuleNodesConn.getLength,1);
crole = cell(XMLRuleNodesConn.getLength,1);

bpropflag = zeros(length(bpath));
cpropflag = zeros(length(cpath));

for i = 1:XMLRuleNodesConn.getLength
    tempNode = XMLRuleNodesConn.item(i-1);
    childNodes = tempNode.getChildNodes;
%         Find the destination variable id# of each connector
            bpath{i} =
char(childNodes.item(1).getAttributes.getNamedItem('xmi:id').getValue);
            brole{i} =
char(childNodes.item(1).getAttributes.getNamedItem('role').getValue);

    %         Find the source variable id# of each connector
            cpath{i} =
char(childNodes.item(3).getAttributes.getNamedItem('xmi:id').getValue);
            crole{i} =
char(childNodes.item(3).getAttributes.getNamedItem('role').getValue);

end

% counter variables used for debugging whether all id#s had been substituted
    % unfilledb = 0;
    % unfilledc = 0;
```

```
% search for matching portprop to each connector end and assign the port name
[~,loc] = ismember(brole,port(:,1));
for i = 1:length(loc)
    if loc(i) ~= 0
        brole{i} =  port{loc(i),2};
    end
end

[~,loc] = ismember(brole,prop(:,1));
for i = 1:length(loc)
    if loc(i) ~= 0
        brole{i} =  [prop{loc(i),4},'.',prop{loc(i),2}];
        bpropflag(i) = 1;
    end
end

[~,loc] = ismember(crole,port(:,1));
for i = 1:length(loc)
    if loc(i) ~= 0
        crole{i} =  port{loc(i),2};
    end
end

[~,loc] = ismember(crole,prop(:,1));
for i = 1:length(loc)
    if loc(i) ~= 0
        crole{i} =  [prop{loc(i),4},'.',prop{loc(i),2}];
        cpropflag(i) = 1;
    end
end

% check to see if connector is nested, if so, assign nested path id
[~,loc] = ismember(bpath,nested);
for i = 1:length(loc)
    if loc(i) == 0
        bpath{i} = '';
    else
        bpath{i} = nested{loc(i),2};
%          unfilledb = unfilledb + 1;
    end
end

% check for occurences of property id#'s in the path and substitute
% their names
for i = 1:length(prop)
    k = strfind(bpath, prop{i,1});
    for j = 1:length(k)
        if k{j,1} > 0
            bpath{j} =
strrep(bpath{j},prop{i,1},['.',prop{i,4},'.',prop{i,2},'.']);
%              unfilledb = unfilledb - 1;
        end
    end
end


% repeat both processes for other end of connectors
[ind,loc] = ismember(cpath,nested);
for i = 1:length(loc)
    if loc(i) == 0
        cpath{i} = '';
    else
        cpath{i} = nested{loc(i),2};
```

```
%         unfilledc = unfilledc + 1;
    end
end

for i = 1:length(prop)
    k = strfind(cpath, prop{i,1});
    for j = 1:length(k)
        if k{j,1} > 0
            cpath{j} =
strrep(cpath{j},prop{i,1},['.',prop{i,4},'.',prop{i,2},'.']);
%             unfilledc = unfilledc - 1;
        end
    end
end

% properly format path names
for i = 1:length(brole)
        bpath{i} = bpath{i}(2:length(bpath{i}));
        bpath{i} = strrep(bpath{i},' ','');
        bpath{i} = strrep(bpath{i}, '..', '.');
        bpath{i} = strcat(bpath{i},brole{i});

        cpath{i} = cpath{i}(2:length(cpath{i}));
        cpath{i} = strrep(cpath{i}, ' ', '');
        cpath{i} = strrep(cpath{i}, '..', '.');
        cpath{i} = strcat(cpath{i},crole{i});
end

for ind = 1:length(bpath)
    if bpropflag(ind) == 1
        propvars{ind,1} = bpath{ind};
        portvars{ind,1} = cpath{ind};
    else
        propvars{ind,1} = cpath{ind};
        portvars{ind,1} = bpath{ind};
    end
end
```

```
filename =

C:\Users\Kyle\Documents\SRL\SysML\Thesis results\XML Test Files\trans329.xml
```

```
%     find constraints
    XMLRuleNodes = xDoc.getElementsByTagName('ownedRule');

    ct = 0;
    varPaths = cell(1);
    varExp = cell(1);

    for ind = 0:XMLRuleNodes.getLength - 1
%         First ownedRule and finding its specification
%         try %need to get this to go to nextIter if error
          if isempty(XMLRuleNodes.item(ind).getChildNodes.item(3))
              continue
          end

        eqn =
char(XMLRuleNodes.item(ind).getChildNodes.item(3).getAttributes.getNamedItem('b
ody').getValue);

        lhs = eqn(1:strfind(eqn, '=')-1);
        rhs = eqn(strfind(eqn, '=')+1:length(eqn));
```

```
%         Process Variable Names (constraint variables must start with an
%         alphabetic character or underscore)
%         invars = regexp(rhs,'[a-zA-Z_]\w*','match');

        invars = getVarNames2(rhs);

        outvars = getVarNames2(lhs);

%         Find Parent Class
%         Set tempNode = XMLRuleNodes.item(0).parentNode
%         Do While Not tempNode.baseName = 'packagedElement'
%             Set tempNode = tempNode.parentNode
%         'Loop
        eqnOrig = eqn;
%         Find all Attributes of this class
        for jnd = 0:XMLRuleNodesAttr.getLength - 1

            if
isempty(XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('type'))
                continue
            end

            if
XMLRuleNodes.item(ind).getChildNodes.item(1).getAttribute('xmi:idref') ==
XMLRuleNodesAttr.item(jnd).getAttributes.getNamedItem('type').getValue

                eqn = rhs;

                for knd = 1:length(invars)
                    varPaths{ct + knd,1} =
[char(XMLRuleNodesAttr.item(jnd).getParentNode.getAttribute('name')),'.',char(X
MLRuleNodesAttr.item(jnd).getAttribute('name')),'.',invars{knd}];
                    varExp{ct + knd,1} = 'SYSML_INPUT_VARIABLE';
                    eqn = regexprep(eqn, ['\<',invars{knd},'(?!\.)'],
['(',varPaths{ct + knd,1},')']);
                end
                ct = ct + length(invars);

                varPaths{ct + 1,1} =
[char(XMLRuleNodesAttr.item(jnd).getParentNode.getAttribute('name')),'.',char(X
MLRuleNodesAttr.item(jnd).getAttribute('name')),'.',outvars{1}];
%                   eqn = regexprep(eqn,
['\<',outvars{1},'(?!\.)'],['(',varPaths{ct + 1,1},')'])
                eqn = regexprep(eqn,'ln\s?\(?','log(');
                varExp{ct + 1,1} = eqn;

                ct = ct + 1;
            end
        end
% nextiter:

%         catch ME

%             continue
%         end
    end

%     ' Substitute connectors and add project name to variable paths
varPathsOrig = varPaths;
    for ind = 1:length(varPaths)
        for jnd = 1:length(portvars)
            if strcmp(varPaths{ind},portvars{jnd})
                varPaths{ind} = propvars{jnd};
```

```
            end
        end
    end


%     Substitute expressions if equation variables match alias variables
varExpOrig = varExp;
    for ind = 1:length(varPaths)
        if ~strcmp(varExp{ind},'SYSML_INPUT_VARIABLE')
            for jnd = 1:length(propvars)
                varExp{ind} = regexprep(varExp{ind}, ['\(',portvars{jnd},'\)'],
['(',propvars{jnd},')']);
            end
        end
    end


%     populate final cell matrix with all unique variable names
varPaths2 = varPaths;
cells = cell(length(varPaths),7);
    numUnique = 0;
    uniqueFlag = 1;
     for ind = 1:length(varPaths)
%         for jnd = 1:ind
%             if strcmp(varPaths{ind},cells{jnd, 1})
%                 uniqueFlag = 0;
%                 break
%             end
%         end
        if uniqueFlag == 1
            numUnique = numUnique + 1;
            cells{numUnique, 1} = varPaths{ind};
        end
        uniqueFlag = 1;

% uniqueVarskip:
     end

while length(cells)>numUnique
    cells(numUnique+1,:) = [];
end

    ct = length(varPaths);
%     assign causalities and expressions for each unique variable
    for ind = 1:numUnique
        ct = 1;
%         Check to see if any input/output variable matches, with outputs
%         getting priority (note: this leaves duplicate variables not
%         flagged as done, but I don't think it affects functionality)
        for jnd = 1:length(varPaths)
            if strcmp(varPaths{jnd},cells{ind, 1}) & ~
strcmp(varExp{jnd},'SYSML_INPUT_VARIABLE')
                ct = jnd;
                cells{ind, 3} = 'Target';
                break
            elseif strcmp(varPaths{jnd},cells{ind, 1}) &
strcmp(varExp{jnd},'SYSML_INPUT_VARIABLE')
                cells{ind, 3} = 'Given';
                ct = jnd;
            end
        end
        if ~ strcmp(varPaths{ct},'done')
            if ~strcmp(varExp{ct}, 'SYSML_INPUT_VARIABLE')
```

```
                cells{ind, 2} = strcat('=',varExp{ct});
            end
            varPaths{ct} = 'done';
        end
    end

% initialize inputs

%     x = cells{:,6};
for i = 1:length(cells)
%     regexprep(cells{i,1},'.','_');
    cells{i,4} = ['x(',num2str(i),')'];
    eval([cells{i,4},' = 0;'])
    cells{i,6} = '0';
    if strcmp(cells{i,3}, 'Given')
        cells{i,2} = '0';
    end
     cells{i,7} = sym(cells{i,4});
end

% find inputs that match specified Excel connections and insert them
excelfile = 'inputs.xlsx';
excelworksheet = 'Main Inputs';
[data,text,raw,cells] = excelinputs(excelfile,excelworksheet,cells,2);

for i = 1:length(cells)
    if strcmp(cells{i,3},'Given')
        for j = 1:length(cells)
            if ~isempty(regexp(cells{i,1},[cells{j,1},'(?!\w)'],'once')) &
strcmp(cells{j,3},'Target')
                cells{i,2} = cells{j,2};
                cells{i,3} = 'Target';
            end
        end
    end
end

cells(:,5) = cells(:,2);

for i = 1:length(cells)
    cells{i,2} = regexprep(cells{i,2},'=','');
    for j = 1:length(cells)
        if ~strcmp(cells{j,3},'Given')
            cells{j,5} =
regexprep(cells{j,5},['\(',cells{i,1},'\)'],['(','x(',num2str(i),'))']);
        end
    end
end

for i = 1:length(cells)
    cells{i,2} = [cells{i,1},' = ',cells{i,2},';'];
    cells{i,5} = [cells{i,4},' = ',cells{i,5},';'];
    if length(cells{i,5}) > 1
        if strcmp(cells{i,5}(1:2),'if')
            cells{i,3} = 'Conditional';
            cells{i,5} = ifwrapper(cells{i,4},cells{i,5});
        end
    end
end

givnum = 1;
tarnum = 1;
for i = 1:length(cells)
```

```
    if strcmp(cells{i,3},'Given')
        givenList{givnum,1} = cells{i,2};
        givnum = givnum+1;
    elseif strcmp(cells{i,3},'Target')
        targetList{tarnum,1} = cells{i,2};
        tarnum = tarnum+1;
    end
end

targetList = unique(targetList);
% evaluate list of inputs to initialize all input variables
for i = 1:length(givenList)
    eval(givenList{i,1})
end

% iterate system of equations and sort which eqs are successfully solved
% vs. which are still unresolved.  Loop continues until system is fully
% solved
done = 0;
order = zeros(length(targetList),1);
iter = 0;
while done == 0
    done = 1;
    for i = 1:length(targetList)
        try
            eval(targetList{i,1})
        catch ME
            ME;
            done = 0;
            order(i) = order(i) + 1;
            [order,ix] = sort(order);
            continue
        end
    end
    targetList = targetList(ix);
    iter = iter+1;
end

% format inputs (givens) and expressions for formal output
givenList = unique(givenList);
expList = char(cat(1,givenList,targetList))

toc

% Unused Code Snippets:
% --------------------------

% % for ind = 1:length(cells)
% %     for jnd = 1:length(propvars)
% %         cells{ind,1} = regexprep(cells{ind,1}, portvars{jnd},
propvars{jnd});
% %     end
% % end
%
%
% for i = 1:numUnique
%     propvars{i} = regexprep(propvars{i},'\.','_');
%     portvars{i} = regexprep(portvars{i},'\.','_');
%     if isempty(cells{i,2})
%          cells{i,2} = '0';
%     else
%         cells{i,2} = regexprep(cells{i,2},'=','');
%         cells{i,2} = regexprep(cells{i,2},'\.','_');
```

```
%     end
%     cells{i,1} = regexprep(cells{i,1},'\.','_');
%
% end
%

% for ct = 1:5
%     for i = 1:length(cells)
%         if strcmp(cells{i,3},'Conditional');
%             eval(cells{i,5});
%             cells{i,6} = eval([cells{i,4},';']);
%         else
%             eval([cells{i,4},'=',cells{i,5},';'])
%             eval([cells{i,5}]);
%         end

%     end
% end
```

```
expList =

AirVehicle.ptrain.Powertrain_Turbine.motor.Motor_Turbine.fuelChoice.Fuel.LHV =
0;
AirVehicle.ptrain.Powertrain_Turbine.turbFuelEfficiency = 0;
AirVehicle.vehicleParam.VehicleParameters.travelDist = 0;
Fuel.LHV = 0;
Fuel.co2Density = 0;
OnroadVehicleElec.totalCO2Factor = 0;
OnroadVehicleElec.vehicleParam.VehicleParameters.travelDist = 0;
OnroadVehicleElec.wtwEfficiency = 0;
OnroadVehicleHuman.ptwEfficiency = 0;
OnroadVehicleHuman.totalCO2Factor = 0;
OnroadVehicleHuman.vehicleParam.VehicleParameters.travelDist = 0;
OnroadVehicleICE.ptrain.Powertrain_ICE.iceFuelEfficiency = 0;
OnroadVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.LHV = 0;
OnroadVehicleICE.vehicleParam.VehicleParameters.travelDist = 0;
Rail.martaRail.RailVehicleElec.vehicleParam.VehicleParameters.occupancy = 0;
Rail.martaRail.RailVehicleElec.vehicleParam.VehicleParameters.travelDist = 0;
Rail.num_rail = 0;
RailVehicleElec.totalCO2Factor = 0;
RailVehicleElec.vehicleParam.VehicleParameters.travelDist = 0;
RailVehicleElec.wtwEfficiency = 0;
RailVehicleICE.ptrain.Powertrain_ICE.iceFuelEfficiency = 0;
RailVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.LHV = 0;
RailVehicleICE.totalCO2Factor = 0;
RailVehicleICE.vehicleParam.VehicleParameters.travelDist = 0;
Road.autoICE.OnroadVehicleICE.vehicleParam.VehicleParameters.occupancy = 0;
Road.autoICE.OnroadVehicleICE.vehicleParam.VehicleParameters.travelDist = 0;
Road.num_auto = 0;
AirVehicle.ptrain.Powertrain_Turbine.motor.Motor_Turbine.fuelChoice.Fuel.co2Fac
tor =  (Fuel.co2Density) / (Fuel.LHV);
AirVehicle.ptwCO2Output =
(AirVehicle.ptrain.Powertrain_Turbine.motor.Motor_Turbine.fuelChoice.Fuel.co2Fa
ctor) * (AirVehicle.ptwEnergyConsumption);
AirVehicle.ptwEfficiency =  (AirVehicle.ptwEnergyConsumption) /
(AirVehicle.vehicleParam.VehicleParameters.travelDist);
AirVehicle.ptwEnergyConsumption =
(AirVehicle.ptrain.Powertrain_Turbine.motor.Motor_Turbine.fuelChoice.Fuel.LHV)
* (AirVehicle.ptwLiquidFuelConsumption);
AirVehicle.ptwLiquidFuelConsumption =
(AirVehicle.vehicleParam.VehicleParameters.travelDist) /
(AirVehicle.ptrain.Powertrain_Turbine.turbFuelEfficiency);
Fuel.co2Factor =  (Fuel.co2Density) / (Fuel.LHV);
```

```
OnroadVehicleElec.ptwCO2Output =  (OnroadVehicleElec.totalCO2Factor) *
(OnroadVehicleElec.ptwEnergyConsumption);
OnroadVehicleElec.ptwEfficiency =  (OnroadVehicleElec.ptwEnergyConsumption) /
(OnroadVehicleElec.vehicleParam.VehicleParameters.travelDist);
OnroadVehicleElec.ptwEnergyConsumption =  (OnroadVehicleElec.wtwEfficiency) *
(OnroadVehicleElec.vehicleParam.VehicleParameters.travelDist);
OnroadVehicleHuman.ptwCO2Output =  (OnroadVehicleHuman.totalCO2Factor) *
(OnroadVehicleHuman.ptwEnergyConsumption);
OnroadVehicleHuman.ptwEnergyConsumption =  (OnroadVehicleHuman.ptwEfficiency) *
(OnroadVehicleHuman.vehicleParam.VehicleParameters.travelDist);
OnroadVehicleHuman.wtwEfficiency =  (OnroadVehicleHuman.ptwEnergyConsumption) /
(OnroadVehicleHuman.vehicleParam.VehicleParameters.travelDist);
OnroadVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.co2Facto
r =  (Fuel.co2Density) / (Fuel.LHV);
OnroadVehicleICE.ptwCO2Output =
(OnroadVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.co2Fact
or) * (OnroadVehicleICE.ptwEnergyConsumption);
OnroadVehicleICE.ptwEfficiency =  (OnroadVehicleICE.ptwEnergyConsumption) /
(OnroadVehicleICE.vehicleParam.VehicleParameters.travelDist);
OnroadVehicleICE.ptwEnergyConsumption =
(OnroadVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.LHV) *
(OnroadVehicleICE.ptwLiquidFuelConsumption);
OnroadVehicleICE.ptwLiquidFuelConsumption =
(OnroadVehicleICE.vehicleParam.VehicleParameters.travelDist) /
(OnroadVehicleICE.ptrain.Powertrain_ICE.iceFuelEfficiency);
Rail.martaRail.RailVehicleElec.ptwCO2Output =  (RailVehicleElec.totalCO2Factor)
* (RailVehicleElec.ptwEnergyConsumption);
Rail.martaRail.RailVehicleElec.ptwEnergyConsumption =
(RailVehicleElec.wtwEfficiency) *
(RailVehicleElec.vehicleParam.VehicleParameters.travelDist);
Rail.railDist =
(Rail.martaRail.RailVehicleElec.vehicleParam.VehicleParameters.travelDist) *
(Rail.num_rail);
Rail.railPTWCO2Output =  (Rail.martaRail.RailVehicleElec.ptwCO2Output) *
(Rail.num_rail);
Rail.railPTWEnergyUse =  (Rail.num_rail) *
(Rail.martaRail.RailVehicleElec.ptwEnergyConsumption);
Rail.railPass =
(Rail.martaRail.RailVehicleElec.vehicleParam.VehicleParameters.occupancy) *
(Rail.num_rail);
Rail.railPassDist =  (Rail.railDist) * (Rail.railPass);
RailVehicleElec.ptwCO2Output =  (RailVehicleElec.totalCO2Factor) *
(RailVehicleElec.ptwEnergyConsumption);
RailVehicleElec.ptwEfficiency =  (RailVehicleElec.ptwEnergyConsumption) /
(RailVehicleElec.vehicleParam.VehicleParameters.travelDist);
RailVehicleElec.ptwEnergyConsumption =  (RailVehicleElec.wtwEfficiency) *
(RailVehicleElec.vehicleParam.VehicleParameters.travelDist);
RailVehicleICE.ptwCO2Output =  (RailVehicleICE.totalCO2Factor) *
(RailVehicleICE.ptwEnergyConsumption);
RailVehicleICE.ptwLiquidFuelConsumption =
(RailVehicleICE.vehicleParam.VehicleParameters.travelDist) /
(RailVehicleICE.ptrain.Powertrain_ICE.iceFuelEfficiency);
RailVehicleICE.ptwEfficiency =  (RailVehicleICE.ptwEnergyConsumption) /
(RailVehicleICE.vehicleParam.VehicleParameters.travelDist);
RailVehicleICE.ptwEnergyConsumption =
(RailVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.LHV) *
(RailVehicleICE.ptwLiquidFuelConsumption);
Road.autoICE.OnroadVehicleICE.ptwCO2Output =
(OnroadVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.co2Fact
or) * (OnroadVehicleICE.ptwEnergyConsumption);
Road.autoICE.OnroadVehicleICE.ptwEnergyConsumption =
(OnroadVehicleICE.ptrain.Powertrain_ICE.motor.Motor_ICE.fuelChoice.Fuel.LHV) *
(OnroadVehicleICE.ptwLiquidFuelConsumption);
```

```
Road.roadDist =
(Road.autoICE.OnroadVehicleICE.vehicleParam.VehicleParameters.travelDist) *
(Road.num_auto);
Road.roadPTWEnergyUse =  (Road.autoICE.OnroadVehicleICE.ptwEnergyConsumption) *
(Road.num_auto);
Road.roadPass =
(Road.autoICE.OnroadVehicleICE.vehicleParam.VehicleParameters.occupancy) *
(Road.num_auto);
Road.roadPTWCO2Output =  (Road.autoICE.OnroadVehicleICE.ptwCO2Output) *
(Road.num_auto);

Elapsed time is 32.974516 seconds.
```

Published with MATLAB® 7.9

REFERENCES

Alberti, M. (1996). "Measuring urban sustainability." *Environmental Impact Assessment Review*, 16(4-6), 381-424.

American Community Survey: (2008). "Means of Transportation to Work by Selected Characteristics." U.S. Census Bureau.

Ansaldobreda. (2007). *Atlanta HRV Specifications*.

Bailey, L., Mokhtarian, P., and Little, A. (2008). *The Broader Connection Between Public Transportation, Energy Conservation and Greenhouse Gas Reduction*. ICF International.

Barth, M., and Todd, M. (1999). "Emerging Technologies : Simulation model performance analysis of a multiple station shared vehicle system." *Transportation Research Part C*, 7(4), 237-259.

Barth, M. J., and Norbeck, J. M. (1994). *Transportation Modeling For The Environment*. California Partners for Advanced Transit and Highways (PATH).

Bertolini, L., le Clercq, F., and Kapoen, L. (2005). "Sustainable accessibility: a conceptual framework to integrate transport and land use plan-making. Two test-applications in the Netherlands and a reflection on the way forward." *Transport Policy*, 12(3), 207-220.

Bertolini, L., and Dijst, M. (2003). "Mobility Environments and Network Cities.." *Journal of Urban Design*, 8(1), 27.

Black, W. R. (1996). "Sustainable transportation: a US perspective." *Journal of Transport Geography*, 4(3), 151-159.

Bollinger, C. R., and Ihlanfeldt, K. R. (1997). "The Impact of Rapid Rail Transit on Economic Development: The Case of Atlanta's MARTA,." *Journal of Urban Economics*, 42(2), 179-204.

Bonabeau, E. (2002). "Agent-based modeling: Methods and techniques for simulating human systems." *Proceedings of the National Academy of Sciences of the United States of America*, 99(Suppl 3), 7280-7287.

Brundtland, G. (1987). *Our Common Future: Report of the World Commission on Environment and Development*. World Commission on Environment and Development, Brussels.

Cervero, R., and Kockelman, K. (1997). "Travel demand and the 3Ds: Density, diversity, and design." *Transportation Research Part D: Transport and Environment*, 2(3), 199-219.

Chandler, K., Norton, P., and Clark, N. (1999). *Update from the NREL Alternative Fuel Transit Bus Evaluation Program*.

Chapman, J., and Frank, L. (2004). *Integrating Travel Behavior and Urban Form Data to Address Transportation and Air Quality Problems in Atlanta*. Active Transportation Collaboratory, University of British Columbia.

Davis, S. C., Diegel, S. W., and Boundy, R. G. (2008). *Transportation Energy Data Book*. Oak Ridge National Laboratory: Center for Transportation Analysis Energy and Transportation Science Division.

Dawson, C. (2008). *Heavy Rail Transit Ridership Report: Third Quarter 2008*. American Public Transit Association.

Delucchi, M. (2003). *A Lifecycle Emissions Model (LEM): Lifecycle Emissions from Transportation Fuels, Motor Vehicles, Transportation Modes, Electricity Use, Heating and Cooking Fuels, and Materials*. Institute of Transportation Studies.

Delucchi, M. A. (2004). *Conceptual and Methodological Issues in Lifecycle Analyses of Transportation Fuels*. Research Report, University of California, Davis, Institute of Transportation Studies.

Energy Information Administration. (2009). *Electric Power Monthly: February 2009*. Office of Coal, Nuclear, Electric and Alternate Fuels, U.S. Department of Energy.

Environmental Protection Agency. (1994). *Federal Register: Regulation of Fuels and Fuel Additives: Standards for Reformulated and Conventional Gasoline*.

European Commission. (1997). *Intermodality and Intermodal Freight Transport in European Union: A System Approach to Freight Transport - Strategies and Actions to Enhance Efficiency, Services and Sustainability*. European Commission, Directorate General DG VII, Brussels.

Federal Transit Administration. (2007). *Transit Profiles: The Top 50 Agencies*. National Transit Database.

Fels, M. F. (1975). "Comparative energy costs of urban transportation systems." *Transportation Research*, 9(5), 297-308.

Forsberg, K., Mooz, H., Forsberg, D. K., Harold, M., and Co-principals, M. (1998). "System Engineering for Faster, Cheaper, Better."

Friedenthal, S., Moore, A., and Steiner, R. (2008). *A Practical Guide to SysML: The Systems Modeling Language*. Morgan Kauffman OMG Press.

Garg, A., and Pulles, T. (2006). *2006 IPCC Guidelines for National Greenhouse Gas Inventories: Volume 2, Energy*. Intergovernmental Panel on Climate Change.

Garvin, A. (2006). *The Beltline Emerald Necklace: Atlanta's New Public Realm*. Trust for Public Land, Washington DC.

Georgia Department of Transportation. (2007a). *Mileage by Route Type and Road System*. GDOT, Office of Transportation Data.

Georgia Department of Transportation. (2007b). *City Mileage Report*. GDOT, Office of Transportation Data.

Goldman, T., and Gorham, R. (2006). "Sustainable urban transport: Four innovative directions." *Technology in Society*, 28(1-2), 261-273.

Graham, S., and Marvin, S. (1996). *Telecommunications and the CIty: Electronic SPaces, Urban Places*. Routledge, London, New York.

Greene, D. L., and Wegener, M. (1997). "Sustainable transport." *Journal of Transport Geography*, 5(3), 177-190.

Herzog, E., P, A., and Ab, S. (2005). "SysML – an Assessment."

Hunt, J. (2000). *The unified process for practitioners : object-oriented design, UML and Java*. Springer, London ;;New York.

International Organization for Standardization. (2006). "ISO 14040:2006 - Environmental management - Life cycle assessment - Principles and framework." Text,, <http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=37456> (Apr. 28, 2010).

Janic, M. (2001). "Integrated transport systems in the European Union: an overview of some recent developments.." *Transport Reviews*, 21(4), 469-497.

Jobe, J. M., Johnson, T. A., and Paredis, C. (2008). "Multi-Aspect Component Models: A Framework for Model Reuse in SysML." New York, USA.

Jobe, J. M. (2008). "Multi-Aspect Component Models: Enabling the Reuse of Engineering Analysis Models in SysML." Thesis, Georgia Institute of Technology.

Johnson, T. A., Jobe, J. M., Paredis, C., and Burkhart, R. M. (2007). "Modeling Continous System Dynamics in SysML." *IMECE*, Seattle, Washington, USA.

Keating, C., Rogers, R., Unal, R., Dryer, D., Sousa-Posa, A., Safford, R., Perterson, W., and Rabadi, G. (2008). "System of Systems Engineering." *Engineering Management Review*, 36(4), 62.

Kenworthy, J., and Laube, F. (2001). *The Millenium Cities Database for Sustainable Transport*. International Union of Public Transport, Brussels.

Kenworthy, J., and Townsend, C. (2002). “An International Comparative Perspective on Motorisation in Urban China. Problems and Prospects..” *IATSS Res (Int Assoc Traffic Saf Sci)*, 26(2), 99-109.

Lee, J. J., O'Callaghan, P., and Allen, D. (1995). “Critical review of life cycle analysis and assessment techniques and their application to commercial activities.” *Resources, Conservation and Recycling*, 13(1), 37-56.

Litman, T., and Laube, F. (2002). *Automobile Dependency and Economic Development*. Victoria Transport Policy Institute.

Luna-Camara, J., Hankey, R., Cassar, C., McNerney, R., and Harris-Russell, C. (2009). “Electric Power Industry 2007: Year in Review.” Energy Information Administration.

Metropolitan Atlanta Rapid Transit Authority. (2007). *Fiscal Year 2007 Annual Report*.

Metropolitan Atlanta Rapid Transit Authority. (2009). *MARTA Completes Extensive Rail Car Rehabilitation Program*. Press Release, Metropolitan Atlanta Rapid Transit Authority.

Nagurney, A. (2000). “Transport and Environment : Congested urban transportation networks and emission paradoxes.” *Transportation Research Part D*, 5(2), 145-151.

Object Modeling Group. (2008). *OMG Systems Modeling Language: Version 1.1 Specification*.

O'Toole, R. (2008). *Does Rail Transit Save Energy or Reduce Greenhouse Gas Emissions?* Cato Institute.

Pahl, G., and Beitz, W. (1988). “Engineering design: A systematic approach.” *NASA STI/Recon Technical Report A*, 89, 47350.

Pezzey, J. C. V., and Toman, M. A. (2002). “Progress and Problems in the Economics of Sustainability.” *International Yearbook of Environmental and Resource Economics 2002/2003*, Edward Elgar, Cheltenham, U.K, 165-232.

Priemus, H., Nijkamp, P., and Banister, D. (2001). “Mobility and spatial dynamics: an uneasy relationship.” *Journal of Transport Geography*, 9(3), 167-171.

Reap, J., Roman, F., Duncan, S., and Bras, B. (2008). “A survey of unresolved problems in life cycle assessment.” *The International Journal of Life Cycle Assessment*, 13(4), 290-300.

Rees, W., and Wackernagel, M. (2008). “Urban Ecological Footprints: Why Cities Cannot be Sustainable—and Why They are a Key to Sustainability.” *Urban Ecology*, 537-555.

Richardson, B. C. (2005). “Sustainable transport: analysis frameworks.” *Journal of Transport Geography*, 13(1), 29-39.

Rothschild, S., Quiroz, C., and Salhotra, M. (2009). “The Value of eGRID and eGRIDweb to GHG Inventories.”

Schafer, A. (1998). “The global demand for motorized mobility.” *Transportation Research Part A: Policy and Practice*, 32(6), 455-477.

Schrank, D., and Lomax, T. (2009). *The 2009 Annual Urban Mobility Report*. Texas Transportation Institute, Texas A&M University System.

Seebregts, A. J., Goldstein, G. A., and Smekens, K. (2001). *Energy/Environmental Modeling with the MARKAL Family of Models*. Energy Research Centre of the Netherlands (ECN), Policy Studies Unit.

Singh, M., Vyas, A., and Steiner, E. (2004). *VISION Model : description of model used to estimate the impact of highway vehicle technologies and fuels on energy use and carbon emissions to 2050.* United States.

Small, K. A., and Van Dender, K. (2005). “The Effect of Improved Fuel Economy on Vehicle Miles Traveled: Estimating the Rebound Effect Using U.S. State Data, 1966-2001.” University of California Energy Institute. Policy & Economics.

Smith, L., Beckman, R., Anson, D., Nagel, K., and Williams, M. (1995). “TRANSIMS: TRansportation ANalysis and SIMulation System.” United States, Size: 8 p.

Stone, B., Mednick, A. C., Holloway, T., and Spak, S. N.“Mobile Source CO2 Mitigation through Smart Growth Development and Vehicle Fleet Hybridization.” *Environmental Science & Technology*, 0(0).

Taylor, R. A. (1999). “Origin of System Dynamics: Jay W. Forrester and the History of System Dynamics.” *U.S. Department of Energy's Introduction to System Dynamics*.

Turton, H. (2006). “Sustainable global automobile transport in the 21st century: An integrated scenario analysis.” *Technological Forecasting and Social Change*, 73(6), 607-629.

U.S. Census Bureau. (2007). “American Community Survey: Commuting Characteristics by Sex.” Population Reference Bureau.

U.S. Census Bureau, Population Division. (2008). *Annual Estimates of the Population of Metropolitan and Micropolitan Statistical Areas: April 1, 2000 to July 1, 2007*.

U.S. Energy Information Administration. (2009). *Annual Energy Outlook 2010*. U.S. Energy Information Administration, U.S. Department of Energy.

United Nations. (2005). “World Urbanization Prospects: The 2005 Revision.” Department of Economic and Social Affairs, United Nations.

Vivier, J., and Mezghani, M. (2001). *The Millenium Cities Database - A Tool for Sustainable Mobility*. UITP, Brussels.

Wang, J., Lu, H., and Peng, H. (2008). “System Dynamics Model of Urban Transportation System and Its Application.” *Journal of Transportation Systems Engineering and Information Technology*, 8(3), 83-89.

Wang, M. Q. (1999). *GREET 1.5 - transportation fuel-cycle model - Vol. 1 : methodology, development, use, and results.*

Wang, M. Q. (2001). *Development and use of GREET 1.6 fuel-cycle model for transportation fuels and vehicle technologies.* United States, Size: vp.

Wang, M. (2002). “Fuel choices for fuel-cell vehicles: well-to-wheels energy and emission impacts.” *Journal of Power Sources*, 112(1), 307-321.

World Business Council for Sustainable Development. (2001). *Mobility 2001 - World Mobility at the End of the Twentieth Century and Its Sustainabiltiy*. Sustainability Working Group, Massechusetts Institute of Technology.

Yang, X., and Lo, C. (2003). “Modelling urban growth and landscape changes in the Atlanta metropolitan area..” *International Journal of Geographical Information Science*, 17(5), 463.

Zielinksi, S. (2006). “New Mobility: The Next Generation of Sustainable Urban Transportation.” *Papers from the 12th U.S. Frontiers of Engineering*, The Bridge, 36(4).