# DEVELOPMENT OF A FRAMEWORK FOR PROJECTING LINE-HAUL TRUCK TECHNOLOGY ADOPTION AND GREENHOUSE GAS EMISSIONS IN THE U.S. USING A SYSTEM-OF-SYSTEMS METHODOLOGY

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To my husband, Justin, and my parents, Lilia and Arturo.

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Going back to school after a few years of working in the industry was a difficult task. I was strongly motivated to continue developing my skills as an engineer; however, after years of having graduated from a master's degree, the need to create a space where I could succeed as a student required commitment from people other than myself. I owe so much to these people, who were there for me and helped me succeed and grow in every step of the way. I realize the strain I placed on them, and I am forever grateful for their kindness and support.

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# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

Figure Page

Figure Page

# ABSTRACT

Guerrero de la Peña, Ana Ph.D., Purdue University, May 2020. Development of a Framework for Projecting Line-Haul Truck Technology Adoption and Greenhouse Gas Emissions in the U.S. using a System-of-Systems Methodology. Major Professor: Neera Jain, School of Mechanical Engineering.

In order to displace diesel fuel consumption and reduce greenhouse gas emissions in the line-haul freight transportation system, a strong uptake of low and zero emission vehicle technologies must be incentivized by manufacturers and policymakers alike. A simulation tool that can project a wide array of future scenarios and predict the effects of freight transportation system evolution on mixed technology adoption trajectories is needed. This tool can assist the system stakeholders identify the level of innovation and policies necessary to increase the economic attractiveness of cleaner technologies and therefore incentivize the market to reduce system-wide emissions.

In this thesis I present a simulation framework for projecting adoption and utilization of emerging technologies and network-wide emissions in a line-haul freight transportation system network. A System-of-Systems engineering methodology is followed to realize the definition, abstraction and simulation of the system. This results in a framework capable of modeling the evolution of system factors with respect to time and their influence across a set of representative heterogeneous line-haul fleets operating on a regional network. A constrained mixed-integer linear program is used to represent the decision-making process for heterogeneous fleets selecting vehicles and allocating them on freight delivery routes to minimize total cost of ownership. The proposed model is parametrized and validated using a Design of Experiments (DOE) and historical adoption data. The results of this SoS model demonstrate 90% accuracy in prediction outcome when modeling historical technology adoption across a set of 12 heterogeneous representative fleets over an 11-year period. The formula-

tion is then implemented to project alternative powertrain technology adoption and utilization trends for a set of line-haul fleets. Alternative powertrain technologies include compressed and liquefied natural gas engines, diesel-electric hybrid, battery electric, and hydrogen fuel cell. Future policies, economic factors, and availability of fueling and charging infrastructure are input assumptions to the proposed modeling framework. Three mixed-adoption scenarios, including BE, HFC, and CNG vehicle market penetration, are identified by the DOE study to demonstrate the potential to reduce cumulative $CO_2$ emissions by more than 25% between 2018–2028. Next, the framework is exercised to project powertrain adoption, utilization, and emissions from 2019–2035 given a set of assumptions for the impact different levels of autonomy may have on purchase costs, vehicle efficiency, driver wages, vehicle reliability, and hours of service regulations. The proposed model formulation, which predicts both adoption *and* utilization, can enable stakeholders with a deeper understanding of *how and why* different levels of autonomy impact the broader freight transportation network. Finally, the framework is extended to predict adoption and utilization behaviors upon introduction of intra-fleet 2-vehicle platooning. A study on the effects of platooning fuel efficiency and freight demand on adoption, utilization, and resulting network emissions is presented.

# 1. INTRODUCTION

In order to displace diesel fuel consumption and reduce greenhouse gas emissions in the line-haul freight transportation system (FTS), a strong uptake of low and zero emission heavy-duty Class 8 technologies must be incentivized by policymakers. Trucks move more than 13 billion tons of freight annually, representing more than 80% of all freight movement by weight in the U.S. [1–3]. Moreover, heavy-duty Class 7 and 8 trucks, those weighing over 26,000 pounds, represent more than 70% of the vehicle miles traveled by freight transportation trucks in the U.S. [3]. Presently, an overwhelming majority of these vehicles use diesel internal combustion engines, with less than 2% using natural gas or other alternative fuels [4]. Since 1990, greenhouse gas emissions from freight trucking have increased five times faster than emissions produced from passenger travel. These numbers are expected to increase by more than 40% by 2040 [2, 3].

Alternative powertrain technologies—compressed (CNG) and liquefied natural gas (LNG), hybridization, battery electric, and hydrogen fuel cells—have been proposed for their benefits in terms of energy savings and reduction of greenhouse emissions. Moreover, autonomous vehicles are similarly anticipated to enter the line-haul segment as highway routes provide the ideal platform for this type of operation. Autonomous capability is also expected to produce benefits in the fuel economy of Class 8 vehicles. For example, Delorme et al. [5] present fuel savings potential between 3 and 17% for mild-hybrid (starter-alternator configuration with no electric-only mode) and full-hybrid (series-parallel configuration and electric-only mode) electric diesel vehicles with a 5 to 25 kWh battery capacity over a conventional diesel architecture for Class 8 long-haul trucks given the hybrid configuration, route type, and route grade. Zhao et al. [6] present a fuel savings comparison for LNG, hybrid electric, battery electric, and fuel cell heavy-duty vehicle architectures over a diesel baseline by simulating their operation on day, short-haul, and long-haul drive cycles. Their study demonstrates $CO_2$ emissions reduction between 24-39% for day drive cycles and 12-29% reduction for short- and long-haul cycles for vehicles with alternative powertrain configurations. Lammert et al. [7] present fuel consumption reduction of more than 10% for two Class 8 tractor-trailer diesel conventional vehicles operating in platooning mode at varying gap distances, steady-state speeds, and gross vehicle weight during a series of track tests. Furthermore Graham et al. [8] compare tailpipe greenhouse gas emissions produced by diesel, biodiesel, CNG, LNG, and hythane heavy-duty vehicles over standardized drive cycles. Note, however, that these studies present the potential reduction of $CO_2$ emissions for *a single vehicle operating over a predetermined drive-cycle.*

On the other hand, modeling and projecting the technology adoption trajectories that result in a targeted reduction in emissions *across a network* is a complex task. Emerging technologies may bring revolutionary and unexpected changes to the way fleet vehicles are operated since their performance (efficiency, range, payload capacity, etc.) differs from the well-known diesel baseline. Moreover, infrastructure for alternative fuels and electric vehicles must proliferate to support the introduction of new technologies. Finally, future fuel prices and active and new regulatory policies and incentives will affect the attractiveness of emerging technologies. Ultimately, it is the economic competitiveness, as perceived by Class 8 line-haul fleets, that will determine the levels of penetration these technologies will have in the sector. *Given that the evolution of these freight transportation system factors is uncertain, a simulation tool that can be used to project a wide array of future scenarios and predict the effects on mixed technology adoption trajectories is needed.*

## 1.1 Background

Given the variation in fleet characteristics and the effect the allocation of fleet vehicles will have on network traffic and route vehicle speeds, adoption and utilization behaviors must be cumulatively observed across the set of heterogeneous fleets operating over the network of interest. A large majority, 86%, of Class 8 tractors used in line-haul freight transportation are company-owned and operated as a fleet, whereas only 14% are owner-operator trucks. A heavy-duty vehicle fleet may contain a diverse range of equipment types, with different operational and usage profiles. This may be particularly true when different technologies, or fuels, are used within a single fleet. The engine, chassis, and body of trucks and trailers are often produced by different manufacturers, and in reality, fuel consumption and economic attractiveness will be determined by the features of the complete vehicle [6, 9].

Fleets purchase vehicles annually to satisfy demand growth or necessary vehicle replacement using Total Cost of Ownership (TCO) as the most common purchasing criteria. The TCO is a function of acquisition price as well as any costs incurred during operation of the vehicle. An individual fleet owner will not only select the vehicle architectures it adopts but also control the routes over which its vehicles operate in order to move freight in a cost-efficient and timely manner. In this way, the fleet owner can be thought of as exerting *centralized* control over their fleet. In the context of the FTS, though, fleets demonstrate *operational and managerial independence* as they operate independently of one another over a single regional network. This *decentralized behavior* at the network level in turn has significant impact on the projection of widespread vehicle adoption because vehicle purchase and allocation decisions are in no way coordinated across fleets. Figure 1.1 shows a schematic of the structure of the line-haul FTS, in which a regulating authority defines a set of policies influencing regional fleets, yet does not make decisions for them. This results in a heterogeneous array of fleets of different size and composition.

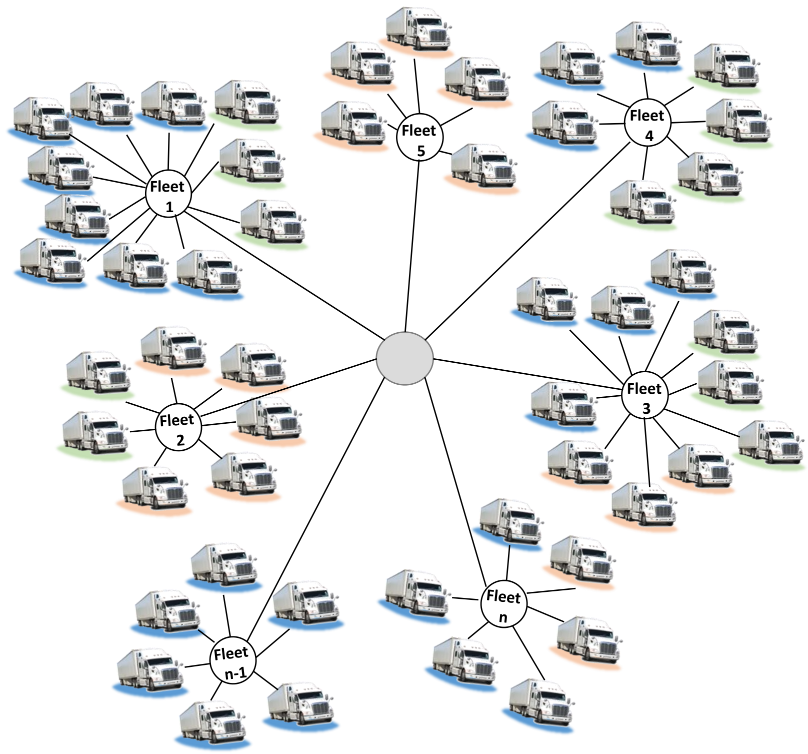



Figure 1.1. : Schematic representing the decentralized structure of the line-haul FTS.

While the search for a strategic transition to cleaner trucks is not new in the literature, few studies have focused on modeling the way fleets, particularly Class 8 fleets, adopt vehicles based on their perceived utility. A few studies present vehicle ownership cost minimization models for a single fleet that consider cost of acquisition and operational costs. Moreover, the literature on this subject is at best limited to a single fleet's adoption behaviors, therefore assuming a homogeneity that is not realistic across the FTS. Davis et al. [10] present a TCO optimization model assuming a commercial delivery fleet is homogeneous; that is, all vehicles of the same type–diesel or electric–are selected to deliver all freight demand. Feng and Figliozzi [11] present an ownership cost minimization model for a single mixed-fleet of diesel and electric delivery vehicles, introducing replacement cycles and vehicle salvage revenue. Although both studies take into consideration ownership cost sensitivity to vehicle speed, battery life, and tax incentives, these models do not consider vehicle route allocation as a decision metric and instead, predetermined route lengths and daily energy consumption estimates are imposed. Any effects of system evolution and operational requirements of different technologies—fueling and charging needs, infrastructure changes, traffic, etc.—on vehicle allocation are not taken into account. Janic [12] presents a model to calculate the reduced total costs of a single intermodal collection and distribution fleet when heavier and longer vehicles are used. The costs are based on historical local and global aggregated data, and not on the operational decisions made at the fleet level.

Although fleets demonstrate *operational and managerial independence* as they operate independently of one another, they are influenced by a common environment: the FTS. The line-haul FTS shows *evolutionary development* traits. The introduction of alternative fuels and powertrains, as well as advanced automation capabilities, will cause both infrastructure and operational policies to evolve in order to support and regulate the operation of these new technologies. Moreover, the dynamic cost of fuel and electricity, freight demand, and even technological capabilities will vary with time. It is precisely the effects of these system dynamics that are generally not captured by modeling approaches that rely on extrapolation of previous historical trends to project the effect on adoption and utilization of future generations of technology. For example, authors in [13–15] project emissions reductions by simply extrapolating historical trucking data (e.g. projected number of vehicles, annual miles traveled) and assuming potential market penetration scenarios. They do not provide readers with an understanding of how to achieve the vehicle adoption rates that are assumed to be necessary for a significant reduction in emissions.

Furthermore, few studies have focused on modeling the way fleets, particularly Class 8 fleets, adopt vehicles based on their perceived economic attractiveness *as the freight transportation system (FTS) evolves over time.* If we consider the FTS as a system of systems (SoS), *emergent behavior* properties may also appear in the SoS that are not apparent (or predicted) from its constituent systems, but can be observed at higher levels of the system hierarchy. For example, the combined effects of fuel and electricity costs, powertrain performance, and availability of regional charging infrastructure may reveal new adoption behaviors and traffic trends in the region of operation. Future trucking metrics and trends, including vehicle miles traveled, preferred routes, and number of vehicles purchased, should not be assumed to follow those trends observed in the past. These metrics should not be extrapolated from historical data, but instead, their evolution should be modeled as a result of dynamic changes in the FTS.

Table 1.1 summarizes the literature on emerging vehicle technology adoption, indicating that current studies only account for variables within a few domains (e.g. vehicle performance, single fleet decisions, etc.), while assuming all other FTS considerations, e.g. number of vehicles, vehicle miles traveled and other utilization metrics, or energy costs, remain indefinitely constant. These assumptions, while at times necessary to manage scalability of the problem, mask the interacting effects of the FTS evolution on adoption and utilization behaviors across a set of heterogeneous fleets and can lead to an incomplete study of market adoption and the viability of reduced network emissions.

Table 1.1. : FTS Gaps in Literature Summary

| Study | Vehicle cost analysis | Fleet utility analysis | Policy effects on adoption & emissions | Heterogeneous market composition & emissions | Effects of system evolution | Vehicle allocation & utilization trends |
|---|---|---|---|---|---|---|
| Davis and Figliozzi [10] | X | X | X | | | |
| Delorme et al. [5] | X | | | | | |
| Feng and Figliozzi [11] | X | X | X | | | |
| Fulton and Miller [13] | X | | | X | | |
| Graham et al. [8] | | | | X | | |
| Janic [12] | | X | | | | |
| Kleiner et al. [16] | X | X | | | | |
| Lammert et al. [7] | X | | | | | |
| Moultak et al. [15] | X | X | | X | | |
| Schafer and Jacoby [14] | X | | | X | | |
| TRB and NCFRP [9] | X | | | | | |
| Wadud et al. [17] | X | | X | | | |
| Zhao et al. [6] | X | X | | | | |

Greenhouse gases produced by the transportation system are a product of the vehicle composition—diesel, alternative fuel, zero emission, and autonomous vehicles—of fleets operating in a region, as well as the utilization of the vehicles. As mentioned before, it is the fleets who adopt vehicles in order to satisfy freight transportation needs in a cost-efficient manner, and their adoption and utilization behaviors are a product of their environment. In order to capture the evolutionary dynamics of the FTS and emerging vehicle adoption and utilization behaviors, it is necessary to develop parametrized, models of the FTS components. These time-varying models can then be integrated as the environment of inputs and constraints influencing fleet behaviors to create a holistic simulation framework. This simulation framework can determine how changes in the physical and functional characteristics of the vehicles, fueling and charging infrastructure, and policy components can be modified to target desirable adoption paths and a significant reduction in emissions in a region of study.

## 1.2 Thesis Objective and Contribution

In this thesis, I present a mathematically rigorous framework for projecting adoption and utilization of emerging technologies and network-wide emissions by modeling the evolution of FTS factors with respect to time and their influence across a set of representative heterogeneous line-haul fleets. In order to develop this framework, I make the following contributions:

1. Follow a System-of-Systems engineering methodology to realize the definition, abstraction, and simulation of the FTS as a complex system of independent and distributed systems, the set of line-haul fleets, that are collectively influenced by, and in return impact, the evolution of the FTS.

2. Develop a model for heterogeneous fleet behavior recognizing that fleets independently optimize vehicle selection and allocation over the network based on their own size, budget, cargo demand, etc.

3. Develop parametrized models of the FTS subsystems and fleet characteristics that consider time-varying fuel and energy costs, technology purchase costs, vehicle traffic allocation, availability of supporting infrastructure, policy effects, and freight demand in order to project mixed-composition scenarios of emerging powertrains and vehicle autonomy.

4. Through integration of the models in items 2 and 3, and simulation and analysis, determine how changes in the physical and functional characteristics of the vehicles, fueling and charging infrastructure, and policies and incentives must be shaped over time to target a desirable market penetration of emerging powertrain technologies and reduction of $CO_2$ emissions.

In this thesis, I present a model of the behaviors of a fleet selecting vehicles for purchase and operation as it is influenced by vehicle highway performance, fleet management considerations, infrastructure availability, and external influences such as cost of energy, regional freight demand, and policies. Furthermore, the parametrized model of the FTS representing the evolution of these factors is integrated with this fleet behavioral model to comprise a heterogeneous set of line-haul fleets, with varying characteristics, that together represent the FTS network-wide adoption using trends of heavy-duty Class 8 vehicle technologies.

## 1.3 Outline

This dissertation is organized as follows. Chapter 2 describes the System-of-Systems engineering methodology followed to develop the simulation framework and the abstraction and implementation of the fleet behavior model. Moreover, this section presents the validation of the framework with historical data. Chapter 3 presents the extension, calibration, and use of the framework to project adoption and utilization of diesel and 5 alternative powertrain technologies and the resulting network emissions. A sensitivity analysis of the framework to different system factors, including vehicle performance parameters, fuel costs, infrastructure availability, and policies, among others is also presented in Chapter 3. Chapter 4 describes the extended model formulation and key assumptions made regarding the effect of various autonomy levels on fleet-wide and network-wide operations. An analysis of different case scenarios in which Levels 2, 4 and 5 of vehicle autonomy are introduced to the market is also presented in this chapter. Chapter 5 presents the introduction of intra-fleet 2-vehicle platoons to the formulation, and the resulting effects of platooning capability and powertrain options on technology adoption and utilization. Finally, conclusions are stated in Chapter 6, including a discussion of potential future work.

# 2. FREIGHT TRANSPORTATION AS A SYSTEM-OF-SYSTEMS

A freight transportation system (FTS) is a critical element of an industrial and globalized economy, but it also imposes a high cost on the environment. In the US alone—where 60% of freight is moved on highway roads by Class 8 trucks—freight transportation trucking generates an estimated 450 million tons of $CO_2$ emissions annually [1]. Presently, an overwhelming majority of heavy-duty Class 8 vehicles use diesel internal combustion engines, with less than 2% using natural gas or other alternative fuels [4]. Adoption of cleaner vehicle technologies in the heavy-duty trucking segment is regarded as a promising strategy to reduce emissions in the transportation sector. However, the market penetration levels that these emerging technologies will ultimately achieve depends on their economic attractiveness as perceived by the fleets that will acquire and operate them. It is also well known that freight technology adoption is a function of not only the acquisition price of a given technology or its performance benefits (e.g. as characterized by an average increase in fuel economy), but also state and federal policies and incentives, regional fuel costs, fleet operation strategies, network characteristics, etc. [18]. Moreover, these factors also affect how a fleet operates the vehicles they purchase given the varied performance capabilities of said vehicles. More importantly, the decision-making behavior of fleets servicing the FTS vary as a function of their size, operating strategy, annual growth, vehicle replacement cycles, etc. Ostensibly, these fleet entities make their acquisition decisions independent of each other, however they operate and interact on a single, shared transportation network, altogether influenced by the evolution of the FTS environment. In other words, in order to capture emergent mixed technology adoption trends in the freight transportation network, its evolution must be modeled across the *heterogeneous mix* of fleets that service it.

The search for a strategic transition to cleaner trucks is not new in the literature. However, while many researchers and stakeholders are interested in modeling technology adoption across the freight transportation sector, the literature on this subject is at best limited to a single fleet's adoption behaviors, therefore assuming a homogeneity that is not realistic across the FTS. Davis et al. [10], for example, introduce a series of scenarios for which adoption of electric vehicles offer a reduction in cost of ownership, when compared to diesel adoption, for a single mixed-composition delivery fleet over an 11-year period. Feng and Figliozzi [11] present a similar diesel and electric delivery vehicle adoption model for a single mixed-fleet, additionally introducing replacement cycles and vehicle salvage revenue. Although both studies take into consideration ownership cost sensitivity to vehicle speed, battery life, and tax incentives, they impose daily energy consumption estimates and fixed routes, without considering the dynamic effects of the FTS evolution on vehicle utilization. The aforementioned studies do not consider the availability of charging infrastructure and route optimization, thereby ignoring the relationship between infrastructure system evolution and vehicle operation planning. Furthermore, Janic [12] presents a model to calculate the reduced total costs of an intermodal collection and distribution fleet when heavier and longer vehicles are used. The costs are based on historical local and global aggregated data, and not on the operational decisions made at the fleet level.

Moreover, a majority of the literature on projection of trucking freight technology adoption focuses on evaluating the *drive-cycle* performance of emerging vehicle technologies and resulting fuel or energy savings as a measure of their economic attractiveness and potential for widespread adoption, rather than the direct effects that vehicle performance and FTS evolution will have on fleet adoption behaviors [5–7]. Finally, other studies take into account drive-cycle performance and extrapolated historical data—projected number of vehicles, annual vehicle miles traveled, etc.—and project resulting emissions reduction given different assumed market penetration scenarios. For example, Fulton et al. [13] explore high levels of market penetration of different low-carbon vehicle technologies, such as alternative fuel architectures and electric vehicles, and the resulting capability to meet 80% reduction of $CO_2$ emissions in the U.S. by 2050. Schafer et al. [14] present rates of adoption for different personal vehicles and heavy-duty Class 8 diesel truck technologies under $CO_2$ emission constraints and penalty costs. Finally, Wadud et al. [17] present a qualitative estimate of changes in energy consumption and carbon impact of light-duty and heavy-duty vehicles given the levels of automation adopted in four assumed scenarios. While these studies describe projected adoption scenarios and resulting emissions levels, they do not provide any further understanding on the mechanisms that lead FTS fleets to exhibit the vehicle adoption behaviors in the proposed scenarios.

The future technology composition of the FTS will likely be mixed as a result of the many independent fleets that purchase and operate vehicles based on their individual management and operational strategies; however, these fleets are altogether influenced by, and collectively affect, the dynamics and evolution of their common environment. Individual fleets of varying characteristics will maintain their independence by self-regulating their adoption cycles and vehicle utilization strategies, all the while contributing and taking resources from other FTS systems (e.g., road network, traffic, freight demand, policy incentives) [19]. System-of-Systems Engineering (SoSE) [20] is an emerging and specialized field of research in complex systems that addresses the capabilities resulting from the interaction and collaboration of large-scale independent and distributed systems. A foundational principle of SoSE is that the constituent systems maintain their independence (e.g., fleets) but contribute to, or take resources from, other systems (e.g., road network, traffic) for mutual benefit [19]. Any change in one system, therefore, ultimately impacts other systems and the resultant System-of-Systems (SoS) capability (i.e., the transportation of freight). SoSE concepts and methodologies offer significant value to the study of technology adoption rates and emissions at a large scale, e.g. a line-haul FTS, resulting from the behaviors of the multiple independent and distributed fleets operating in such a system. Even though the evidence of an SoS perspective on freight technology adoption is lacking in the literature, many researchers are beginning to recognize the value of SoSE methods for investigating transportation related problems. [21] utilize SoSE concepts to discover emergent behavior in integrated traffic control problems, while, [22] develop an SoS model for real-time scheduling of dangerous good transportation to meet regulatory requirements under business delivery constraints. [23] claim the SoS framework to be the foundational element for developing innovations for future intelligent transportation systems because of its ability to accommodate a diverse set of stakeholders and complex constituent systems.In addition to the transportation related examples, the SoSE concepts are being applied across diverse application domains where multiple complex independent systems are integrated, e.g., space applications [24], emergency management [25], and supply chain management [26], to name a few.

In this chapter, I contribute an approach for modeling the heterogeneity of fleet vehicle purchase decision-making behaviors by first modeling the FTS as a system-of-systems and then designing and validating a representative set of fleets to project technology adoption trends. The SoSE principles allow for the development of a holistic FTS model that captures the interaction of the multiple complex systems that compose it. Here, I pose the problem of projecting mixed technology adoption across the FTS as a cost minimization problem in which I consider how the FTS affects, and is affected by, the purchase and vehicle allocation decisions of multiple heterogeneous fleets. The proposed model is parametrized and validated using a Design of Experiments (DOE) and historical adoption data. The results of this SoS model demonstrate 90% accuracy in prediction outcome when modeling historical technology adoption across a set of 12 heterogeneous representative fleets over an 11-year period.

## 2.1 Background

The U.S. line-haul freight transportation system (FTS) is composed of interconnected systems of vehicles, inter and intra-city highways, and support infrastructure.

Vehicles—and the technology that forms part of a vehicle's architecture—are produced, adopted, operated, and regulated by independent entities with differing objectives. While policy-makers deploy incentives and regulations to improve overarching system conditions like emissions levels, fleet owners seek to increase the productivity of their vehicles in a cost-efficient manner to maximize revenue [27].

The increasing complexity of independent systems and the dependability of new capabilities on the multiple systems, created a need to study the engineering of systems-of-systems [28–30]. An SoS is defined when multiple interdependent, yet independently managed and operated, systems collaborate to achieve common goals [20]. [19], regarded as one of the most influential contributors [29] in the SoS field, notes that an SoS is formed when the constituents components of a system exhibit operational and managerial independence, meaning that a component has a defined purpose outside its participation in the larger system. Building upon Maier's work, [31] have proposed underlying traits of an SoS which can be applied as differentiating criteria to distinguish an SoS from an otherwise 'monolithic complex system'. These traits are summarized in Table 2.1; the more a system exhibits the SoS traits, the more important it is to view and analyze it as an SoS [32].

Table 2.1. : System-of-System Traits [31]

| Trait | Description |
|---|---|
| Operational Independence | Elements have their own useful purpose outside the SoS. |
| Managerial Independence | Elements operate independently and are provided unique purposes by owners and operators. |
| Geographical Distribution | Elements are physically distributed, linked by information. |
| Evolutionary Development | The SoS and its constituent systems are developed over-time. |
| Emergent Behavior | Properties of the whole emerge from the assembly and interaction of elements. |

When considered from the perspective of the entire FTS, it is clear that individual fleet owners demonstrate a level of *operational and managerial independence and geographical distribution*. The FTS itself exhibits *evolutionary development*, as it has evolved over many years and will continue to do so in the future. For example, the introduction of electric and autonomous vehicles will cause both infrastructure and operational policies to evolve in order to support and regulate the operation of these new technologies, which will likely operate contemporaneously with the existing technologies. Furthermore, *emergent behavior* properties may also appear in the SoS that are not apparent (or predicted) from the constituent systems, but can be observed at higher levels of the system hierarchy. For example, the combined effects of fuel and electricity costs, powertrain performance, and availability of regional charging infrastructure may reveal new adoption behaviors of fleets operating in the region. Evolutionary development and emergent behavior of technology adoption, as it is driven by fleet-owner decision-making, are among the prominent SoS traits that have not been explored by previous studies in transportation literature.

In order to model fleet-owner decision-making and its effect on the adoption of freight vehicle technologies, it is important to model the aforementioned traits, along with system interconnections and the operational and policy constraints that impact them. Recognizing the need for a holistic methodology to engineer and understand capabilities that result from the collaboration of multiple systems in the transportation domain, [33] developed an SoS modeling and analysis methodology. This framework provides the foundations for building an SoS model that accounts for the evolutionary development of the constituent systems and stakeholders decisions relevant to that SoS. This SoS framework has three main phases: definition, abstraction, and implementation [34].

The purpose of the *definition* phase is to decompose the SoS across two dimensions. The first one spans the breadth of the SoS and includes defining considerations for the SoS Resources, Operations, Policy, and Economics (ROPE). The second is the identification of elements and stakeholders at various hierarchical levels across the ROPE categories, where the $\alpha$-level is considered the base level of the SoS, and subsequent levels build on a network/collection of subordinate level entities. Figure 2.1 provides an illustration of the SoS ROPE construct.

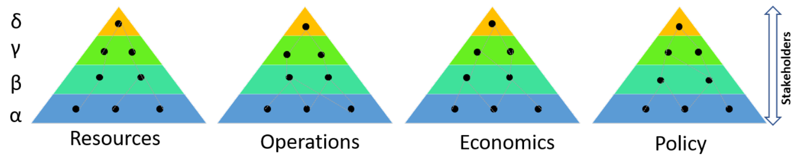



Figure 2.1. : SoS ROPE Construct [adapted from [33]]

The purpose of the *abstraction* phase is to model the relationships between the ROPE categories and hierarchical levels, including the stakeholders and the networks, that define the SoS. The abstraction phase decomposes the SoS into sub-domains and identifies the sub-models, variables, and parameters which represent them at an appropriate level of abstraction. Furthermore, this phase also identifies how the variables are linked by information flows that are responsible for creating dependence among, and between, ROPE table hierarchical levels and SoS stakeholders. Finally, the *implementation* phase realizes all or part of the abstraction within a modeling and simulation environment. It is in this final phase that specific hypotheses about the SoS can be proposed and evaluated.

## 2.2 Heterogeneous Fleet Behavior as a System of Systems

### 2.2.1 Definition

First I define the scope of the SoS as it currently exists, establish the ROPE categories and hierarchical levels, and identify the stakeholders (e.g. fleet-owners, policy makers, technology providers) that, in practice, define the goals, objectives, and considerations that influence technology attractiveness. The interested reader is referred to [33] for a detailed description of the ROPE categories.

When considering fleet behavior over the FTS, different powertrain technology options can be considered an $\alpha$-level resource, while the integration of different powertrain and vehicle technologies in the form of a heavy duty class-8 truck can be considered a $\beta$-level resource. A fleet of Class 8 trucks is considered to be the $\gamma$-level resource, and so on. Similarly, on the policy side, regulations regarding emission restrictions can be considered an $\alpha$-level policy; class-8 vehicle weight limits a $\beta$-level policy; and driver hours of service limits the $\gamma$-level policy. In the context of modeling heterogeneous fleet behavior, the SoS model could be used to analyze how a change in $\beta$-level policy would impact the $\beta$-level resources and its constituent $\alpha$-level resources, and ultimately economics that drive decision-making at the $\gamma$-level. The above information regarding resources and policy, along with the information pertaining to the entire SoS ROPE construct, can be organized and represented in the form of the ROPE Table, which is provided in Table 2.2.

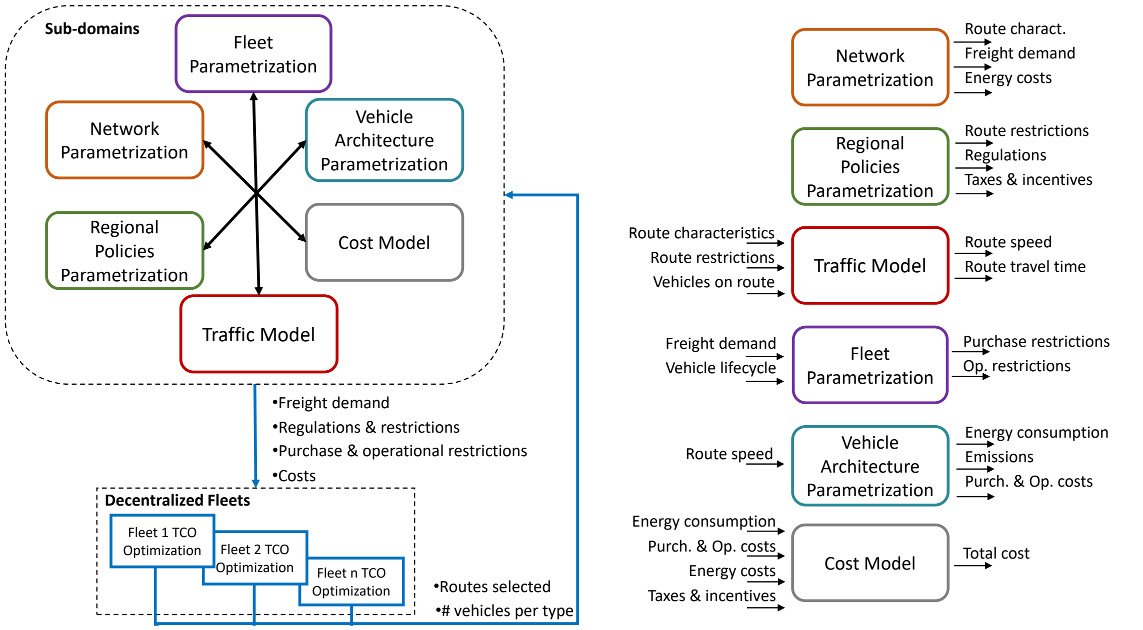
Beginning at the bottom level of the hierarchy, the $\alpha$-level of the ROPE table encompasses the powertrain technologies used by heavy-duty Class 8 vehicles at the $\beta$-level. This may not only encompass powertrain technologies such as diesel or hybrid-electric, but may also be comprised of other vehicle technologies such as advanced aerodynamic features that enable them to operate with improved efficiency at highway speeds. At the $\gamma$-level, we consider the set of vehicles that comprise a single regional fleet. The line-haul fleets considered here are comprised of heavy-duty Class 8 trucks that are operated on regional highway routes shorter than 500 miles. Fleets purchase vehicles annually to satisfy demand growth or necessary vehicle replacement using Total Cost of Ownership (TCO) as the most common purchasing criteria. The TCO is a function of acquisition price as well as any costs incurred during operation of the vehicle. At this level we observe vehicle adoption behaviors (by fleets) that are in turn influenced by factors defined at the $\delta$-level—the regional freight transportation network—such as regional freight demand, network characteristics, and policies. Any effects that regional policies, network characteristics, infrastructure availability, and costs may have on the operation of the vehicles should be reflected on the incurred fleet costs. The ROPE table draws out this important consideration; in other words, the adoption trends for different vehicle technologies cannot be observed only at the $\alpha-$ and $\beta-$levels as they are dominated by the operations, economics, and policies at the higher levels. This implies that evaluation of vehicle-level powertrains based on their performance alone, and detached from higher SoS levels in the hierarchy, will be insufficient to observe evolution of market adoption behaviors.

Table 2.2. : Regional Line-Haul Freight Transportation System ROPE matrix

| Level | Resources | Operations | Economics | Policy |
|---|---|---|---|---|
| Alpha | -Powertrain Type | -Powertrain fuel consumption | -Cost of fuel | -Emission restrictions |
| Beta | -Heavy duty Class 8 vehicles<br>-Vehicle architecture | -Ton-mi/gal efficiency<br>-Average day operation<br>-Vehicle life cycle<br>-Cargo load/capacity<br>-Miles driven based on selected routes<br>-Operate at constant speed over route<br>-Operator hours<br>-Vehicle range | -Cost of fuel consumed<br>-Cost of driver/hour<br>-Cost of maintenance | -80,000 lb<br>-Cost of purchase weight limit |
| Gamma | -Vehicles in single regional fleet | -Fleet distribution<br>-Fleet size<br>-Vehicle replacement cycles and years of service limits | -Total cost of ownership decision metrics per year | -Driver hours of service limits |
| Delta | -4-city network: cities 1-4 | -Total freight demand between cities by weight<br>-Traffic conditions: vehicles on road, road density capacity, travel time | -Cost of fuel<br>-Cost of using infrastructure | -Speed limit<br>-Regional emissions restrictions |

### 2.2.2 Abstraction

Based on the above scope and the SoS definition of the FTS, the abstraction phase identifies the sub-domains of the FTS SoS space as well as the flow of information that affects a fleet's total costs (and therefore the economic attractiveness and adoption of technologies), as shown in Figure 2.2. Here, for example, we recognize that fuel consumption over a selected route will be influenced by the vehicle efficiency parametrization as well as the network parametrization, including route distance, and route speed.




(a) Abstraction into sub-domains and decentralized fleets.

(b) Flow of information between sub-domains.

Figure 2.2. : Abstraction of the regional line-haul freight transportation system.

The abstraction model represents the decision process of fleets to purchase and operate those vehicle architectures that are economically attractive to them given the architectures' operational and purchase costs as these metrics are affected by the SoS environment. Our intent is to estimate and optimize the fleet-wide TCO for heavy-duty Class 8 trucking highway operation given vehicle highway performance, fleet management considerations including budget and vehicle replacement periods, network characteristics, and external influences such as cost of energy, regional freight demand, and policies regulating the purchase and operation of Class 8 vehicles. This optimization problem can be abstracted as a mixed-integer linear program.

### Single-fleet TCO Optimization

Here, I describe the objective function, constraints, and associated models used to construct the mixed-integer linear program representative of a fleet's adoption behaviors. New vehicle purchase costs and turnover sales revenue are included as metrics for vehicle acquisition. Moreover, a system optimal [35] traffic allocation approach is used to select the routes over which all vehicles in the fleet are allocated for delivery of freight, therefore estimating the dynamic effects of FTS evolution on vehicle utilization and fleet-wide operational costs. Fleet management, policies, and vehicle operational considerations are formulated as constraints. Table 2.3 describes the decision variables, while Table 2.4 shows the parametrization of the abstracted model. This program is then used to capture annual adoption behaviors for all fleets operating in the network, as indicated in the Implementation section.

Table 2.3. : Variable Definition

| **Decision Variables** | **Description** |
|---|---|
| $x^s_{qn}$ | Number n of vehicles type q that originate at s per year. |
| $x^s_{qn,ij}$ | Vehicle n of type q originating at $s$, traveling on link (i,j). |
| $y^h_{ij}$ | Cargo flow between links, originating at $h$. |
| $x_{q,new}$ | Number of new vehicles of type $q$ purchased per year. |
| $x_{q,r}$ | Number of vehicles of type $q$ sold per year. |
| $u^s_q$ | Intermediate binary variable, 1 if new vehicles are purchased. |
| $v^s_q$ | Intermediate binary variable, 1 if vehicles are sold. |

***Objective Function.*** The objective function represents the TCO criteria commonly used by fleet owners in order to select vehicles for purchase. In practice, a single fleet will select the vehicle architectures that reduce purchasing or lifecycle operational costs, therefore *minimizing* their TCO. On average, fuel consumption, repair and maintenance of a vehicle, and driver wages incur the highest percentage of total operational costs on a per mile basis over a vehicle's lifecycle [36]. Fleets commonly purchase vehicles on a yearly basis, and therefore this decision-making process is exercised annually throughout the projection period. The decision variables are defined as $x_{qn}^s$, the number of $n$ vehicles of type $q$ that originate at $s$ per year, $x_{qn,ij}^s$, vehicle $n$ of type $q$ originating at $s$ traveling on link $(i, j)$, and $y_{ij}^h$, the cargo link flow originating at $h$.

Table 2.4. : Model Parametrization

| | | |
|---|---|---|
| $\beta$ Level-Vehicle Architecture Parametrization | | |
| Operational | | |
| $\xi_q$ | Efficiency function of vehicle type $q$ | $\frac{\text{gal}}{\text{mi}}$ |
| $R_q$ | Driving range of vehicle type $q$ | mi |
| $W_q$ | Capacity for vehicle type $q$ | ton |
| $E_{q,co2}$ | $CO_2$ emission rates for vehicle architecture $q$ | $\frac{\text{g}}{\text{mi}}$ |
| $B_q$ | Reliability of vehicle architecture $q$ | $\frac{\text{\%trips}}{\text{year}}$ |
| Economic | | |
| $C_{M,q}$ | Cost of maintenance per mile | $\frac{\$}{\text{mi}}$ |
| $C_{p,q}$ | Cost of purchase for vehicle type $q$ | \$ |
| $C_{r,q}$ | Resale value for vehicle type $q$ | \$ |
| $\gamma$ Level-Fleet Management Parametrization | | |
| $l_{min}$,$l_{max}$ | Vehicle turnover range | years |
| $\gamma$ | Projected fleet's TCO outlook period | years |
| $C_{driver}$ | Driver wages | $\frac{\$}{\text{mi}}$ |
| $B_f$ | Fleet's budget for vehicle purchase | \$ |
| $C_{delay,c}$ | Revenue loss due to delay for cargo type $c$ | $\frac{\$}{\text{hr}}$ |
| $\delta$ Level-Network Parametrization | | |
| $b_i^h$ | Cargo demand from origin $h$ to destination $i$ | ton |
| $d_{ij}$ | Length (distance) of link $(i, j)$ | mi |
| $h_{os}$ | Hours of service limit | hours |
| $C_{eq}$ | Cost for energy consumed by vehicle type $q$ | \$ |

The objective function is defined as follows: $J_k = C_{op} + C_{purch}$. Here, the subscript $k$ indicates that the total cost of ownership is computed every year. To simplify the notation, the subscript $k$ is dropped throughout the formulation with the exception of cases where required to indicate the use of values from previous years. The cost of operation includes the cost of energy consumed $C_{ec}$, cost of driver wages $C_{wages}$, cost of maintenance $C_M$, and cost of revenue losses $C_R$, as a function of reliability such that $C_{op} = C_{ec} + C_{wages} + C_M + C_R$.

Energy consumption costs will vary depending on the vehicle technology used, given the parametrization of energy costs and vehicle efficiency. The cost of energy is defined as

$$C_{ec} = \gamma \sum_{q} \sum_{(i,j)\in A} x_{q,ij} d_{ij} C_{q,ij} \tag{2.1}$$

where $x_{q,ij} = \sum_s \sum_n x^s_{qn,ij}$ represents the flow of vehicles of type $q$ over highway link $(i,j)$ regardless of their origin, and $A$ is the set of city-nodes in the network. The cost of energy consumed per mile, $C_{q,ij} = \xi_q(u_{ij})C_{eq}$, is a function of fuel cost and vehicle efficiency, $\xi_q$, which is itself a simple function of average vehicle speed. Operational costs are computed as a function of the total number of trips in an average operational day. In order to estimate lifecycle costs, the cost of energy consumed over an average day is multiplied by $\gamma$, the number of years in a fleet's TCO outlook period.

The total driver wages, $C_{wages}$, are computed on a per mile basis, given the total number of miles traveled by fleet vehicles on an average operational day. Similar to the energy consumption costs, the driver costs are weighted over the vehicle's expected lifecycle:

$$C_{wages} = \gamma \sum_{q} \sum_{(i,j)\in A} x_{q,ij} d_{ij} C_{driver}. \tag{2.2}$$

The technology type and age of a vehicle often affect its maintenance and repair costs and are commonly used as a metric by fleet owners to identify the appropriate turnover age of their vehicles [37]. Maintenance costs are defined as

$$C_M = \gamma \sum_{q} \sum_{(i,j)\in A} x_{q,ij} d_{ij} C_{M,q}. \tag{2.3}$$

Reliability of cargo delivery may be affected by vehicle or component break-down. Here, I assume technology reliability issues result in time delays, $T_{d,q}$, and that scheduling of a second vehicle for completion of delivery is not necessary. In that manner, reliability costs are modeled as losses in revenue due to the incurred delay and are a function of both vehicle and cargo type:

$$C_R = \gamma \sum_q \sum_{(i,j)\in A} x_{q,ij} B_q T_{d,q} C_{delay,c}. \tag{2.4}$$

Finally, the cost of purchase includes the cost of buying new vehicles and the revenue generated by selling used ones: $C_{purch} = C_{nv} - C_{sr}$. Fleets will purchase new vehicles 1) to replace those beyond their economic lifecycle or 2) to increase fleet volumes due to an increase in freight demand. Here I assume that all vehicles are purchased new, such that

$$C_{nv} = \sum_q x_{q,new} C_{p,q}. \tag{2.5}$$

The variable $x_{q,new}$ is introduced to represent the vehicles of technology type $q$ newly adopted in the current year of projection, $k$. This means there is a surplus of vehicles $q$ originating at node $s$ that were not allocated in the previous years. These new vehicles are either needed to satisfy an increase in freight demand or represent a switch to a more economically attractive technology. The variable $x_{q,new}$ is given by $[x_q]_k - [x_q]_{k-1}$, where $x_q = \sum_s \sum_n x^s_{qn}$. Furthermore, $x_{q,new}$ is positive only if new vehicles are allocated to origin $s$, and zero otherwise.

Fleets will sell older vehicles when they are near the end of their economic life—the age at which maintenance and repair costs increase and the efficiency and performance are no longer attractive [11, 37]. It is at this point that fleets may consider switching to a newer replacement or to adopt an alternative architecture. The revenue obtained from a sale is computed as

$$C_{sr} = \sum_q x_{q,r} C_{r,q} \tag{2.6}$$

and then implemented as an offset to the purchasing budget for the current year.

The turnover period, $[l_{min}, l_{max}]$, during which a vehicle approaches the end of its economic life and is considered for replacement, varies by fleet. Here I assume that a line-haul fleet has a fixed range for vehicle turnover age. In contrast to new vehicles purchased, the variable $x_{q,r}$ is given by $[x_q]_{k-1} - [x_q]_k$ and is introduced to represent vehicles sold by the fleet. The value is positive if vehicles of type $q$ allocated to origin $s$ during the current year of projection are less than in the previous year, and zero otherwise.

In summary, the cost function $J$ to be minimized is defined as the TCO and computed via a combination of Eqs. (1)-(6) as follows:

$$\begin{aligned} J =& \gamma \sum_q \sum_{(i,j)\epsilon A} x_{q,ij}[d_{ij}(C_{q,ij} + C_{driver} + C_{M,q}) \ + B_q T_{d,q} C_{delay,c}] + \\ & \sum_q x_{q,new} C_{p,q} - \sum_q x_{q,r} C_{r,q}. \end{aligned} \tag{2.7}$$

***Constraints.*** The vehicle demand over the network is defined as a function of cargo demand, $b_i^h$, between $(h, i)$ city pairs. Vehicle link flow will be optimized in order to satisfy cargo demand, vehicle flow balance entering and leaving nodes, and capacity constraints, as given by Eqs. (2.8a)-(2.8d). The hours of service limit, $h_{os}$, as shown in Eq. (2.8e), will also have an effect on the number of vehicle trips taken within the time constraint and, therefore, the number of vehicles needed for allocation over the network. An intermediate binary variable, $x_{qn}^s$, is introduced and assigned a value of 1 if the $n$th vehicle of type $q$ is used over the network. This assists in the computation of total number of vehicles of type $q$ purchased and allocated to city $s$, such that $x_{qn}^s \leq M \sum_j x_{qn,ij}^s$ and $M x_{qn}^s \geq \sum_j x_{qn,ij}$ for all $i = s$, where $M$ is a sufficiently large number.

$$\sum_j y_{ji}^h - \sum_j y_{ij}^h = b_i^h \tag{2.8a}$$

$$\sum_h y_{ij}^h \leq \sum_s \sum_q \sum_n x_{qn,ij}^s W_q \tag{2.8b}$$

$$\sum_j x_{qn,ji}^s - \sum_j x_{qn,ij}^s \geq 0, \ i \neq s \tag{2.8c}$$

$$x_{qn,ii}^s = 0, \quad y_{ii}^h = 0 \tag{2.8d}$$

$$\sum_i \sum_j x_{qn,ij}^s t_{r,ij} \leq h_{os}, \forall s, q, n \tag{2.8e}$$

An intermediate binary variable, $x^s_{qn}$, is introduced such that $x^s_{qn} \leq M \sum_j x^s_{qn,ij}$ and $Mx^s_{qn} \geq \sum_j x_{qn,ij}$ for all $i = s$. This indicates the allocation of the $n$th vehicle of type $q$ over the network, assisting in the computation of total number of vehicles of type $q$ purchased and originating in city $s$. In order to determine the number of new vehicles purchased at any given city of origin $s$ during the present year, an intermediate binary variable, $u^s_q$ is introduced as shown in Equations (2.9a)-(2.9e), where $x^s_q = \sum_n x^s_{qn}$.

$$[x^s_q]_k - [x^s_q]_{k-1} + M(1 - u^s_q) \geq 0 \tag{2.9a}$$

$$[x^s_q]_k - [x^s_q]_{k-1} - M(1 - u^s_q) \leq 0 \tag{2.9b}$$

$$x^s_{q,new} - [x^s_q]_k + [x^s_q]_{k-1} + M(1 - u^s_q) \geq 0 \tag{2.9c}$$

$$x^s_{q,new} - [x^s_q]_k + [x^s_q]_{k-1} - M(1 - u^s_q) \leq 0 \tag{2.9d}$$

$$x^s_{q,new} \leq Mu^s_q\,, \quad x^s_{q,new} \geq 0 \tag{2.9e}$$

New vehicle purchases, $x^s_{q,new}$, are constrained by a user-defined fleet budget which is offset by the revenue created from vehicles sales, $x^s_{q,r}$, such that

$$\sum_s \sum_q x^s_{q,new} C_{p,q} - \sum_s \sum_q x^s_{q,r} C_{r,q} \leq B_f. \tag{2.10}$$

A market penetration constraint, $\sum_s x^s_{q,new} \leq Q_{avail}$ for all $q \in Q$, is also added to represent the availability of vehicle technologies entering the market. The parameter $Q_{avail}$ can be calibrated to limit the rate of penetration of newer technologies with lower production rates as existing technologies are phased out. Vehicle resale is also constrained such that

$$x^s_{q,new}(t_{yk} - l_{max}) \leq x^s_{q,r} \leq x^s_{q,new}(t_{yk} - l_{max}) + x^s_{q,new}(t_{yk} - l_{min}). \tag{2.11}$$

Vehicles older than the maximum allowable age will be sold, while vehicles within the turnover range may be considered for replacement.

### Traffic Model

Vehicle efficiency will vary with respect to average vehicle speed over a network route [9]. The solution $u_{ij}$ to Greenshield's macroscopic traffic flow model [38] provides the average traffic speed based on the number of vehicles $q_{f,ij}$, both freight and passenger, introduced to the link and the route characteristics such that

$$-\frac{k_{ij}}{v_{f,ij}}u_{ij}^2 + k_{ij}u_{ij} - \frac{q_{f,ij}}{N_{ij}} = 0. \tag{2.12}$$

The Greenshield equation incorporates a nonlinear term based on the traffic speed, $u_{ij}$, which is itself a function of freight traffic flow. In order to facilitate the use of a linear solver, the traffic speed is solved a-priori as a function of the number of freight vehicles to travel over each link $(i, j)$ in the previous year. Vehicle efficiency, $\xi_{q,ij}$ is then computed as a function of average vehicle speed over a network route [9]. Finally, route time is computed as $t_{r,ij} = \frac{d_{ij}}{u_{ij}}$.

### 2.2.3 Implementation

The mixed-integer linear program proposed in the previous subsection represents purchasing behaviors of a *single* fleet given the minimization of their TCO. In order to predict technology adoption across a *heterogeneous* mix of fleets, in which each fleet has different cargo demand targets, annual growth, and fleet management parameters, we must first calibrate the models described earlier and then solve the MILP as shown in Figure 2.3. Doing so constitutes the *implementation phase* of the SoS process. More specifically, the TCO of each individual fleet is optimized, and the coupled effect of the total number of vehicles introduced by all fleets to the simulated FTS network is used to estimate the traffic flow speed conditions for the following year. This process continues over the duration of the simulation period. The proposed model is implemented in MATLAB 2016b as shown in Figure 2.3. The YALMIP toolbox [39] is used to facilitate the definition of optimization variables, constraints, and objectives in the MATLAB environment and the Gurobi Optimizer 7.5.1 mixed-integer linear programming solver [40] is used to find the optimal solution to the TCO minimization program.

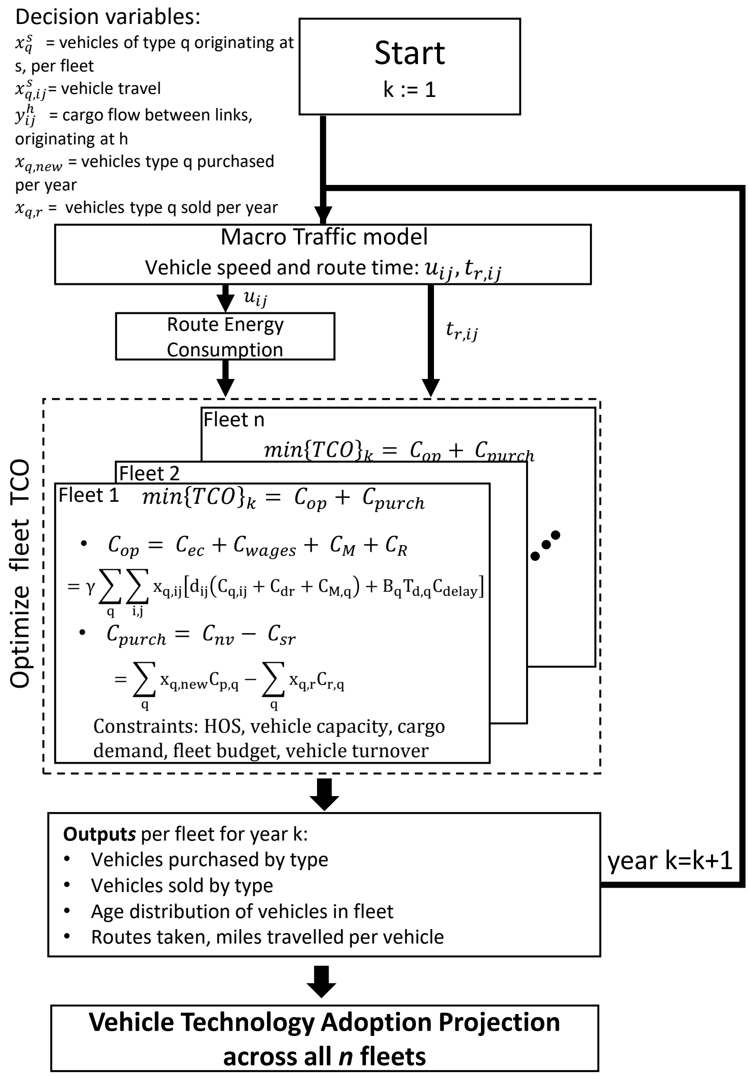



Figure 2.3. : Implementation of the mixed-integer linear program to project vehicle technology adoption across regional fleets.

## 2.3 Calibration and Validation of the Proposed Model

The future technology composition of a representative FTS will be a result of the adoption and utilization behaviors of the heterogeneous set of fleets that service it. To determine whether the proposed model does indeed capture the behavior of interest—i.e. adoption of emerging technologies by a *heterogeneous mix of fleets* operating over a shared FTS—the model must be calibrated and validated. The process used is outlined in Figure 4. The model is first parameterized using publicly available data that describes freight demand, route distance and traffic for a representative freight network in the U.S., vehicle maintenance and driver costs per mile, among others [1, 9, 36, 37]. This serves as a baseline for a Design of Experiments (DOE) study to evaluate the influence of selected factors on the adoption behavior of a single fleet operating over a small region. Once influential factors are identified, the calibration of the multi-fleet model is conducted by selecting an appropriate range of values for these factors, based on a range of values found in publicly available data and literature. As part of the calibration process, a set of 12 representative fleets of different sizes and characteristics is proposed and used to simulate adoption behaviors in the network. This representative set of fleets is needed because the technology adoption data available for widely adopted Class 8 tractor aerodynamic technologies [37], described in Section 2.3.1, does not provide any detailed specifications for fleet size, vehicle turnover age, cargo demand, geographic routes, or drive cycles corresponding to the reported adoption levels that can be used for calibration of the model. Finally, once the model has been calibrated, resulting adoption projections are compared to the aforementioned technology adoption data, available from 2005 to 2015 [37], to quantify model error.

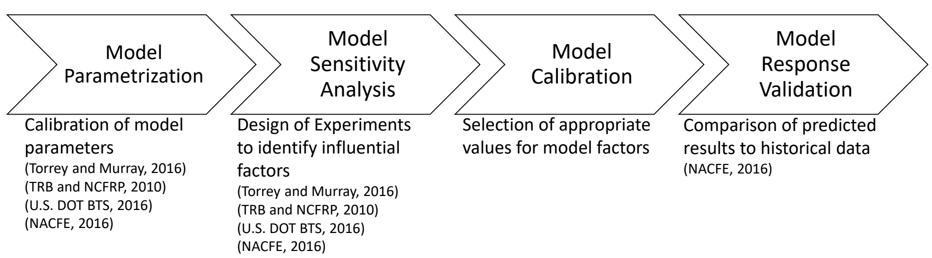



Figure 2.4. : Diagram describing the model validation process.

### 2.3.1 Parameterization and Validation Data

Here I describe the publicly available studies and datasets that are used to conduct a baseline parameterization of vehicle fuel efficiency, maintenance costs, vehicle capacity, and network characteristics [1, 9, 36, 37], and ultimate validation of the proposed model [37]. Since 2011, the North American Council for Freight Efficiency (NACFE) has published an annual report on the adoption of over 60 technologies and practices for Class 8 tractor-trailers among 15 major fleets operating over 62,000 tractors in the U.S. [37]. As opposed to an individual fleet owner's purchasing data, the NACFE data captures aggregate heterogeneous adoption behavior across the FTS; therefore, this data represents the adoption behaviors we are modeling and seek to predict. A *subset* of the technology list captured in the NACFE study is used to validate the line-haul freight transportation model presented in Section II. The selected technologies, which enhance tractor aerodynamics, offer a significant increase in vehicle fuel efficiency, are directly applicable to the line-haul operation modeled, and had high levels of adoption throughout the time period of interest (see Figure 2.5). Other technologies presented as part of the NACFE study—idle reduction, natural gas powertrain, low-weight chassis and low resistance tire strategies, etc.—are either outside the scope of highway operation or have negligible vehicle efficiency benefits and adoption when compared to tractor aerodynamic technologies; for these reasons, they are not considered for validation.

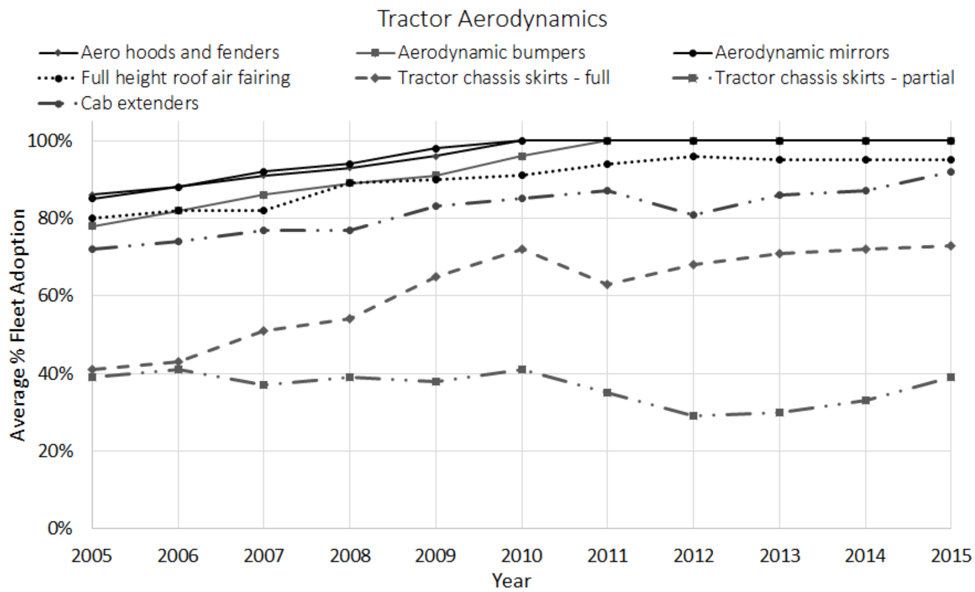



Figure 2.5. : Average adoption of tractor aerodynamic technologies [37].

In 2004 the EPA began implementation of SmartWay, a certification program that specifies a collection of technologies for efficient tractor-trailer combinations to reduce emission of greenhouse gases [9]. The Smartway certification includes the following tractor aerodynamic technologies listed by the NACFE study: aerodynamic hoods and fenders, aerodynamic bumpers, aerodynamic mirrors, full height roof air fairing, and cab extenders. Most tractor manufacturers offer these technologies as part of a package, and they are considered as such for this validation. Therefore, I assume SmartWay adoption to be the average adoption of all technologies contained in the package, as shown in Figure 2.6.

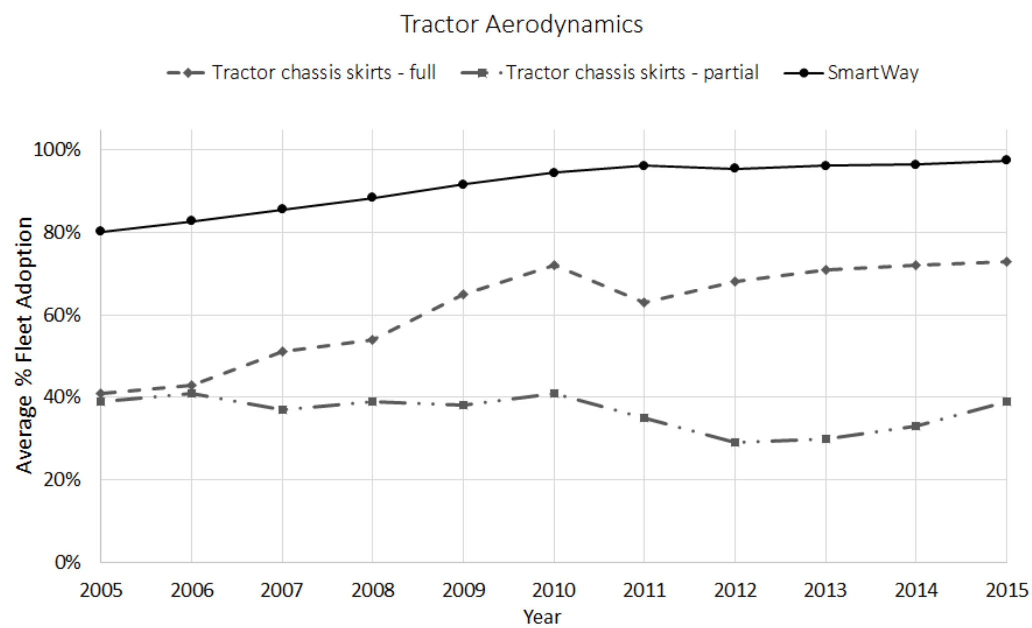



Figure 2.6. : Tractor aerodynamic technologies considered for model validation.

By 2015, full chassis skirts had reached a reported 70% adoption and partial chassis skirts had achieved 35%; in other words, all fleets had adopted either of the two technologies with a few fleets potentially reporting use of both. Similarly, we can see from Figure 2.6 that in 2015, the SmartWay package had achieved nearly 100% adoption. Therefore, I assume the existence of three vehicle architectures for the purposes of validation. I define Architecture 1 as a conventional diesel vehicle and define two additional architectures containing a combination of these aerodynamic packages. The latter are called Architecture 2 (consisting of the diesel baseline + SmartWay + full chassis skirts) and Architecture 3 (consisting of diesel baseline + SmartWay + partial chassis skirts). The conventional diesel package, Architecture 1, is included as a baseline for the study and represents the "business-as-usual" heavy-duty Class 8 tractor-trailer without improvements.

As suggested by the NACFE study, the average fuel consumption, in miles per gallon, of business-as-usual fleets varied throughout the 2005-2015 period due to the introduction of emissions restrictions affecting engine performance. Figure 2.7 shows the estimated fuel consumption trends used for Architecture 1. Fuel consumption trends for the SmartWay architectures, with full and partial chassis skirts, are derived by imposing the assumed increase in peak efficiency, shown in Table 3.7, to the baseline trends. For the SmartWay package, savings in fuel consumption of 7-10% have been reported for roof fairings alone, while chassis skirts can offer benefits up to 4% at a $2000 dollar up-charge [9]. In these latter cases, I assume that peak performance for aerodynamic technologies is achieved at 65 mph. These fuel efficiency trends, $\xi_q$, are an input to the model, where $\xi_q = f(k, u_{i,j})$. Table 3.7 shows vehicle parameter values for peak efficiency, capacity, maintenance costs, and reliability used throughout the validation study.

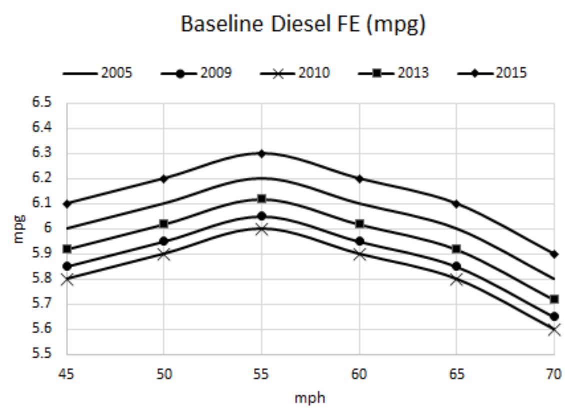



Figure 2.7. : Baseline diesel vehicle efficiency, in miles per gallon, as a function of year of purchase and vehicle speed.

Table 2.5. : Vehicle Architecture Parametrization

| Architecture | Description | Peak Efficiency | Capacity | Maintenance Cost | Reliability |
|---|---|---|---|---|---|
| Architecture 1 | Base Powertrain + baseline tractor | 6.3 mpg | 20 ton | $0.15 ($/mi) | 1 % trips/year |
| Architecture 2 | Base Powertrain + SW + FCS | +13% FE | 20 ton | $0.158 ($/mi) | 1.5% trips/year |
| Architecture 3 | Base Powertrain + SW + PCS | + 11% FE | 20 ton | $0.156 ($/mi) | 1.3% trips/year |

### 2.3.2 Model Sensitivity Analysis

A design of experiments (DOE) is used to determine the model parameters that significantly influence single-fleet adoption of the vehicle architectures listed in Table 3.7. Vehicle efficiency tables, maintenance costs, vehicle capacity, and network characteristics remain fixed as their values are known with high certainty for the period of study [1,36,37]. Table 2.6 shows the fixed cargo demand values used for evaluation of single-fleet purchasing behaviors throughout the DOE study.

Table 2.6. : Initial fleet cargo demand for the year 2005

| Cargo Demand (tons/day) | | | | |
|---|---|---|---|---|
| O/D | City 1 | City 2 | City 3 | City 4 |
| City 1 | 0 | 220 | 200 | 0 |
| City 2 | 260 | 0 | 180 | 160 |
| City 3 | 200 | 180 | 0 | 140 |
| City 4 | 180 | 160 | 120 | 0 |

Ten factor parameters are varied as shown in Table 2.7, and a 120 point response screening DOE was defined with the use of JMP Statistical Analysis software [41] in order to reduce the number of executions from a full factorial design. Each point represents an 11-year projection given a set of values for the ten factor parameters. Figure 2.8 shows the variation in (a) Architecture 1, (b) Architecture 2 and (c) Architecture 3 purchases as a response to factor variation. The vehicle purchase values shown on the x-axis of Figure 2.8 represent the total number of vehicles of type $q$ acquired throughout the 11-year projection period. Diesel baseline purchases remain low with a maximum probability that less than 10 vehicles are purchased throughout the period of study. However, Architectures 2 and 3 have a higher mean value and larger standard deviation of vehicle purchases as compared to Architecture 1. This means that diesel conventional vehicles with no aerodynamic technologies remain low in adoption regardless of the parameter variation introduced, while adoption is mostly distributed between the two architectures consisting of aerodynamic technologies.

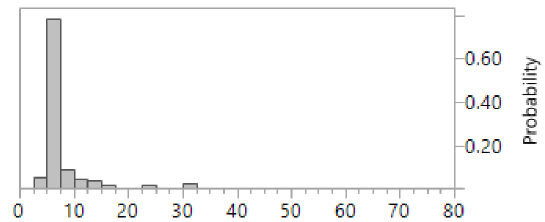
Table 2.7. : Design of experiment (DOE) factor levels

| Turnover | Gamma ($\gamma$) | Budget ($B_f$) | Cargo growth | $C_{eq}$ | $C_{driver}$ | $C_{p1}$ | $C_{p2}$ | $C_{p3}$ | Depr. rate |
|---|---|---|---|---|---|---|---|---|---|
| years | years | $ | %/year | $/gal | $/mi | $ | $ | $ | %/year |
| [1,3] | 4 | low | 2 | increase | 0.33 | 90000 | 97000 | 93000 | 0.1 |
| [2,4] | 5 | medium | 4 | decrease | 0.417 | 93000 | 98000 | 96000 | 0.2 |
| [2,5] | 6 | high | | | | | 99000 | 97000 | |
| [3,6] | | | | | | | | | |

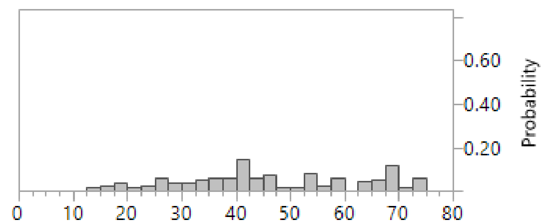
The histograms shown in Figure 2.8 quantify response variation due to changes in the selected parameters. Moreover, the $p$-values and logworth (defined as -$\log_{10}$($p$-value)) shown in Table 2.8 identify the most influential factors with respect to metric response variation. A logworth value greater than 2 indicates factor significance. The JMP software produces a corrected logworth value, also known as the False Discovery Rate (FDR) logworth [42], by eliminating data outliers. Table 2.8 shows all factors with an FDR value greater than 1 for each response metric, indicating that *vehicle turnover age, vehicle purchase costs, and $\gamma$ (the TCO outlook period) are the factors identified to have an effect on fleet purchase behavior* with the highest level of confidence.

Table 2.8. : FDR LogWorth table for factor influence on purchasing response.

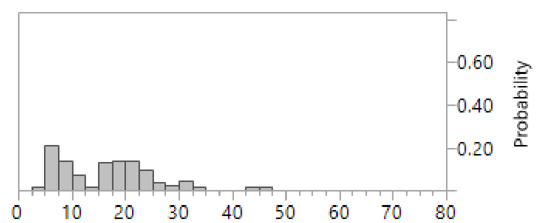
| **Y** | **X** | **FDR LogWorth** |
|---|---|---|
| Architecture 1 Purchases | $C_{p2}$ | 2.16 |
| | Budget ($B_f$) | 1.24 |
| | $C_{eq}$ | 1.01 |
| Architecture 2 Purchases | Turnover age | 26.8 |
| | $C_{p3}$ | 10 |
| | $C_{p2}$ | 4.8 |
| | gamma ($\gamma$) | 2.2 |
| | $C_{eq}$ | 1.01 |
| Architecture 3 Purchases | $C_{p3}$ | 10.46 |
| | $C_{p1}$ | 2.32 |
| | $C_{p2}$ | 1.57 |
| | gamma ($\gamma$) | 1.57 |




(a) Architecture 1: Diesel Baseline




(b) Architecture 2: SmartWay + Full Chassis Skirts




(c) Architecture 3: SmartWay + Partial Chassis Skirts

Figure 2.8. : Histograms showing distribution of vehicles purchased throughout 11-year period as a result of the DOE factor variation.

In order to quantify parameter influence on projected adoption, a linear least-squares regression model is computed from the simulation model response data and used to determine response sensitivity to the individual factors varied as part of the DOE study. Figure 2.9 shows the actual model response value on the y-axis and the linear regression predicted response on the x-axis. Predicted values close to the diagonal are desirable; the model shows an $R^2$ measure of 0.87. Figure 2.10 shows the relative effect of factor variation on predicted total number of purchases of Architecture 2 vehicles throughout the period of study. The factors are ordered vertically given the size of their effect on response variation from a base value as indicated on the x-axis. Levels 1-4 indicate the variation levels for each factor shown in Table 2.7. This tornado chart shows that the predicted response is highly sensitive to variation in turnover range, the purchase costs of Architecture 2 and Architecture 3 ($C_{p2}$ and $C_{p3}$), and $\gamma$, while the effects of other parameters are negligible in comparison. The influential factors revealed in this study are a rational result. Turnover age is the age period of a vehicle when it is considered for replacement, and it is during this time when a fleet may consider an economically attractive alternative technology. A higher turnover age may cause the fleet to disregard system changes during that period of time, including a high variation in fuel cost or changes in vehicle efficiency caused by introduction of emission restrictions, while *a lower turnover age limit may cause fleet adoption trends to be more sensitive to system changes within the time frame*. Figure 2.10 provides a relevant *managerial insight*: by introducing shorter turnover ages (Level 1), fleets are able to adopt Architecture 2 vehicles (SmartWay with full chassis skirts) at a higher rate. Since these vehicles are more efficient, this also helps fleets to drive down ownership costs. Similarly, vehicle purchase costs significantly impact the economic attractiveness of a vehicle architecture. However, for cases in which the vehicles being evaluated may be using different sources of energy—e.g. diesel, natural gas, battery-electric, hydrogen fuel—the cost of fuel could also be a significant source of variation in purchasing trends. Figure 2.11 shows the predicted total number of purchases of Architecture 2 given the variation in the four most influential factors, demonstrating, for example, that Architecture 2 purchases vary between 20 and 60 vehicles as turnover age varies.

It is of interest to note that while turnover age has a significant effect on Architecture 2 purchases, it does not result in a FDR logworth value greater than 2 for Architecture 1 and Architecture 3 purchases. Adoption of these vehicles is instead primarily sensitive to purchase costs. Moreover, while $C_{p2}$ having a strong effect on Architecture 1 purchases could indicate that this architecture is losing its competitive advantage primarily to Architecture 2 vehicles, adoption of Architecture 3 vehicles depends on their own purchase cost and that of Architecture 1. Figure 2.12 shows the quality of fit for the regression model used to predict sensitivity of Architecture 3 purchases to factor variation, with the two most influential factor effects, $C_{p1}$ and

$C_{p3}$, shown in Figure 2.13. These results suggest that *while lower limits on turnover age enable the purchase of Architecture 2 vehicles throughout the projection period, remaining vehicle purchases are then distributed between those architectures with lower cost albeit a lower efficiency* (Architecture 1 and Architecture 3 vehicles), given the purchasing costs. This reveals a rational *managerial insight*: fleets will choose inefficient, yet more affordable, vehicles as necessary to satisfy freight demand within a specified budget.

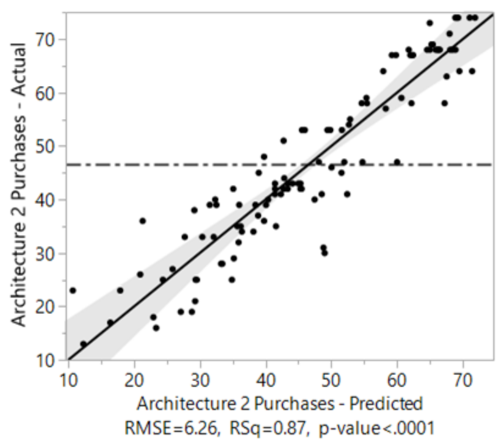



Figure 2.9. : Summary of regression fit showing mean of response, RMSE, $R^2$, and overall $p$-value for the regression model for Architecture 2 purchases.

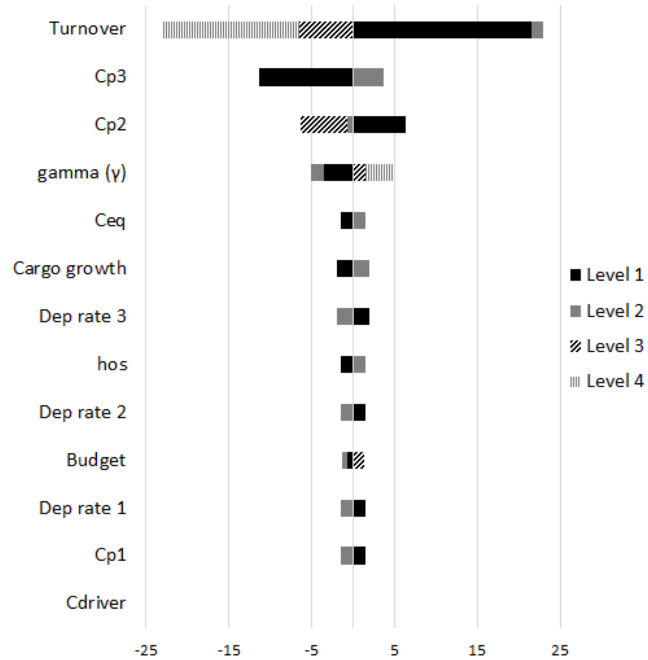



Figure 2.10. : Tornado chart of factor effect on number of Architecture 2 (SmartWay + full chassis skirts) vehicle purchases.

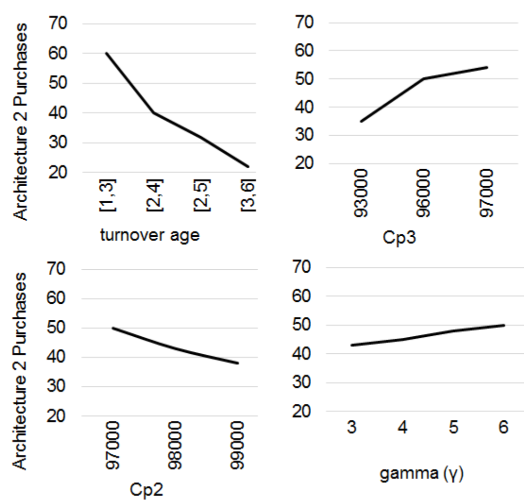



Figure 2.11. : Prediction profile of factor effect on number of Architecture 2 vehicle purchases.

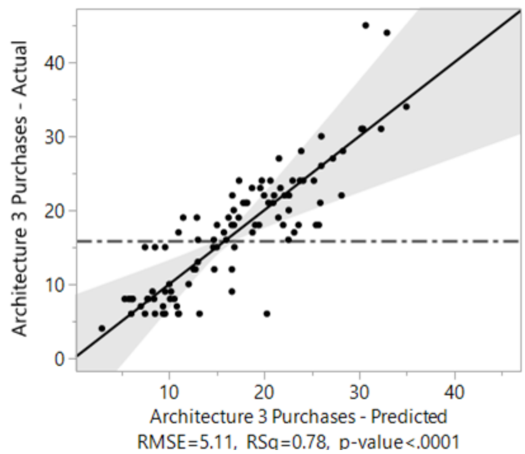



Figure 2.12. : Summary of regression fit showing mean of response, RMSE, $R^2$, and overall $p$-value for the regression model for Architecture 3 purchases.

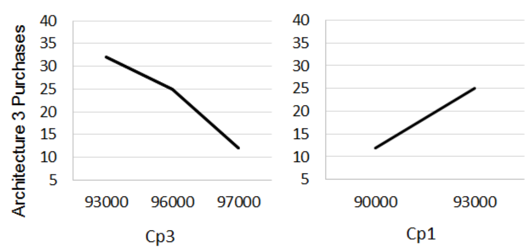



Figure 2.13. : Prediction profile of factor effect on number of Architecture 3 vehicle purchases.

### 2.3.3 Calibration of Multi-fleet Adoption Projection

Based upon the FDR logworth table and prediction profiles presented in the previous section, turnover range, vehicle purchase cost, and TCO outlook ($\gamma$) factors have the highest effect on purchasing trends. Having identified the most influential factors, the calibration process for multi-fleet adoption projection can now be conducted in order to validate adoption of tractor aerodynamic technologies during the 2005-2015 period. As mentioned earlier, the technology adoption data reported by NACFE, described in Section 2.3.1, does not provide any detailed specifications on the characteristics of the specific fleets that were surveyed. Therefore I reproduce the NACFE technology adoption results by simulating 12 *representative* line-haul fleets operating over a regional highway circuit connecting a 4-city network. The fleets vary in size depending on the cargo demand. Here I assume three different fleet sizes—small, medium, and large—and introduce a variation on the annual cargo growth experienced by each fleet. The Department of Transportation reports an average annual increase in cargo transport, by weight, of 1.3% during the period of study [1], and therefore this parameter is assumed to be between $0 - 2\%$ per fleet. Similarly, two budget levels are added at each fleet size to represent annual capital available for vehicle purchase. An hours of service, $h_{os}$, value of 11 hours is used throughout the simulation; this limit is representative of the regulation imposed on property-carrying drivers by the Federal Motor Carrier Safety Administration in the U.S. [43].

Table 2.9. : Cargo Demand Parametrization

| Small Fleet (ton/day) | | | | |
|---|---|---|---|---|
| O/D | City 1 | City 2 | City 3 | City 4 |
| City 1 | 0 | 120 | 100 | 0 |
| City 2 | 100 | 0 | 80 | 80 |
| City 3 | 0 | 0 | 0 | 0 |
| City 4 | 0 | 0 | 0 | 0 |
| Medium Fleet (ton/day) | | | | |
| O/D | City 1 | City 2 | City 3 | City 4 |
| City 1 | 0 | 160 | 140 | 20 |
| City 2 | 140 | 0 | 100 | 100 |
| City 3 | 20 | 20 | 0 | 0 |
| City 4 | 0 | 0 | 0 | 0 |
| Large Fleet (ton/day) | | | | |
| O/D | City 1 | City 2 | City 3 | City 4 |
| City 1 | 0 | 260 | 140 | 20 |
| City 2 | 180 | 0 | 200 | 100 |
| City 3 | 40 | 40 | 0 | 0 |
| City 4 | 0 | 0 | 0 | 0 |

Table 2.10. : Network Route Parametrization

| Route Distance (mi) | | | | |
|---|---|---|---|---|
| O/D | City 1 | City 2 | City 3 | City 4 |
| City 1 | 0 | 182 | 297 | 470 |
| City 2 | 182 | 0 | 242 | 289 |
| City 3 | 297 | 242 | 0 | 309 |
| City 4 | 470 | 289 | 309 | 0 |

Finally, the influential parameters identified earlier are calibrated as follows. Vehicle turnover age, reported at an average of 5 to 7 years of age for heavy-duty Class 8 tractors [36, 37], is varied among the fleets, with the shortest period between 1 and 3 years of age and the longest period between 5 and 7 years of age. A projected vehicle life-cycle outlook, $\gamma$, of 5 or 6 years was assigned to each fleet. Tables 2.9, 2.10, 3.5, and 2.12 show cargo demand between origin and destination (O/D) pairs, route distance, fleet parameter values, and vehicle purchase costs, respectively, used for the validation study.

Table 2.11. : Multi-Fleet Parametrization

| Fleet | Gamma($\gamma$) | Cargo ($b_i^h$) | Turnover | Budget ($B_f$) | Cargo growth |
|---|---|---|---|---|---|
| | years | ton | years | $ | %/year |
| 1 | 5 | small | [2,4] | low | 1% |
| 2 | 5 | small | [1,3] | low | 1% |
| 3 | 5 | medium | [3,5] | high | 0 |
| 4 | 5 | large | [2,4] | low | 2% |
| 5 | 6 | small | [3,5] | high | 0 |
| 6 | 5 | large | [1,3] | low | 1% |
| 7 | 6 | small | [2,4] | high | 1% |
| 8 | 5 | medium | [2,4] | low | 1% |
| 9 | 5 | large | [3,5] | high | 0 |
| 10 | 6 | medium | [5,7] | high | 0 |
| 11 | 5 | medium | [1,3] | high | 0 |
| 12 | 6 | large | [5,7] | high | 2% |

Table 2.12. : Vehicle Purchase Costs

| Architecture | Description | Purchase Cost |
|---|---|---|
| Architecture 1 | Base Powertrain + baseline tractor | $90,000 |
| Architecture 2 | Base Powertrain + SW + FCS | $94,000 |
| Architecture 3 | Base Powertrain + SW + PCS | $93,500 |

### 2.3.4 Validation of Multi-fleet Adoption Projection

The adoption data published by NACFE was defined in terms of technology adoption, whereas I am modeling adoption of two different vehicle architectures containing a combination of said aerodynamic technologies. In order to create a data set for validation purposes, a Monte Carlo simulation is used to estimate the annual adoption, $[P_i]_k$, of the vehicle architectures under consideration. The following equation is used:

$$[P_i]_k = \frac{[P_{i1}]_k + [P_{i2}]_k + ... + [P_{in}]_k}{N_{fleets}}, \quad n = \{1, 2, ...N_{fleets}\}, \tag{2.13}$$

where $[P_{in}]_k$ is the annual adoption of vehicle architecture $i$ for fleet $n$, and $[P_{in}]_k \sim N(\mu_k, \sigma_k^2)$. Here, the technology adoption percentages reported by NACFE, shown in Figure 2.6, are used as the mean values, $\mu_k$, and a standard deviation of 5% is used for each fleet adoption curve. The resulting historical adoption trends used to validate the model response are shown in Figures 2.14 and 2.15 along with error bars representing the standard deviation. In order to produce the adoption projections, initial conditions, that is the vehicles purchased and allocated by the fleets in the year 2005, are imposed on the model by number and vehicle type in order to match the validation data for the first year of study. The annual average value for the cost of diesel, as reported by the NACFE study and shown in Figure 2.14, is used. Figure 2.14 shows the architecture adoption trends as estimated by an intermediate step of the calibration process, compared against NACFE data, over the 11-year projection period. Here, modeled adoption trends for Architectures 1 and 3 diverge from the historical data, and the model as calibrated is not able to properly capture adoption behaviors. The calibration effort is then placed in identifying the appropriate set of heterogeneous fleet characteristics that represent the adoption behaviors observed from 2005 to 2015. Figure 2.15 shows the error reduction in the model projections as variation in the characteristics of the fleets, particularly short turnover periods between 1 and 3 years, are introduced as indicated in Table 3.5.

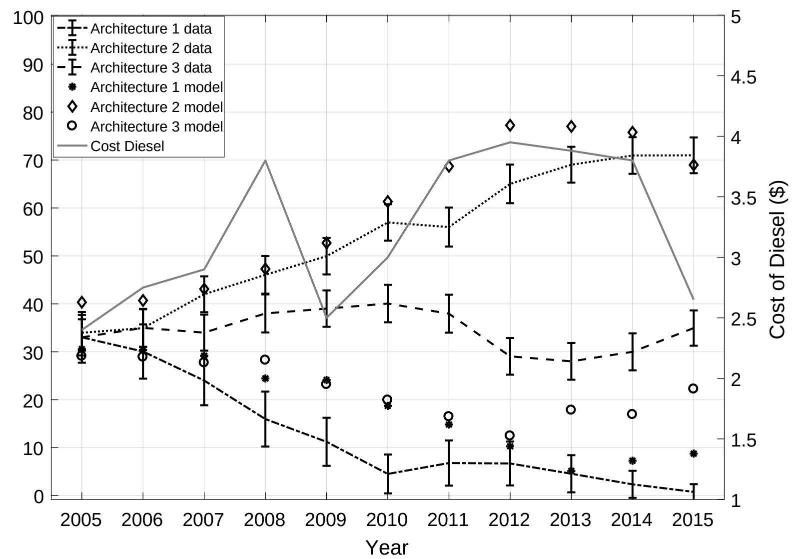



Figure 2.14. : Comparison of NACFE adoption data estimates and adoption projections as predicted by the intermediate calibration step. Cost of diesel over the projection period is labeled on the right y-axis.

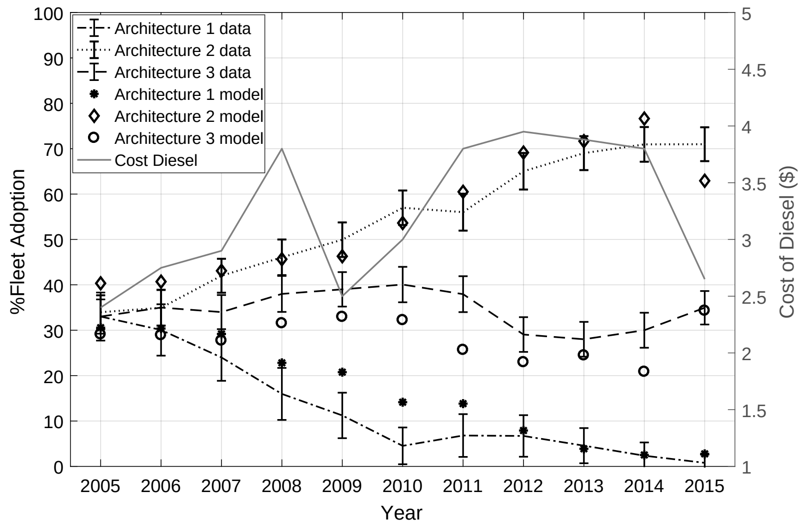



Figure 2.15. : Final comparison of NACFE adoption data estimates and adoption projections as predicted by the calibrated SoS model once variation in fleet characteristics is introduced. Cost of diesel over the projection period is labeled on the right y-axis.

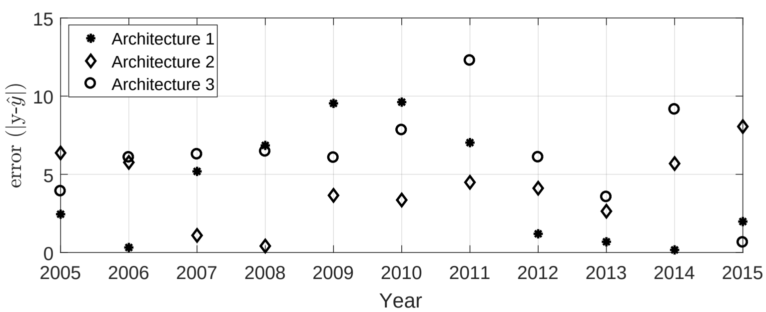



Figure 2.16. : SoS Model prediction error of % *Fleet Adoption* with respect to NACFE data mean values.

Figure 2.16 shows the absolute error in the model projections, defined as $|y - \hat{y}|$ where $y$ is the mean adoption data shown by the dotted lines in Figure 2.15 and $\hat{y}$ represents the model's projections at each year. The model's prediction of Architecture 2 (SmartWay plus full chassis skirts) adoption is within one standard deviation throughout the 11 year period with the exception of the first and last 2 years.

The Architecture 1 (diesel baseline) and Architecture 3 (SmartWay + partial chassis skirt) adoption predictions show a higher error; however, both follow the reported trends, with adoption of Architecture 1 reaching zero at the end of the period as expected. Figure 2.16 shows that, with the exception of Architecture 3 adoption in 2011, the error in predicted adoption remains bounded within 10% of the mean expected value.

It is worth reiterating that detailed fleet calibration data—including budget constraints, vehicle turnover age, annual growth, etc.—for the fleets surveyed by NACFE is *not* available. Nevertheless, by using a design of experiments, I was able to identify factors that have a significant effect on the predicted purchasing behaviors and focus our calibration efforts on these parameters in order to create a model with the predictive capability demonstrated above. Validation of technology adoption trends is rarely done in the literature; instead adoption projections are typically focused on evaluating competitiveness of emerging technologies [11]. Here, the inclusion of fleet management parameters as well as vehicle and network characteristics in the model has allowed us to emulate historic adoption trends for widely adopted diesel vehicle architectures with 10% error.

With confidence in the calibrated model based upon its ability to predict vehicle adoption, other model outputs can be analyzed, including the impact of the introduction and adoption of different vehicle architectures on vehicle miles traveled, routes taken, fuel consumption, and truck loading. Figure 2.17 shows vehicle miles traveled (VMT) per vehicle type, normalized against the VMT of Architecture 1 in the first year of the study. Figure 2.18 shows the annual diesel fuel consumption per vehicle type, again normalized against the annual fuel consumption of Architecture 1 in the first year of the study, as well as the annual total cargo demand in the network.

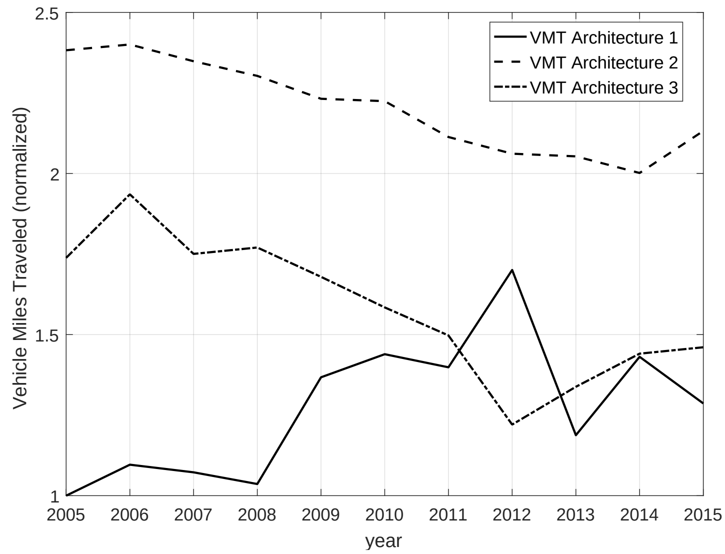



Figure 2.17. : Model projected daily vehicle miles traveled (VMT) per vehicle type.

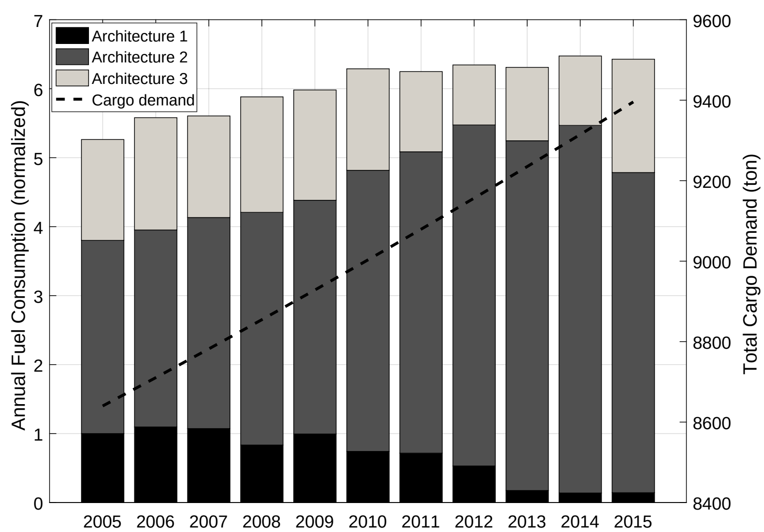



Figure 2.18. : Model projected annual fuel consumption per vehicle type. Total regional cargo demand over the projection period is labeled on the right y-axis.

The VMT values of Architecture 1 (diesel baseline) vehicles increase between 2008 and 2012, while adoption of the architecture decreases. On the other hand, the number of miles traveled by Architecture 2 vehicles (SmartWay plus full chassis skirt) decreases throughout most of the projection period but increase from 2014 to 2015 when the cost of diesel decreases. Figure 2.17 shows that vehicles with SmartWay plus full chassis skirts are not only the most purchased, but also the most utilized on a daily basis given their lower fuel consumption costs. Figure 2.18 shows that fuel consumption trends by vehicle type follow vehicle adoption projections. Fuel consumption by diesel baseline vehicles decreases towards the year 2015 while adoption and therefore fuel consumption of Architecture 2 vehicles increases. However, analysis of Figure 2.18 shows that total diesel consumption by all vehicles in the system does not increase linearly with cargo demand as would be expected, indicating that underlying dynamics exist due to the adoption and allocation of more efficient vehicle architectures over the network routes. The VMT and total diesel consumption trends show interesting behavior, as estimated by the model, that cannot be observed by the technology adoption trends alone.

## 2.4 Summary

Recognizing the U.S. freight transportation system (FTS) as a system-of-systems (SoS), the SoS engineering methodology was used to define, abstract, and simulate the truck technology adoption behaviors of multiple heterogeneous fleets operating over the FTS. A constrained mixed-integer linear program was developed to determine optimal vehicle technology adoption rates based on purchasing and operational costs of vehicle architectures over a multi-city network with respect to minimization of total cost of ownership of individual fleets operating over a shared highway network. A traffic model was used to capture the effect of individual fleet decisions (vehicle purchases and route allocation) on system-wide technology adoption. The proposed approach was used to project total adoption trends of 12 line-haul fleets operating over the same regional network over an eleven-year time horizon.

Vehicle technology adoption depends on the economic attractiveness of different technologies as perceived by fleets. Here, the SoS methodology enabled the projection of technology adoption as it is affected, not only by multiple independent fleet stakeholders and the vehicles available to them, but by the operational and economic considerations that affect the system throughout different levels of its hierarchical structure. More importantly, the proposed framework accounts for the heterogeneity among fleets—different budgets, vehicle turnover range, etc.—and how this affects system-wide technology adoption.

Adoption trends were projected for three vehicle architectures: a diesel baseline vehicle and two architectures with tractor aerodynamic improvements. A design of experiments study demonstrated sensitivity of modeled adoption response to economic parameters and fleet management constraints. Fleet management parameters (including turnover range, TCO outlook period, and budget) and vehicle costs were shown to be influential on adoption response. A low turnover range, in particular, increased the adoption of vehicle architectures with higher fuel efficiency. Given that fleet management parameters were shown to be influential on adoption, a heterogeneous set of 12 fleets was introduced, identifying variation in their management characteristics, in order to represent adoption for U.S. fleets from 2005 to 2015. The resulting trends were validated with available adoption data over the same period of time. The framework was able to reproduce adoption trends for technologies that improve the performance of diesel conventional vehicles without detailed information about the actual set of fleets from which the NACFE data was collected. Of equal importance was the definition of a set of 12 fleets as an outcome of the validation process. This set of fleets is used to represent the line-haul Class 8 vehicle market for future studies.

Despite considering a simplified route circuit to represent a line-haul network, the proposed framework was capable of reproducing adoption trends for technologies that improve the performance of diesel conventional vehicles. As a result, future chapters focus on extending the framework to consider the introduction of emerging technologies—connected and autonomous vehicles, alternative fuel powertrains, battery electric vehicles, and others.

# 3. PROJECTING ADOPTION OF TRUCK POWERTRAIN TECNOLOGIES AND $CO_2$ EMISSIONS IN LINE-HAUL NETWORKS

In recent decades, introduction of the National Highway Traffic Safety Administration's Corporate Average Fuel Economy (CAFE) standards, the EPA GHG emissions regulations, and incentive programs including SmartWay certification, have resulted in a reduction in both fuel consumption and $CO_2$ emissions for heavy-duty vehicles [9, 27, 44]. This has been achieved by requiring manufacturers to increase average fuel economy of vehicles sold in the U.S. However, an overwhelming majority of the medium and heavy-duty vehicles in the country use diesel engines today, with less than 2% using natural gas or other alternative fuels [4]. In 2012, heavy-duty trucks alone emitted more than 70% of the $CO_2$ emissions in the U.S. freight transportation system [1, 2] as approximately 22.4 pounds of $CO_2$ are produced per gallon of diesel fuel combusted [45]. Alternative powertrain technologies, including compressed (CNG) and liquefied natural gas (LNG) engines, hybridization, battery electric, and hydrogen fuel cells (HFC), have been proposed for energy savings and emission reductions. These technologies, however, may require significant changes to vehicle operations and infrastructure. For example, a wide network of hydrogen fueling and electric charging stations does not presently exist, and vehicle range and payload capacity may decrease given adoption of alternative powertrain options when compared to diesel. Moreover, there is uncertainty as to how these emerging technologies will impact vehicle reliability and what policies will be introduced to regulate or incentivize their adoption. Thus, this framework can be used to understand the effects of freight system evolution on fleet adoption behaviors and market penetration of new powertrain technologies and identify the factors that maximize adoption of cleaner technologies and target desired emissions outcomes.

In Chapter 2, I developed a model of fleet vehicle purchasing behaviors by modeling the FTS as an SoS and defined a representative set of heterogeneous fleets to project historical technology adoption trends in the line-haul segment. Here, I build significantly upon the initial model to capture the evolution of line-haul freight transportation system factors and their influence on the future economic attractiveness of *emerging and alternative* vehicle powertrain technologies for freight transportation. The systematic approach followed in this chapter to extend the definition, abstraction, and implementation of the model of the FTS is presented in Figure 3.1.

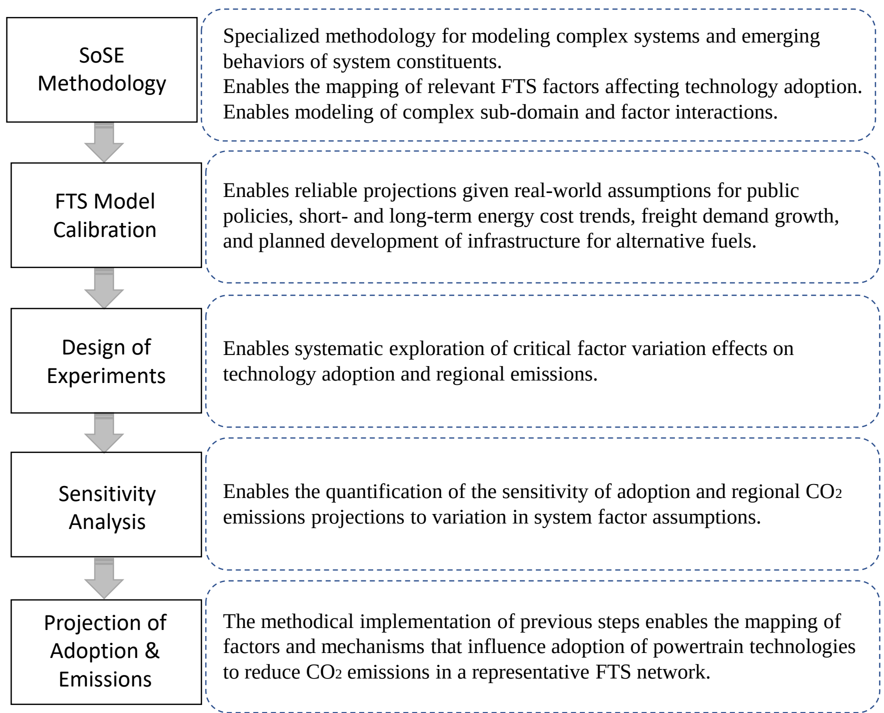



Figure 3.1. : Methodology presented to define, abstract, and implement a model of a regional FTS to project adoption of powertrain technologies for line-haul vehicles.

## 3.1 Modeling Emerging Powertrain Technology Adoption

The ROPE matrix is extended to focus on those factors and considerations of the FTS that affect the adoption trends of powertrain technologies, and is shown in Table 3.1. The different powertrain options considered—diesel, CNG, LNG, hybrid electric diesel, battery electric, and hydrogen fuel cell—are introduced as the $\alpha$ level resources of the SoS. The engine, chassis, and body of the trucks are often produced by different manufacturers but are integrated as a single vehicle. As such, fuel consumption and economic attractiveness must be determined by the features of the complete vehicle architecture [6,9]. For this reason, the next level of the hierarchy, the $\beta$-level, represents the heavy-duty Class 8 vehicle architectures encompassing the powertrain technologies introduced. Moreover, the $\delta$-level, the regional freight transportation network, now must also consider the infrastructure necessary to support the operation of different powertrain options in the network.

Finally, it is by inclusion of operational, economic and policy factors at the $\delta$ level that we can observe the collective impact of individual and isolated decisions in the SoS. The particular set of policies that are active in the region, whether to regulate or to provide economic incentives for cleaner technologies will influence the attractiveness of the powertrain technologies introduced and fleet adoption behaviors in a particular manner.

Table 3.1. : Regional Line-Haul Freight Transportation System ROPE matrix

| Level | Resources | Operations | Policy | Economics |
|---|---|---|---|---|
| **Alpha** | -Powertrain Type:<br>Diesel<br>Natural gas (CNG,LNG)<br>Hybrid electric<br>Battery electric<br>Hydrogen fuel cell | -Powertrain fuel consumption<br>-Powertrain reliability<br>-Maintenance | -Emission restrictions<br>-GHG regulations | -Cost of fuel<br>-Cost of energy<br>-Cost of maintenance |
| **Beta** | -Heavy duty Class 8 vehicles<br>-Vehicle architecture | -Ton-mi/gal efficiency<br>-Average day operation<br>-Vehicle life cycle<br>-Cargo load/capacity<br>-Miles driven based on selected routes<br>-Operate at constant speed over route<br>-Vehicle range<br>-Fueling/charging time | -80,000 lb weight limit<br>-Tax or purchase incentives | -Cost of fuel, energy consumed<br>-Cost of driver per hour<br>-Cost of maintenance<br>-Cost of purchase<br>-Cost of equipment |
| **Gamma** | -Vehicles in single regional fleet | -Freight distribution<br>-Fleet size<br>-Vehicle replacement cycles and years of service limits<br>-Operator hours<br>-Fuel/charging stops<br>-Return-to-base operation | -Driver 11 hours of service limits<br>-14 hr window of operation | -Total cost of ownership decision metrics per year<br>-Tax and cash incentives<br>-Cost to use/own infrastructure |
| **Delta** | -Regional highway network:<br>Cities 1-4<br>Distribution centers 1, 2<br>Highways, roads and supporting infrastructure | -Total freight demand between cities by weight<br>-Traffic conditions: vehicles on road, road density capacity, travel time<br>-Availability of fueling and charging stations<br>-Available on-road charging | -Route speed limit<br>-Regional emissions restrictions<br>-Regional incentive programs | -Cost of fuel, electricity<br>-Charges for use of infrastructure |

### 3.1.1 Extended Fleet TCO Optimization for Powertrain Considerations

Table 3.2. : Variable Definition

| Decision Variables | Description |
|---|---|
| $x^s_{qn}$ | Number n of vehicles type q that originate at s per year |
| $x^s_{qn,ij}$ | Vehicle n of type q originating at $s$, traveling on link (i,j). |
| $y^h_{ij}$ | Cargo flow between links, originating at $h$. |
| $x_{q,new}$ | Number of new vehicles of type $q$ purchased per year. |
| $x_{q,r}$ | Number of vehicles of type $q$ sold per year. |
| $e_{q,ij}$ | Feasibility of travel for vehicle type $q$ over route *(i,j)*. |
| $\Phi_{BS}$ | Binary variable, 1 if battery-electric vehicles use battery swap stations. |
| $\Phi_{CR}$ | Binary variable, 1 if battery-electric vehicles travel on charging roads. |
| $\Phi_{qn,c}$ | Number of times vehicle $n$ of type $q$ stops to fuel, charge, or perform a battery swap. |

Energy consumption costs will vary depending on the powertrain technology used, as a result of fuel and electricity costs and vehicle efficiency. In the case of diesel, natural gas, and hydrogen fuel cell vehicles, the use of conventional fueling stations is assumed. The primary differentiator between these fueling stations is the time required to fuel the different powertrains. In the case of battery electric vehicles, (BE), however, three different methods of charging are considered: fast-charging stations, battery swap stations, and on-road charging. The fast-charging stations are analogous to conventional fueling stations. Under the battery swap model, service providers own the vehicle batteries and supply users with access to battery swap infrastructure in exchange for a service fee. This option could possibly reduce vehicle upfront costs and battery replacement costs with a predictable annual fee, while expanding BE vehicle range without jeopardizing time spent at the station [46, 47].

Table 3.3. : Parameter Definition

| Parameters | Description |
|---|---|
| $\gamma$ | Estimated vehicle life-cycle period in years |
| $\eta$ | Hours of service window of operation |
| $\Psi_{ttq,q}$ | Tank-to-wheel (tailpipe) $CO_2$ emissions in kg per energy consumption |
| $\Psi_{wtt,q}$ | Well-to-tank $CO_2$ emissions in kg per energy consumption |
| $\xi_q$ | Efficiency function of vehicle type $q$ gallons or kWh per mile |
| $B_{cap}$ | Battery capacity in kWh |
| $B_f$ | Fleet's annual budget for vehicle purchase |
| $b_i^h$ | Cargo demand from origin $h$ to destination$i$ in tons |
| $B_q$ | Reliability of vehicle architecture $q$, % trips delayed per year |
| $C_{driver}$ | Cost of driver per mile |
| $C_{delay,c}$ | Revenue loss due to delay for cargo type $c$ |
| $C_{eq,b}$ | Cost of electricity used by battery electric vehicles in dollars per kWh |
| $C_{eq,f}$ | Cost of fuel consumed by vehicle type $q$ in dollars per gallon |
| $C_{kWh}$ | Cost of battery in $/kWh |
| $C_{M,q}$ | Cost of maintenance per mile for vehicle architecture $q$ |
| $C_{p,q}$ | Cost of purchase for vehicle type $q$ |
| $C_{r,q}$ | Resale value for vehicle type $q$ |
| $d_{ij}$ | Length (distance) of link *(i,j)* in miles |
| $E_q$ | Fuel or Battery charge gained at fueling, charging or battery swap station in kWh |
| $E_{CR}$ | Battery charge gained when traveling on charging road in kWh |
| $F_{q,i}$ | Availability of infrastructure for vehicle type $q$ in city node $i$ |
| $h_{os}$ | Hours of service driving limit |
| $l_{max}$ | Max number of years until replacement for fleet vehicles |
| $l_{min}$ | Min number of years until replacement for fleet vehicles |
| $M$ | A sufficiently large number |
| $R_q$ | Driving range of vehicle type $q$ in miles |
| $S_f$ | Annual service fee, per vehicle, for use of battery swap service |
| $t_{r,ij}$ | Travel time over route *(i,j)* in hours |
| $T_{CR}$ | Toll, in $, for use of on-road charging |
| $T_{d,q}$ | Average length of time delay for vehicle architecture $q$ |
| $u_{ij}$ | Vehicle steady-state speed on link *(i,j)* in miles per hour |
| $U_{CR}$ | Vehicle upcharge cost for wireless road charging capability |
| $W_q$ | Capacity for vehicle type $q$ in tons |

On the other hand, charging roads, also known as inductive, contactless, or dynamic wireless power transfer systems, can charge battery electric vehicles (BEs) without any physical interconnection. These systems can be installed on roadways in order to charge the vehicles while driving and extend the range or decrease the battery size [48, 49]. However, the power transfer capabilities of on-road charging systems are limited and may not be sufficient to fully recharge the large batteries required for line-haul operation. For simplicity, it is assumed that all BE vehicles in a single fleet will use only one mode of charging operation.

***Objective Function.*** The cost of energy for daily operation of a heterogeneous fleet is defined as $C_{ec} = C_{ec,f} + C_{ec,b}$ where

$$C_{ec,f} = \sum_{q} \sum_{(i,j)\in A} x_{q,ij} d_{ij} \xi_{q,ij} C_{eq}\,, \tag{3.1a}$$

$$C_{ec,b} = \sum_{(i,j)\in A} x_{q,ij} d_{ij} \xi_{q,ij} C_{eq}(1 - \Phi_{BS}) + x_{qn} S_f \Phi_{BS} + \Phi_{CR} T_{CR} \sum_{(i,j)\in G} x_{q,ij}\,. \tag{3.1b}$$

Here, $C_{ec,f}$ is the cost of fuel consumed by diesel, natural gas, and hydrogen-powered vehicles. For BE vehicles, a subscription model is assumed if battery swap stations are used ($\Phi_{BS} = 1$), in which case the fleet will pay an annual fee per vehicle, $S_f$, to the service provider. If on-road charging infrastructure is used ($\Phi_{CR} = 1$), fleets will alternatively incur charges for the electricity consumed and associated tolls, $T_f$, per trip. No additional fees, other than the cost of energy, are assumed for the use of conventional charging stations. As a result, the cost $C_{ec,b}$ includes the cost of electricity consumed by battery electric vehicles and associated tolls or fees for use of charging infrastructure. The variable $x_{q,ij} = \sum_s \sum_n x^s_{qn,ij}$ represents the flow of vehicles of type $q$ over highway link $(i, j)$ regardless of their origin. The sets $A$ and $G$ represent the set of city-nodes in the network and the set of road links with wireless charging capability, respectively. The efficiency of a vehicle using technology type q,

$\xi_q$, is a function of average vehicle speed over a route $(i, j)$ such that $\xi_{q,ij} = \xi_q(u_{ij})$. Other operational costs are computed as follows:

$$C_{wages} = \sum_q \sum_{(i,j)\in A} x_{q,ij} d_{ij} C_{driver} \,, \tag{3.2}$$

$$C_M = \sum_q \sum_{(i,j)\in A} x_{q,ij} d_{ij} C_{M,q} \,, \tag{3.3}$$

$$C_R = \sum_q \sum_{(i,j)\in A} x_{q,ij} B_q T_{d,q} C_{delay,c} \,. \tag{3.4}$$

The cost of purchase is defined as in Chapter 2, comprising the cost of buying new fleet vehicles and offset by the revenue generated by vehicle turnover sales: $C_{purch} = C_{nv} - C_{sr}$. Fleets will purchase new vehicles 1) to replace those beyond their optimal economic lifecycle, or 2) to address an increase in freight demand by increasing fleet volumes. It is assumed that all vehicles are purchased new, such that the purchase costs of a mixed-adoption fleet are given by $C_{nv} = C_{nv,f} + C_{nv,b}$ where

$$C_{nv,f} = \sum_q x_{q,new} C_{p,q} \,, \tag{3.5a}$$

$$C_{nv,b} = x_{q,new}(C_{p,q} - B_{cap} C_{kWh} \Phi_{BS} + \Phi_{CR} U_{CR}) \,. \tag{3.5b}$$

Similarly, as with operational costs, a subscription model is assumed for the use of battery swap stations. Contrary to direct ownership, the service provider owns the battery and thus upfront vehicle costs are reduced given the battery capacity, $B_{cap}$, and assumed battery cost, $C_{kWh}$. If on-road charging is selected, electric vehicles must have pick-up winding equipment installed [48], incurring an up-charge cost, $U_{CR}$. A traditional direct ownership model is assumed for all other vehicle types. Fleet sales of older vehicles are implemented as in Chapter 2.

In summary, the cost function $J$, defined as the extended TCO, is computed as follows:

$$J = \gamma \sum_{q} \sum_{(i,j)\epsilon A} x_{q,ij}[d_{ij}(\xi_{q,ij}C_{e,q} + C_{driver} + C_{M,q}) \ + B_q T_{d,q} C_{delay,c}]$$
$$+ \gamma \Phi_{BS}(x_{q,n}S_f - \sum_{(i,j)\in A} x_{q,ij} d_{ij} \xi_{q,ij} C_{e,q}) + \gamma \Phi_{CR} T_{CR} \sum_{(i,j)\in G} x_{q,ij} \tag{3.6}$$
$$+ \sum_{q} x_{q,new} C_{p,q} + x_{q,new}(\Phi_{CR} U_{CR} - B_{cap} C_{kWh} \Phi_{BS}) - \sum_{q} x_{q,r} C_{r,q}\,.$$

***Vehicle Fueling and Charging Constraints.*** The method and equations introduced by [50] are implemented to determine feasibility of travel, $e^s_{ij}$, for vehicles originating at $s$ over link $(i, j)$, given the vehicle range and location of fueling and charging stations, as shown in Equations (3.7a)-(3.7f). As summarized by Zheng et al., the variable $L^s_{qj}$ is incremented by the $(i, j)$ link's distance $d_{ij}$, as shown in Equation 3.7a, if node $i$ does not have fueling or charging infrastructure as identified by the parameter $F_{qi}$. The variable $e^s_{q,ij}$ will then have a value of 1 if the total distance $L^s_i$ is within the vehicle's range limits. The location of stations is not optimized in our formulation; it is instead defined as a network parameter. Therefore the status, $F_{qi}$, of a node as a fueling or charging station is an input to the MILP.

$$L^s_{qj} \geq L^{s'}_{qi} + d_{ij} - M(1 - e_{q,ij}) \tag{3.7a}$$

$$L^s_{qi} \leq R_q \tag{3.7b}$$

$$L^{s'}_{qi} \geq L^s_{qi} - MF_{qi}, \qquad L^{s'}_{qi} \leq L^s_{qi} + MF_{qi}, \qquad L^{s'}_{qi} \leq M(1 - F_{qi}) \tag{3.7c}$$

$$x^s_{qn,ij} \leq Me_{q,ij} \quad \forall n,\ q\,\epsilon Q \tag{3.7d}$$

$$L^s_{qi} \geq 0, \quad L^{s'}_{qi} \geq 0 \tag{3.7e}$$

$$e_{q,ij} \in \{0,1\}, \quad F_{qi} \in \{0,1\}, \quad F_{qi} = \begin{cases} 1 & i \in C \\ 0 & \end{cases} \tag{3.7f}$$

As stated earlier, fleet owners seek to increase the productivity of their vehicles in a cost-efficient manner to maximize revenue. Hours of service (HOS) rules limit both the driving time of commercial drivers to 11 hours and their time on-duty to 14 hours per day with a minimum 30 minute break every 8 hours [43]. As a result, any activity that causes downtime for the driver, and vehicle, within hours of operation will negatively impact productivity and, potentially, revenue. The inconvenience of lower vehicle range and longer fueling or charging stops when compared to the diesel baseline, along with time constraints to complete a day's driving, may limit adoption of alternative technologies. Equations (3.8a)-(3.8b) show the daily vehicle miles traveled (VMT) range constraints given fuel or battery energy content, $E_q$, number of fuel or charging stops, $\Phi_{qn,c}$, and energy transfer during on-road charging in the case of battery electric vehicles. It is assumed that a vehicle leaves its city of origin $s$ with a full fuel tank or charged battery. Equation 3.9 limits total operational time, that is driving plus fueling or charging stops, to remain within HOS limits, $\eta$, while range-extending stops are limited to those nodes with station availability as specified by Equation 3.10.

$$\sum_{(i,j)\in A} x^s_{qn,ij} d_{ij} \xi_{q,ij} \leq E_q(1 + \Phi_{qn,c}) \tag{3.8a}$$

$$\sum_{(i,j)\in A} x^s_{qn,ij} d_{ij} \xi_{q,ij} \leq E_q(1 + \Phi_{qn,c}) + \Phi_{CR} \sum_{(i,j)\in G} E_{CR,ij} x^s_{qn,ij} \quad \forall q, n \tag{3.8b}$$

$$\sum_{(i,j)\in A} x^s_{qn,ij} t_{r,ij} + \Phi_{qn,c} t_{en,q} \leq \eta \tag{3.9}$$

$$0 \leq \Phi_{qn,c} \leq \sum_i \sum_j x^s_{q,ji} F_{q,i} \tag{3.10}$$

Here, $t_{r,ij}$ is the time spent driving, $t_{en,q}$ is the time needed to charge or fuel, $\eta$ is the total window of operation, and $\Phi_{qn,c}$ is the number of times a vehicle $n$ of type $q$ stops to fuel or charge.

The wireless power transfer system for on road charging includes long primary windings installed under the road and secondary pick-up windings installed below the chassis of the electric vehicle [48]. The power transferred can recharge the battery while the vehicle is moving; the transfer of energy is proportional to the power of the system and the time the vehicle is above the primary winding. Energy transfer,

$E_{CR,ij}$, for a given charging road depends on the speed of the vehicle, $u_{ij}$, and the length, $L_{ij}$, of the route conditioned with windings, such that

$$E_{CR,ij} = P_{CR,ij} L_{CR,ij} \frac{1}{u_{ij}} \ . \tag{3.11}$$

***Well-to-Wheel Emissions.*** In order to adequately project global emissions given adoption and utilization of vehicle technologies, the analysis must determine the emissions resulting from transportation, production, distribution, and burning of the fuels. A well-to-wheel analysis provides an estimate of the emissions involved from extraction of the source of energy (well) throughout its point of utilization (wheels) [51]. Here, I distinguish between the well-to-tank, $\Psi_{wtt,q}$, emissions resulting from production, transportation, and distribution of fuel, and the tank-to-wheel values, $\Psi_{ttw,q}$, emissions resulting from the burning of the fuel. Both parameters have units of $\frac{kg\mathrm{CO_2}}{EN}$, where $EN$ represents the gallons of fuel or kWh of energy consumed. The annual regional emissions produced by vehicles of type $q$, $\mathrm{CO}_{2,q}$, is computed as

$$\mathrm{CO}_{2,q} = \sum_{(i,j)\in A} x_{q,ij} d_{ij} \xi_{q,ij} (\Psi_{wtt,q} + \Psi_{ttw,q}). \tag{3.12}$$

## 3.2 Powertrain Adoption Scenario

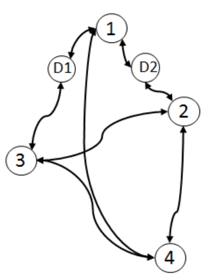
In this section I consider a single powertrain adoption scenario to demonstrate the predictive capabilities of the model under status quo assumptions; I will refer to this as powertrain adoption scenario A. Section 3.2.1 describes the calibration of the model to capture current public policies, short-term energy cost projections, freight demand growth, and limited availability of infrastructure for alternative fuels, over a period of 11 years, when evaluated policies are assumed to remain in effect. In Section 3.2.2 the model is used to project adoption and utilization strategies for emerging vehicle technologies as well as the potential to reduce $\mathrm{CO_2}$ emissions under the assumptions presented in Section 3.2.1. Policies include daily hours of service (HOS) restrictions, GHG Phase 2 regulations, and economic incentives for the use of alternative fuels.

### 3.2.1 Scenario Definition

The model is calibrated to project adoption of six vehicle architectures with conventional and emerging powertrain technologies—diesel, CNG, LNG, hybrid electric diesel (HEVD), battery electric (BE), and hydrogen fuel cell (HFC)—by line-haul fleets operating over a small hypothetical regional network given a set of assumptions for the evolution of the FTS. The network is defined as a representative set of line-haul highway corridors, each under 500 miles long, connecting 4 city nodes and 2 distribution centers, as shown in Figure 5.1. In this scenario, it is assumed that availability of fueling stations for CNG, LNG, and hydrogen, as well as charging stations capable of servicing heavy-duty Class 8 BE vehicles, will be limited in the near future. LNG, hydrogen, and charging stations are only assumed for city 1, while CNG stations are located in cities 1 and 2 and diesel stations are modeled in all city nodes. Fueling and charging times are assumed as follows: 1) 0.2 hours for a diesel or hybrid-diesel vehicle, 2) 1.5 hours for a CNG vehicle, 3) 0.25 hours for an LNG vehicle, 4) 3 hours for a BE vehicle, and 5) 0.4 hours for a HFC vehicle.

The U.S. Department of Energy, through its Alternative Fuels Data Center (AFDC), and the U.S. Energy Information Administration (EIA) provide reports of historical as well as short and long-term projections for retail prices of diesel and alternative fuels [52, 53]. Future fuel and energy cost trends indicated by the EIA are used to project costs of diesel and electricity from 2018-2028. For simplicity, historical prices for CNG and LNG, as published by the AFDC, are assumed for this projection scenario, given their retail price stability relative to diesel fuel costs. In the case of hydrogen fuel, stations servicing transit line heavy-duty buses in California report costs between \$8.00 and \$8.60 per kg of hydrogen dispensed for owning and maintaining stations as well as dispensing hydrogen to buses [54]. Therefore, a constant cost of \$8.00 per kg is assumed for the representative region modeled throughout the projected period of time for this adoption scenario. All fuel and energy costs over the projected time period are shown in Figure 3.3.

The following current policies are assumed to be in effect throughout the period of study: 1) Hours-of-Service (HOS) regulations limiting the driving time and operational time per day for property-carrying drivers [43], 2) GHG Phase 2 fuel efficiency standards for heavy-duty trucks [55], 3) 12% refundable fuel tax credits on compressed natural gas consumed based on those offered in the state of Indiana, and 4) $30,000 tax credit on CNG and LNG fueling equipment based on that currently offered in the state of Indiana [56]. GHG Phase 2 regulations are assumed to have an effect on fuel efficiency and cost of diesel and natural gas vehicles; therefore the effects of the policy are modeled accordingly as indicated in Table 3.4 and Figure 3.4. Policies providing incentives for alternative fuel vehicles in the form of tax credits, such as those modeled here for CNG and LNG fuels, are not available in every state in the U.S. Fleets operating over a cross-state regional network will only get reimbursed for the fuel purchased where the subsidy exists. In order to model this effect, natural gas credits are assumed to be limited to City 2 in this adoption scenario.




Route Distance Between Node Pairs (mi)

| | City 1 | City 2 | City 3 | City 4 | D1 | D2 |
|---|---|---|---|---|---|---|
| City 1 | - | 182 | 297 | 470 | 148 | 91 |
| City 2 | 182 | - | 242 | 289 | - | 91 |
| City 3 | 297 | 242 | - | 309 | 148 | - |
| City 4 | 470 | 289 | 309 | - | - | - |
| D1 | 148 | - | 148 | - | - | - |
| D2 | 91 | 91 | - | - | - | - |

Figure 3.2. : Representative line-haul network with 4 city nodes and 2 distribution centers. All direct routes between nodes are less than 500 miles.

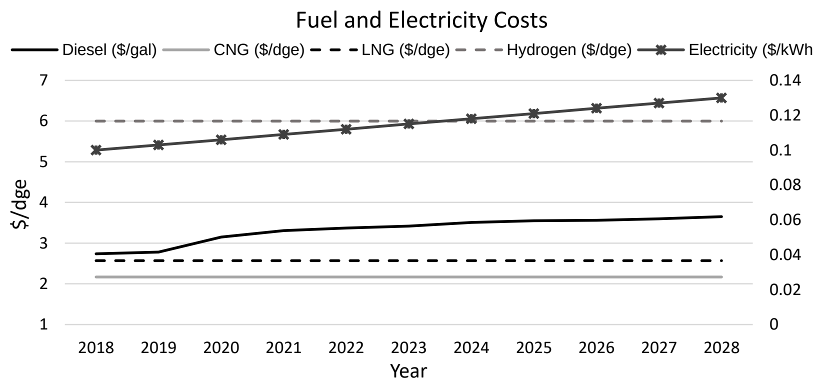



Figure 3.3. : Assumed fuel (in diesel gallon equivalent) and electricity (shown on the right axis) costs for the period of time evaluated.

Table 3.4. : Summary of GHG-2 Expected Fuel Savings and Price for HD Vehicles

| | MY 2021 | MY 2024 | MY 2027 |
|---|---|---|---|
| Maximum Tractor Fuel Savings (%) | 13 | 20 | 25 |
| Increase in Typical Tractor Price (%) | 6 | 10 | 12 |

Values obtained from [55]

The authors have previously identified a representative set of 12 line-haul fleets operating over a 4-city network and varying in size (number of vehicles), budget, annual growth, TCO outlook, and vehicle turnover periods [57]. The selected fleet management parameter values, shown in Table 3.5, were identified by emulating historic adoption trends for widely available Class 8 diesel vehicles with enhanced aerodynamic technologies. Results showed that the parameterized model predictions matched historical adoption trends within an error of 10%. The same set of representative fleets is therefore used here to capture heterogeneous fleet behavior to project adoption of emerging Class 8 powertrain technologies given the set of assumptions for the evolution of the FTS described. Cargo demand, by weight, is parameterized to represent three fleet sizes as indicated in Table 3.6. The freight demand ratio between all 4 cities is equivalent to that between Chicago (1), Indianapolis (2), St. Louis (3), and

Nashville (4), a representative network of high-traffic freight corridors in the U.S. Midwest [58].

Table 3.5. : Multi-Fleet Parametrization [57]

| Fleet | Gamma($\gamma$) years | Cargo ($b_i^h$) ton | Turnover years | Budget ($B_f$) $ | Cargo growth %/year |
|---|---|---|---|---|---|
| 1 | 5 | small | [2,4] | low | 1% |
| 2 | 5 | small | [1,3] | low | 1% |
| 3 | 5 | medium | [3,5] | high | 0 |
| 4 | 5 | large | [2,4] | low | 2% |
| 5 | 6 | small | [3,5] | high | 0 |
| 6 | 5 | large | [1,3] | low | 1% |
| 7 | 6 | small | [2,4] | high | 1% |
| 8 | 5 | medium | [2,4] | low | 1% |
| 9 | 5 | large | [3,5] | high | 0 |
| 10 | 6 | medium | [5,7] | high | 0 |
| 11 | 5 | medium | [1,3] | high | 0 |
| 12 | 6 | large | [5,7] | high | 2% |

Fuel vehicle efficiencies for the alternative powertrain technologies are estimated in a diesel gallon equivalent based on fuel energy content, while BE vehicle efficiency is expressed in kWh/mi. Payload capacity is an important factor for freight vehicles and can be a metric upon which vehicle owners discriminate between technologies. CNG tanks are approximately 2-2.5 times heavier than diesel ones for the same energy capacity, while LNG vehicle tanks are almost 50% heavier [4]. These weight effects are introduced into the model as a vehicle payload capacity parameter, shown in Table 3.7, where it is assumed natural gas vehicles have a decreased capacity as compared to diesel vehicles.

Table 3.6. : Cargo Demand ($b_i^h$) Parametrization

| Small Fleet (ton/day) | | | | | | |
|---|---|---|---|---|---|---|
| O/D | City 1 | City 2 | City 3 | City 4 | D1 | D2 |
| City 1 | 0 | 90 | 60 | 20 | 20 | 20 |
| City 2 | 100 | 0 | 15 | 10 | 0 | 20 |
| City 3 | 55 | 10 | 0 | 5 | 20 | 0 |
| City 4 | 15 | 10 | 5 | 0 | 0 | 0 |
| D1 | 20 | 0 | 20 | 0 | 0 | 0 |
| D2 | 20 | 20 | 0 | 0 | 0 | |
| **Medium Fleet (ton/day)** | | | | | | |
| O/D | City 1 | City 2 | City 3 | City 4 | D1 | D2 |
| City 1 | 0 | 150 | 100 | 30 | 20 | 20 |
| City 2 | 160 | 0 | 25 | 15 | 0 | 20 |
| City 3 | 90 | 20 | 0 | 10 | 20 | 0 |
| City 4 | 0 | 15 | 10 | 0 | 0 | 0 |
| D1 | 20 | 0 | 20 | 0 | 0 | 0 |
| D2 | 20 | 20 | 0 | 0 | 0 | |
| **Large Fleet (ton/day)** | | | | | | |
| O/D | City 1 | City 2 | City 3 | City 4 | D1 | D2 |
| City 1 | 0 | 235 | 160 | 50 | 50 | 50 |
| City 2 | 260 | 0 | 40 | 25 | 0 | 50 |
| City 3 | 140 | 30 | 0 | 20 | 50 | 0 |
| City 4 | 0 | 25 | 10 | 0 | 0 | 0 |
| D1 | 50 | 0 | 50 | 0 | 0 | 0 |
| D2 | 50 | 50 | 0 | 0 | 0 | |

In the case of BE vehicles, Mareev et al. [59] estimate that the engine, fuel tank, exhaust aftertreatment system, and diesel exhaust fluid (DEF) tank that become obsolete on a vehicle with a battery electric powertrain weigh approximately 3700 lb. This estimate, along with the added weight of a 600 kWh battery, assuming a 0.15-0.2 kWh/kg energy density, causes a decrease between 1 and 2 tons in payload capacity for a Class 8 BE vehicle with respect to the diesel baseline. BE vehicles are therefore assumed to have a payload capacity of approximately 2 tons lower than that of a diesel vehicle, as shown in Table 3.7. Finally, a pre-transmission parallel hybrid electric with diesel engine (HEVD) vehicle architecture is assumed as modeled by Zhao et al. [60] and an average increase in fuel efficiency is imposed over the diesel vehicle, also reflected in the vehicle parameterization table.

Table 3.7. : Vehicle Architecture Parameterization

| Vehicle Type | Vehicle Cost ($) | Eff. (mi/EN) (@55 mph) | Range (mi) | Capacity (ton) | Maint. Cost ($/mi) | Reliability (% trips/year) | Emissions[g] (kg $CO_2$/EN) Well-to-tank | Tank-to-wheel |
|---|---|---|---|---|---|---|---|---|
| Diesel[a] | 145,000 | 6 | 1000 | 25 | 0.15 | 1 | 9.45 | 10.16 |
| CNG[b] | 172,000 | 5.1 | 600 | 23 | 0.165 | 2 | 2.23 | 7.11 |
| LNG[c] | 190,000 | 5.25 | 1000 | 23 | 0.165 | 2 | 2.56 | 7.73 |
| HEVD[d] | 175,000 | 6.3 | 1100 | 24 | 0.158 | 5 | 9.45 | 10.16 |
| BE[e] | 210,000 | 0.39 | 300 | 23 | 0.175 | 5 | 0.63 | 0 |
| HFC[f] | 250,000 | 11 | 450 | 24 | 0.175 | 5 | 17.6 | 0 |

Vehicle cost, efficiency, range, and payload capacity values based on a range of sources for HD Class 8 tractors

[a] Approximate range assumed for a conventional diesel tractor with 200 gal fuel tank capacity [4, 6, 13]

[b] Approximate range and payload capacity values based on a 140 dge fuel tank capacity [4, 13]

[c] Approximate range and payload capacity values assumed for a 270 dge fuel tank capacity [4, 6, 13]

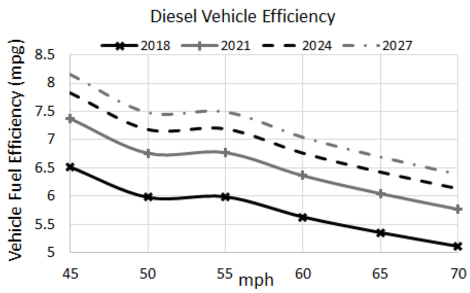
[d] Purchase cost, efficiency, range and payload capacity values assumed for a hybrid electric diesel tractor with 200 gal fuel capacity and 15 kWh battery capacity [6, 13]

[e] Purchase cost, range, and payload capacity values assumed for a conventional tractor with a 600 kWh battery capacity. [6, 13, 59]

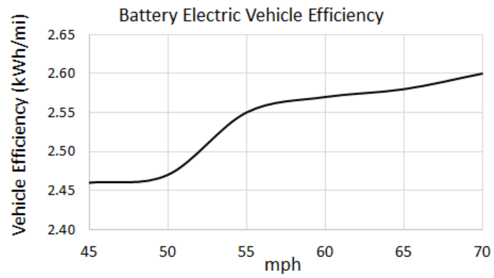
[f] Payload capacity and range assumed for a 65 kg fuel tank capacity and 11 mpg efficiency in diesel gallon equivalent [6, 13, 61, 62]

[g] Values based on US electricity mix, hydrogen produced by natural gas central reforming [13, 51]

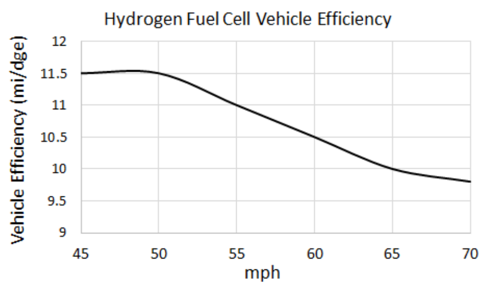
Figure 3.4 shows the efficiency for vehicles with diesel, BE, and HFC powertrain technologies. Vehicle efficiency $\xi_{q,ij}$ is defined as a function of vehicle technology and route speed. In the case of diesel and natural gas vehicles, it is assumed that efficiency will increase given the model year of the vehicle purchased, as indicated by the expected impact of GHG Phase 2 regulations. Moreover, CNG vehicles are assumed to have a loss of 15% efficiency relative to the diesel baseline, while a 12% loss is assumed for LNG vehicles [4, 63]. Therefore, the same trends in diesel vehicle efficiency with respect to speed and year of purchase are used for CNG and LNG, but with the assumed lower efficiency. BE and HFC vehicle efficiency curves are assumed to remain the same throughout the period of study, regardless of the year the vehicles are purchased.




(a) Diesel vehicle efficiency in mpg.




(b) BE vehicle efficiency in mi/kWh.




(c) HFC vehicle efficiency in miles per diesel gallon equivalent.

Figure 3.4. : Vehicle efficiency as a function of vehicle speed.

### 3.2.2 Simulated Results

Following the assumptions and the model parameterization described in the previous subsection, I project displacement of diesel vehicles, adoption of alternative technologies, and $CO_2$ reduction over an 11 year period. This period of time was selected to identify the immediate effects of current and planned policies including GHG Phase 2 regulations, tax credits for alternative fuels, and hours of service (HOS) restrictions. The model is initialized with a 98% composition of diesel and 2% CNG vehicles across all fleets [4], with an assumption that all initially owned vehicles are either 1 or 2 years old. In order to quantify the potential in $CO_2$ reduction given the introduction and market penetration of alternative technologies, a baseline scenario is simulated assuming no changes in the current composition of the line-haul segment. That is, 98% of all vehicles used throughout the period of study are powered by diesel fuel, with only 2% of the vehicles operated using CNG. The $CO_2$ emissions produced in the baseline scenario are plotted as a dotted red line in Figure 3.5 for comparison.

Interesting effects can be observed with respect to adoption, traffic allocation, and most significantly, $CO_2$ emissions. Figure 3.5 shows the market penetration in the modeled region for all 6 vehicle architectures introduced. Given the assumed fuel costs, vehicle costs, limited infrastructure availability for alternative fuels, and continued effects of currently active tax credit incentives, diesel vehicles are primarily displaced, up to 80% in 2028, by CNG vehicles. There is limited adoption, less than 5% as shown in Figure 3.6, of LNG, BE, and HFC vehicles. There is no adoption of HEVD vehicles in this scenario. This analysis demonstrates a *rapid reduction in* $CO_2$ *in both the baseline and mixed adoption scenarios by the year 2021 due to the fuel efficiency impacts of GHG Phase 2 regulations, and an approximate reduction of 30% in* $CO_2$ *emissions (by mass) in 2028 once 80% of all vehicles used are powered by CNG fuel.* In this case, however, the immediate emissions reduction between 2018 to 2021 is higher, by comparison, in the mixed adoption scenario.

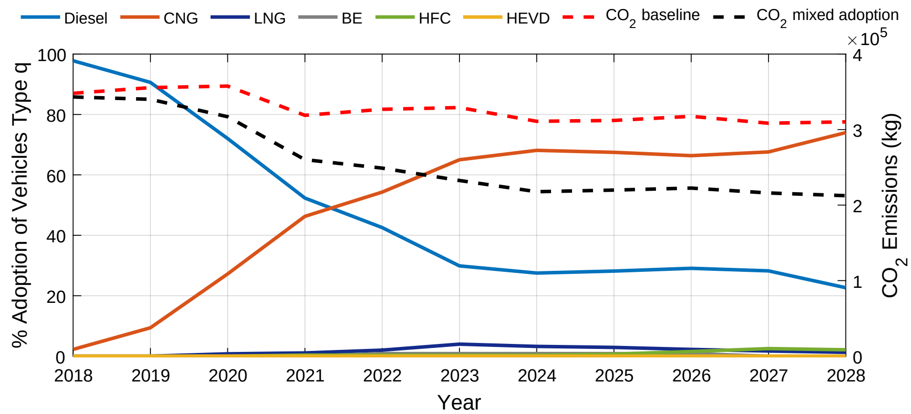



Figure 3.5. : Total percent vehicle adoption throughout period of study across all regional fleets modeled. The red dotted line shows regional emissions for a baseline scenario with 98% diesel and 2% CNG fleet composition (see right y-axis). The black dotted line shows regional $CO_2$ emissions resulting from the projected adoption of the six vehicle architectures as shown on the same plot.

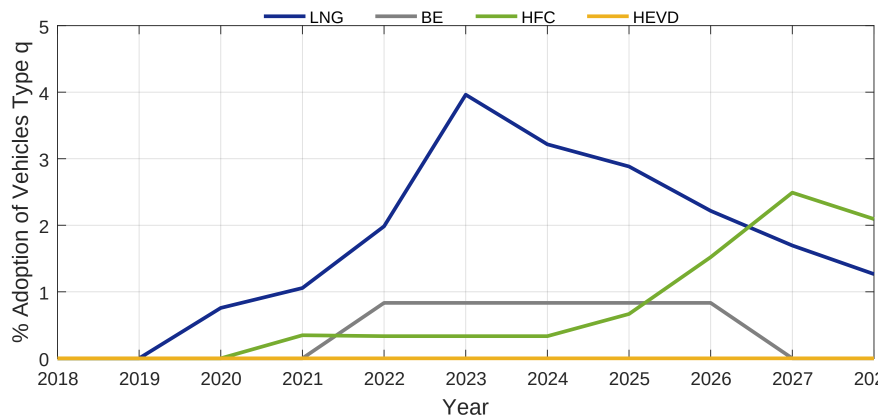



Figure 3.6. : Adoption of LNG, BE, HFC, and HEVD vehicles throughout the scenario period.

As shown in Figure 3.5, the adoption rate for CNG reaches a plateau in the period 2023-2027, at which point we observe adoption of LNG and BE vehicles; this can be seen more closely in Figure 3.6. However, *GHG Phase 2 regulations are assumed to cause a further increase in fuel efficiency of diesel and CNG vehicles in 2027, causing an immediate increase in CNG adoption.* BE vehicles are no longer economically attractive to those few fleets that had adopted them and are therefore sold. Figures 3.7 and 3.8 show total daily vehicle utilization for all truck types and allocation over the freight routes. Figure 3.8 demonstrates a net increase in utilization of CNG vehicles along all routes over the period of study shown as adoption increases, with the exception of the longest route between city 1 and city 4 (Figure 3.8e), which sees a decrease in vehicle traffic throughout the period of study.

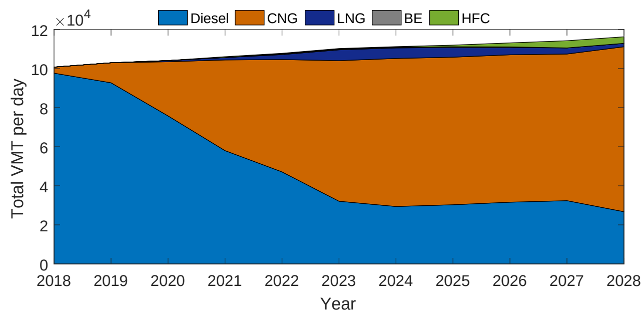



Figure 3.7. : Daily total vehicle miles traveled (VMT) by all vehicle types.

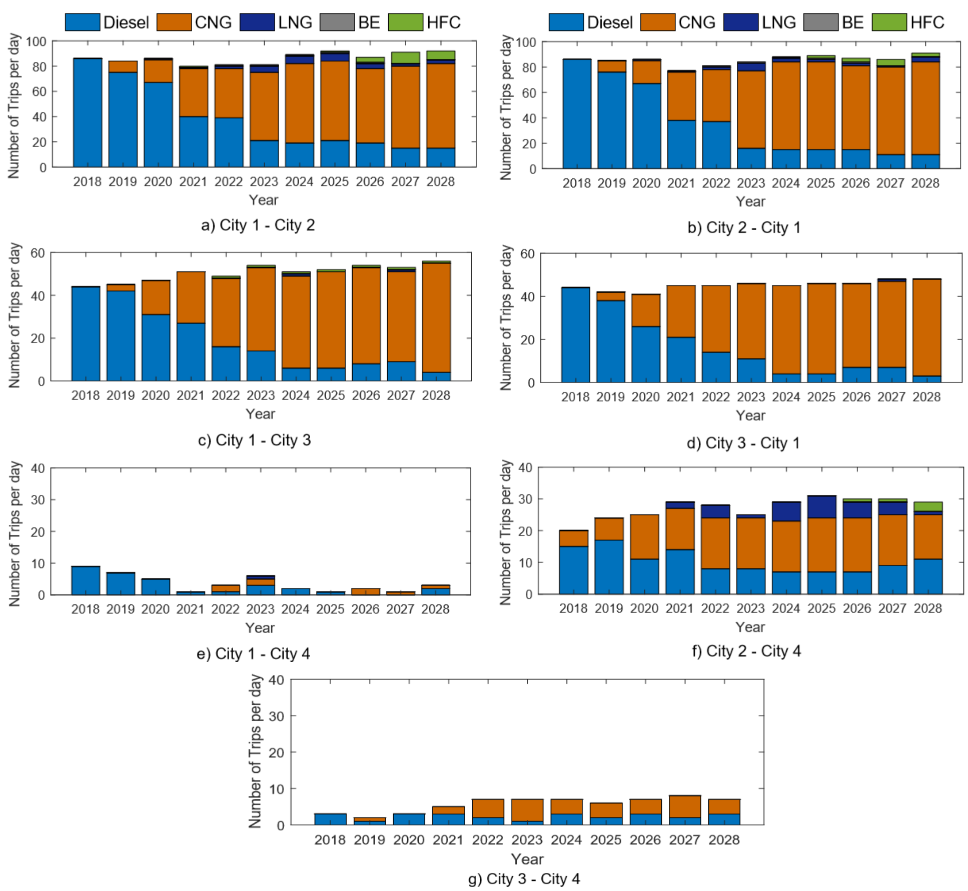



Figure 3.8. : Total number of trips per day between selected cities, showing trips for all vehicle types adopted.

*A higher adoption of CNG vehicles, which have a shorter range than diesel vehicles, could cause a shift in traffic corridors as observed in this evaluation scenario.* This effect is shown in Figure 3.8. Here, the increase in adoption and utilization of CNG vehicles, which have a significantly shorter range as compared to diesel, causes a redistribution of vehicles transporting freight on the direct route from city 1 to 4 (Figure 3.8e) to reallocate through city 2 (Figure 3.8f) and city 3 (Figure 3.8g). At the beginning of the study period, 10 diesel vehicles travel from city 1 to 4; however, by 2021 and throughout 2028, fewer vehicles are taking this route. Alternatively, the routes between city 2 and city 4, and city 3 and city 4 see an equivalent increase in CNG vehicles after the year 2021. The route between city 2 to city 4 sees a small increase in LNG and HFC vehicle allocation after the year 2021.

## 3.3 Sensitivity Analysis

In this section, the proposed model is used to quantify the sensitivity of vehicle adoption and regional $CO_2$ emissions projections to variation in system factor assumptions such as future policies, fuel costs, proliferation of fueling/charging infrastructure, and technology design. Furthermore, I identify the mechanisms and adoption trajectories that result in the maximum reduction in regional $CO_2$ emissions.

### 3.3.1 Design of Experiments

The results presented in the previous section assumed a specific scenario, which I called powertrain adoption scenario A, for the evolution of the FTS, based upon a continuation of existing policies. However, a powerful use of the proposed model is for understanding *how* the adoption of emerging powertrain technologies, and the resulting line-haul system emissions, will be affected if the cost of fuel, policy incentives, or availability of fueling infrastructure varies from the status quo. Are there any vehicle design factors—efficiency, range, payload capacity—that can be improved to enhance adoption of cleaner technologies? Is there a required level of infrastructure proliferation necessary to drive adoption of alternative powertrain technologies? What incentives are necessary to improve the economic output of fleets as they adopt cleaner technologies, and how must they be introduced over a chosen timeline to influence adoption? Moreover, how is viability of adoption affected if several of these factors vary concurrently from the status quo scenario? To answer these questions, a design of experiments (DOE) is used to identify the factors that significantly influence multi-fleet adoption of the powertrain technologies and to quantify the variation of market penetration under different scenarios. Fifteen system parameters are varied as shown in Tables 3.8-3.11. A 180 point design of experiments (DOE) is defined with the JMP Statistical Analysis software [41] in order to reduce the number of executions from a full factorial design to screen the response and produce a satisfactory regression model for sensitivity analysis.

Line-haul fleets are generally concerned with a vehicle's *productive capability*, i.e. the amount of freight it will be able to transport in a given day, particularly when considering a new technology over the well-known capabilities of a conventional diesel vehicle [37]. The perceived uncertainty in fuel economy, range, and payload capacity, particularly for alternative heavy-duty technologies—CNG, LNG, HFC, and BE—causes what is known as "range anxiety" [6]. Variation in these vehicle-level parameters is introduced, as shown in Table 3.8. As heavy-duty Class 8 BE and HFC vehicles are yet to be introduced to the market, there is also perceived uncertainty on the future availability of fueling and charging stations, and their capabilities, to service line-haul trucks in a timely manner. Therefore, parameters affecting infrastructure are also considered as shown in Table 3.9. As of 2016, the only examples of hydrogen stations servicing heavy-duty vehicles are those in California for transit city buses, charging a vehicle with a capacity of 50 kg in approximately 10 minutes [54]. Given the expected tank capacity for a Class 8 truck to be above 60 kg for a range of 450 miles [62], higher fueling times are introduced as shown in Table 3.9. In the case of BE vehicles, exploratory fast-charging values of half an hour are introduced.

However, given that based on current technology projections, fast charging stations with the capability to charge a 600-900 kWh battery pack will likely take more than 1 hour, values greater than 1 hour are introduced as well.

Table 3.8. : DOE Vehicle Parameter Levels

| Truck Type | Efficiency[a] (mi/dge) | | Range (mi) | | Payload Capacity (ton) | | |
|---|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 | Level 3 |
| Diesel | 5.35 | 5.85 | 1000 | 1000 | 25 | 25 | 25 |
| CNG | 4.5 | 5 | 600 | 600 | 23 | 24 | 23 |
| LNG | 4.65 | 5.2 | 1000 | 1000 | 23 | 24 | 23 |
| HEVD | 5.6 | 6.2 | 1100 | 1060 | 24 | 24 | 24 |
| BE[b] | 2.6 | 2.2 | 500 | 300 | 23 | 24 | 25 |
| HFC | 7.2 | 10 | 750 | 450 | 24 | 24 | 24 |

[a] Efficiency shown at a vehicle speed of 65 mph

[b] BE efficiency is defined in units of $\frac{kWh}{mi}$

Table 3.9. : DOE Infrastructure Parameter Levels

| Truck Type | Charging Time (hr) | | | | | Infrastructure Availability | |
|---|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 | Level 1 | Level 2 |
| Diesel | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | all cities | all cities |
| CNG | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | city 1 | all cities |
| LNG | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | city 1 | all cities |
| HEVD | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | all cities | all cities |
| 8BE | 0.5 | 1 | 2 | 3 | 3 | city 1 | all cities/roads |
| HFC | 0.25 | 0.25 | 0.25 | 0.4 | 0.5 | city 1 | all cities |

As stated earlier, three range-extending infrastructure modes have been proposed in support of BE vehicles: 1) charging stations, 2) battery swap stations, and 3) on-road charging. Therefore, the infrastructure type available in the region is imposed as a factor of variation in order to understand the effects on adoption of BE vehicles. Due to uncertainty in related costs to build, maintain, and service the infrastructure, variation is also introduced to the user fees modeled, particularly the fees and tolls related to the use of battery swap stations and on-road charging, as well as the increase in cost of purchase assumed for wireless power transfer capability. These values are shown in Table 3.10.

Table 3.10. : DOE Battery Electric Vehicle Considerations

| | Battery Capacity (kWh) | Battery Cost ( $/kWh) | Infra. Mode $\Phi$ | Swap Station Fee ($/month) | Charg. Rd. Toll ($/trip) | Charg. Rd. Power (kW) | Charg. Rd. Length (%) | Charg. Rd. Veh. Upcharge ($) |
|---|---|---|---|---|---|---|---|---|
| Level 1 | 900 | 50 | 0 | 1500 | 10 | 50 | 0.2 | 1000 |
| Level 2 | 600 | 100 | 1 | 3000 | 20 | 100 | 1 | 5000 |
| Level 3 | | 200 | | | | | | |

Finally, as shown in Table 3.11, a natural gas fuel tax credit is applied to both CNG and LNG fuel. A new economic incentive is also introduced; a voucher, valid at the time of purchase, is made available for hybrid and zero emission vehicles (BE and HFC) similar to the ones provided by the California Air Resources Board Voucher Incentive Project (CARB HVIP) and currently available in the state of California [64].

Table 3.11. : DOE Regional Policies and Economic Factor Levels

| Truck Type | Cost of Fuel ($/EN[a]) | | | | | | Policies | |
|---|---|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 | Level 6 | Level 1 | Level 2 |
| Diesel | Decrease[b] | 2.8 | Increase[c] | Increase | Increase | Increase | None | None |
| CNG | 2.17 | 2.17 | 2.17 | 2.17 | 2.17 | 2.17 | None | 12% fuel tax rebate |
| LNG | 2.57 | 2.57 | 2.57 | 2.57 | 2.57 | 2.57 | None | 12% fuel tax rebate |
| HEVD | Decrease | 2.8 | Increase | Increase | Increase | Increase | None | $20,000 voucher |
| BE | Increase[d] | Increase | Increase | 0.11 | Increase | Increase | None | $45,000 voucher |
| HFC | 6 | 6 | 6 | 6 | 4 | 2 | None | $45,000 voucher |

[a] EN is expressed in units of fuel (gal or diesel gallon equivalent) or electricity (kWh) consumed

[b] Cost of diesel fuel is linearly decreasing between $2.7-$2.2 per gallon during period of study

[c] Cost of diesel fuel is linearly increasing between $2.7-$3.2 per gallon during period of study

[d] Cost of electricity is linearly increasing between $0.1-$0.14 per kWh during period of study

Figure 3.9 shows the total number of purchases, plotted by vehicle type, across all 180 experiments evaluated as part of the DOE study. Each experiment represents the total number of vehicle purchases across all fleets in the region throughout the 2018-2028 period, shown in descending order with respect to the total number of vehicles purchased. On average, approximately 500 new vehicles are purchased throughout the period of study for every DOE case evaluated. However, it can be observed that *the total number of vehicles purchased in the region increases with the number of battery electric vehicles adopted*, as these vehicles have a shorter range than the diesel baseline, while total freight demand in the region remains the same across all DOE cases. This effect is particularly true in the cases where battery swap stations are available and a service fee model is followed instead of direct ownership of BE vehicles, thereby reducing the total cost of ownership.

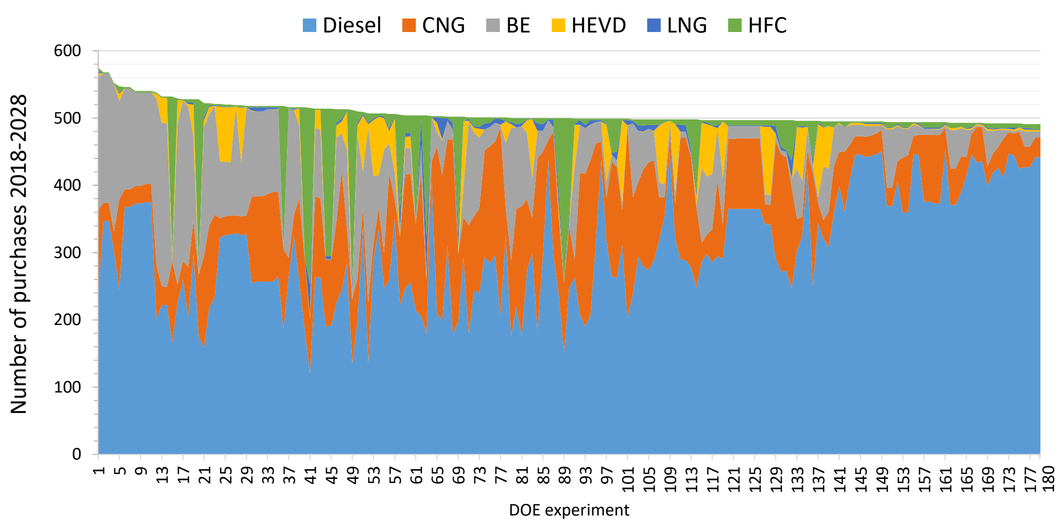



Figure 3.9. : Number of purchases of each vehicle type throughout period of study across all DOE points evaluated.

Figure 3.9 shows that all cases evaluated result in mixed adoption scenarios of diesel, CNG, BE, HFC, and, to a lower extent, HEVD vehicles. There is negligible adoption of LNG vehicles given the factor values assumed for the DOE. Variation of individual adoption metrics to the factor levels evaluated are quantified in the appendix, showing a wide distribution of diesel, CNG, BE, HEVD, and HFC vehicle purchases. Furthermore, $CO_2$ emissions vary approximately between 2.62 Gg to 5 Gg across the different system evolution scenarios evaluated, as shown in Figure 3.10.

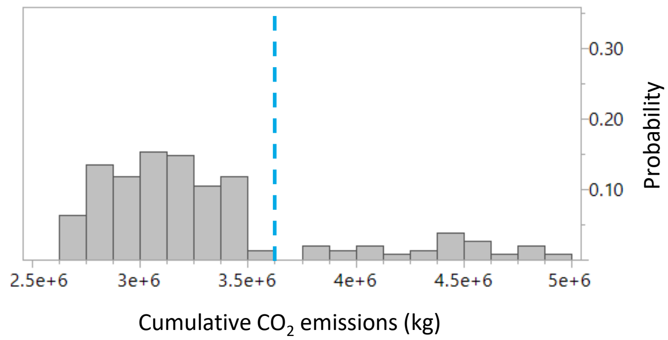



Figure 3.10. : Histogram showing distribution of cumulative $CO_2$ emissions, in kg, produced throughout the 2018-2028 period as a result of the DOE factor variation. Cumulative emissions value for the baseline case (98% diesel adoption) is indicated by the blue dotted line.

In order to quantify sensitivity of vehicle adoption metrics to variation in individual factors, a regression model is computed from the DOE data and used to predict factor influence. The quality of fit for each regression model computed is shown in Table 3.12, indicating root mean square error and coefficient of determination ($R^2$) values. The $R^2$ values for diesel, CNG, HEVD, BE, and HFC purchase predictions, excluding LNG vehicles due to negligible adoption projections, are all above 0.87. Figure A1, shown in the Appendix, demonstrates the quality of fit of the regression models. The regression models are therefore a good representation of vehicle purchase projections, and here they are utilized to predict adoption sensitivity to factor variation. The effects are quantified in Figures 3.11–3.16.

Table 3.12. : Summary of Regression Fit

| Truck Type | $R^2$ | RMSE |
|---|---|---|
| Diesel | 0.87 | 31.6 |
| CNG | 0.9 | 22. |
| HEVD | 0.97 | 6.86 |
| BE | 0.91 | 22.88 |
| HFC | 0.94 | 16.9 |

Tornado charts show individual effects of system factor variation, as indicated by the factor levels evaluated, in total number of vehicle purchases for each architecture. Recall that parameter values for individual factors are listed in Tables 3.8-3.11. Response sensitivity, shown on the y-axes of Figures 3.11-3.14, is computed as the deviation in vehicle purchases from the predicted mean as single factor levels are varied and all other factors are held constant.

In the case of diesel and CNG vehicles, as shown in Figure 3.11 and 3.12 respectively, *cost of diesel fuel is the most influential factor on projected adoption.* This is indicated by the positive effects of Levels 1-2 and negative effects of Levels 3-4 on diesel purchases. For this study, variation is introduced only for the cost of diesel, electricity, and hydrogen; exploratory values for the cost of natural gas were not considered given its stable price relative to the cost of diesel [52]. Cost of electricity and hydrogen fuel are expected to vary regionally or with time as production efficiency progresses [53, 65]. Furthermore, although hydrogen as a transportation fuel is expected to remain high in cost in the near future, exploratory low cost values (Levels 5 and 6) are included in the study and also have a negative effect on diesel vehicle purchases. Moreover, an increase in payload capacity of alternative fuel vehicles—from 23 to 24 tons for CNG, LNG, and BE vehicles as indicated by Levels 1 and 2—has a negative effect on adoption of diesel vehicles while increasing the economic attractiveness of the alternatives (see Figures 3.13 and 3.14). In the case of CNG (Figure 3.12), the availability of battery swap stations (Level 2 of $\Phi_{BS}$ parameter) means that market penetration will be shared with battery electric vehicles (see Figure 3.14).

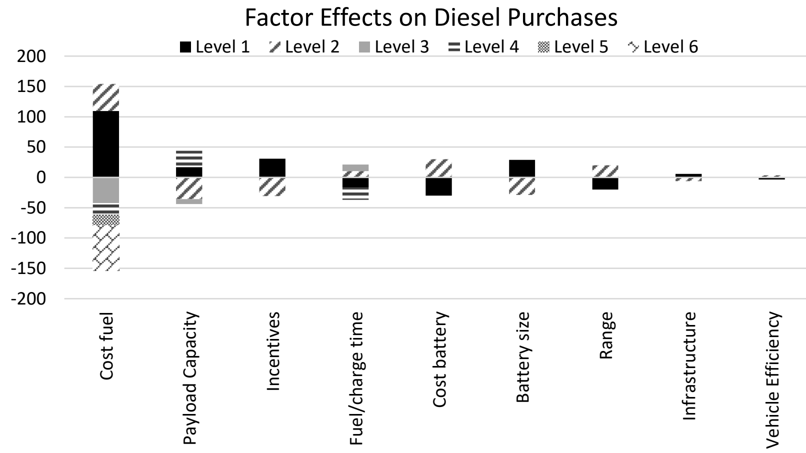



Figure 3.11. : Tornado chart of factor effect on number of diesel vehicle purchases, shown as the deviation from the overall predicted mean of 317 diesel vehicle purchases.

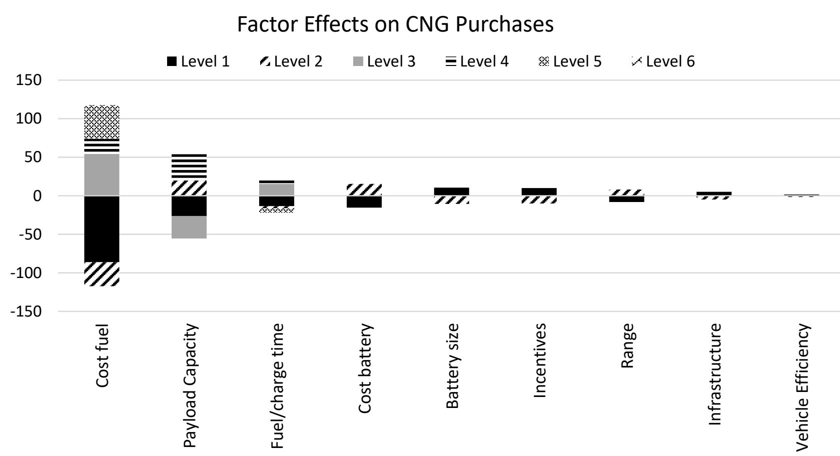



Figure 3.12. : Tornado chart of factor effect on number of CNG vehicle purchases, shown as the deviation from the overall predicted mean of 86 CNG vehicle purchases.

Figures 3.13, 3.14, and 3.15 summarize factor effects on HEVD, BE, and HFC vehicle purchases, respectively. From Figure 3.13 we see that *incentives* are the primary factor influencing adoption of HEVDs, with a positive net effect if a voucher reducing cost of purchase by $20,000 is provided (see Level 2). Moreover, the availability of battery swap stations also causes a decrease in fleet preference of HEVDs, an effect also observed on adoption of CNG vehicles. Finally, Figure 3.14 corroborates the *positive effect of battery swap station availability on the attractiveness of BE vehicles* (see Level 2). As mentioned before, under this model, batteries are owned by service providers and a battery swap is assumed to take only 25 minutes. These assumptions significantly lower vehicle purchase costs, as fleet owners are in turn paying an annual flat service fee, as well as decrease the downtime associated with range-extending stops. Figure 3.14 also shows that variation in charging time, in the case where the use of charging stations is assumed, has a considerable effect on BE adoption. Specifically, faster charging times, 1 or 2 hours (Levels 1 and 2), have a positive effect on adoption as compared to the 3-hour baseline (Levels 3 and 4). *The imposition of on-road charging as the range-extending mode for electric vehicles appears to have a negative effect on BE vehicle adoption, as indicated in Figure 3.14, particularly when compared to the cases where battery swap stations are available.* This is due to the low power transfer capacity assumed possible, with a maximum value of 100 kW, not providing enough energy to fully charge the large battery packs necessary for Class 8 vehicles. In the case of HFC vehicles, Figure 3.15 shows the positive effect of a low cost of hydrogen fuel, demonstrating that values under \$4 per diesel gallon equivalent are necessary for adoption of HFC vehicles.

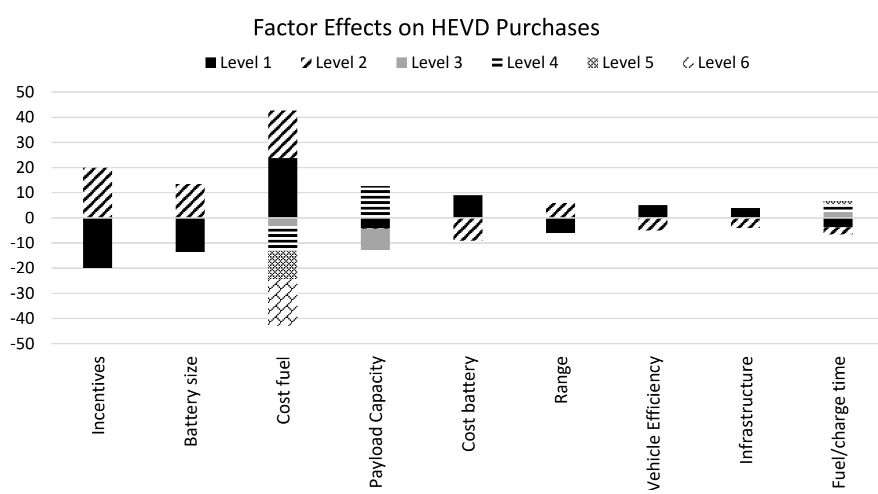



Figure 3.13. : Tornado chart of factor effect on number of hybrid electric diesel vehicle purchases, shown as the deviation from the overall predicted mean of 19 HEVD vehicle purchases.

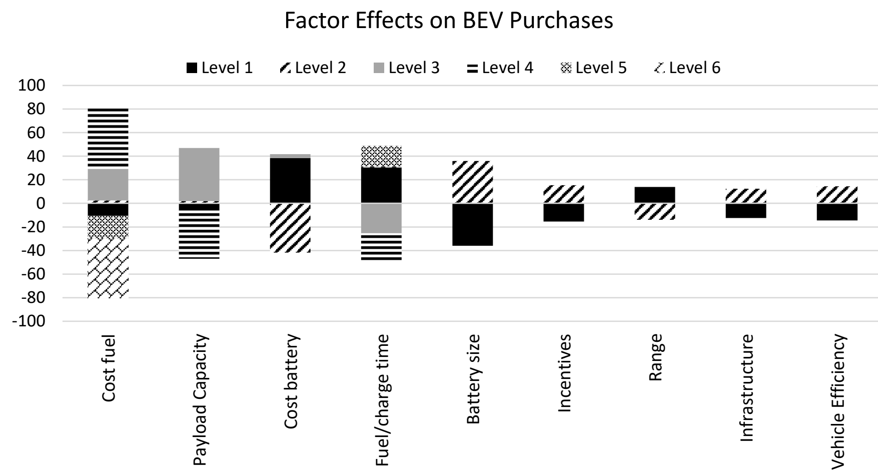



Figure 3.14. : Tornado chart of factor effect on number of battery electric vehicle purchases, shown as the deviation from the overall predicted mean of 74 BE vehicle purchases.

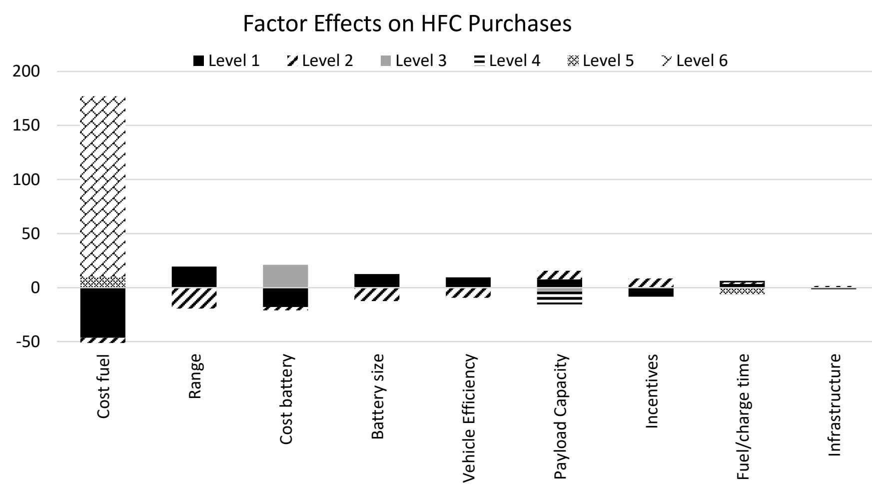



Figure 3.15. : Tornado chart of factor effect on number of hydrogen fuel cell vehicle purchases, shown as the deviation from the overall predicted mean of 70 HFC purchases.

Due to the significant positive effect of battery swap station availability on BE adoption under these assumed scenarios, it is of interest to further inspect the effects of other parameters when this charging model is followed. This case is evaluated by setting $\Phi_{BS} = 1$ which imposes the use of battery swap stations according to the defined availability of infrastructure. In this case, as shown in Figure 3.16, *battery swap stations maximize the adoption of BE vehicles, provided that they are widely available.* As expected, adoption is also dependent on the service fee charged. Future work could focus on identifying an appropriate range in service fees, considering the costs of owning and operating a battery swap station for heavy-duty vehicles with large battery packs, to estimate the likelihood of such large positive effects on BE vehicle adoption.

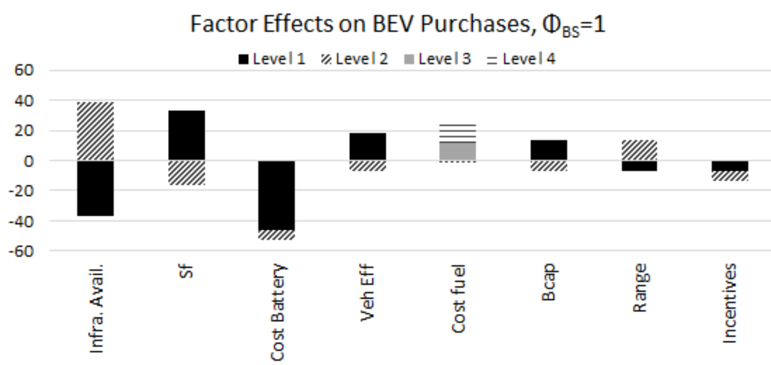



Figure 3.16. : Tornado chart of factor effect on number of battery electric vehicle purchases when battery swap stations are used.

Finally, the direct effects of emerging vehicle penetration on regional $CO_2$ emissions are quantified in Figure 3.17. Here, perhaps most surprisingly, we observe that *an increased adoption of HEVD trucks has a negative impact on $CO_2$ emissions*, causing an increase of almost 2 Gg of $CO_2$ between the *zero adoption* and *maximum adoption* scenarios as indicated in Figure 3.17c. This happens particularly due to the higher vehicle utilization of HEVDs when adopted, an effect that is more pronounced when purchase vouchers are provided for this vehicle type. Here, it is important to note that only diesel-hybrid powertrains were considered. Future work could focus on exploring the effects on network wide emissions if other hybrid alternatives are introduced, for example, CNG-hybrid vehicles.

Moreover, cumulative $CO_2$ emissions in the region decrease as the number of CNG and BE trucks purchased throughout the period of study increases, as shown in Figures 3.17b and 3.17d. *As each of these vehicles reaches a volume of more than 200 vehicles adopted throughout the period of study, there is a potential reduction of approximately 20% in cumulative emissions from the baseline case (98% diesel adoption).*

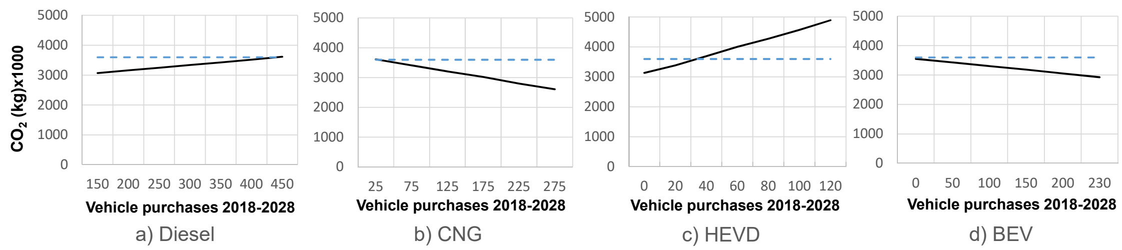



Figure 3.17. : Cumulative $CO_2$ regional emissions, in kg, throughout the 2018-2028 period of study as a function of vehicle purchases. Cumulative emissions for the baseline case (98% diesel adoption) are indicated by the dotted line.

### 3.3.2 Paths towards lowering $CO_2$ emissions

Finally, I explore the mixed adoption trajectories, as identified by the DOE presented in section 3.3.1, that minimize $CO_2$ emissions over the period of study in order to identify the mechanisms necessary to do so. Figure 3.18 shows the cumulative $CO_2$ emissions for all DOE points evaluated as a function of diesel vehicle purchases. As indicated previously by the sensitivity analysis, cases in which hybrid-diesel vehicles are heavily adopted result in high emission scenarios due to their over-utilization.

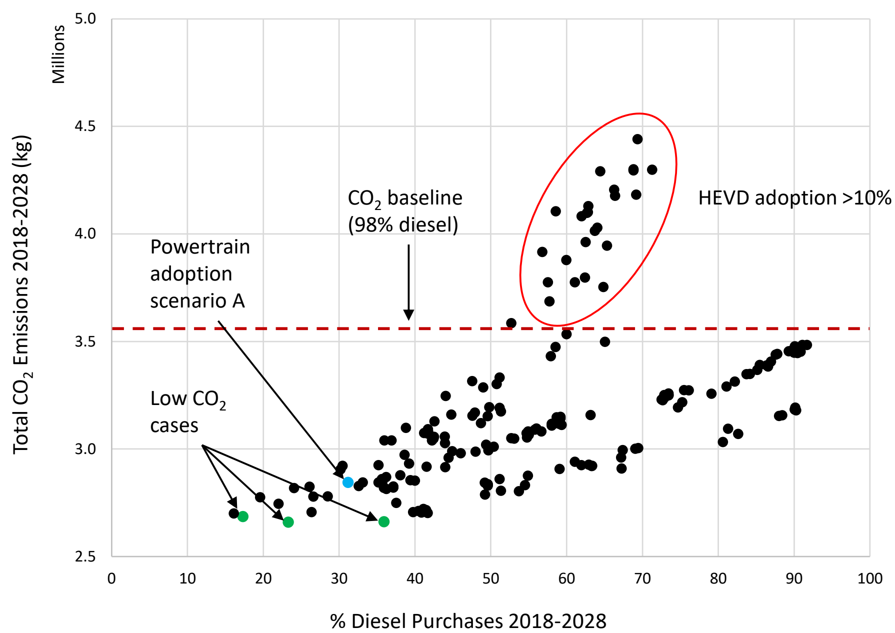
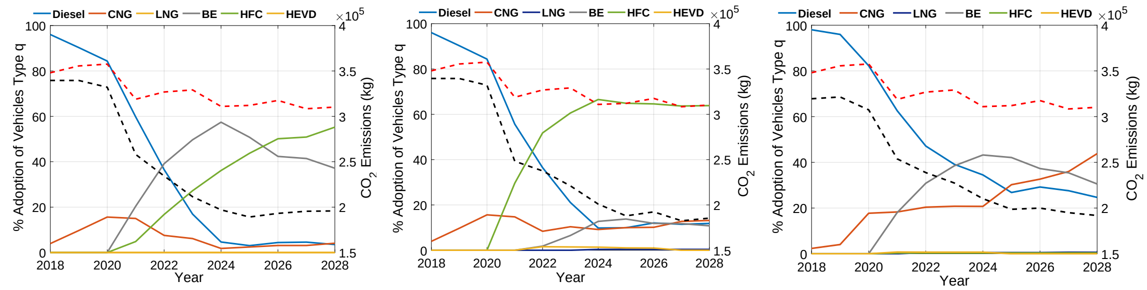



Figure 3.18. : Cumulative $CO_2$ regional emissions shown for all DOE points, in kg, throughout the 2018-2028 period of study as a function of diesel vehicle purchases. Cumulative emissions for the baseline case (98% diesel adoption) are indicated by the dotted line.

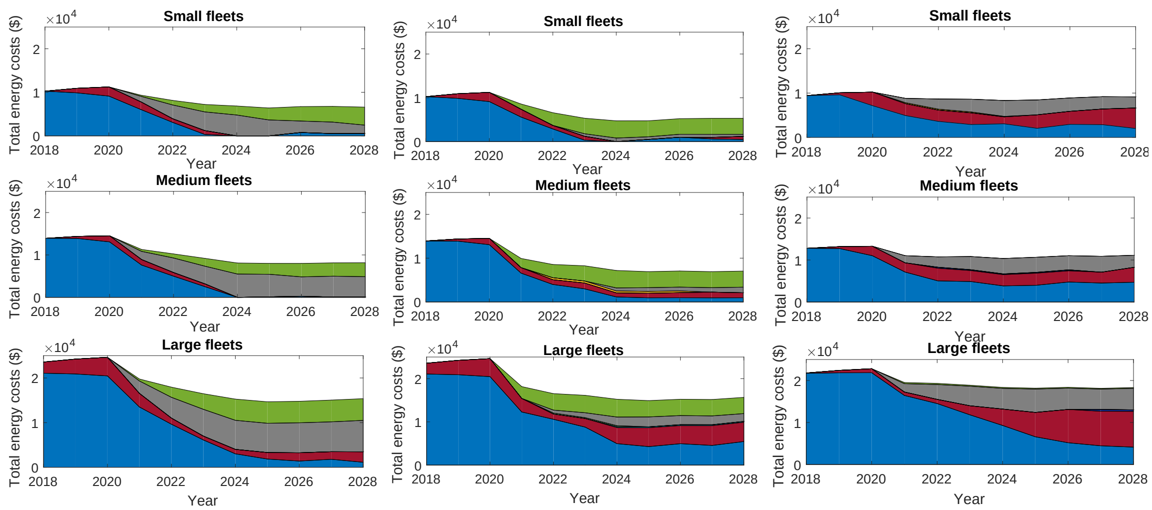
Moreover, the three lowest $CO_2$ points are identified corresponding to significantly varying diesel and emerging technologies adoption scenarios, as shown in Figure 3.19 (a)-(c). Here, BE+HFC mix, primary HFC mix, and BE+CNG mix adoption cases are identified with similar low cumulative emission values. This indicates that *more than one future mixed-adoption scenario can be targeted in order to achieve a desirable reduction in emissions.* Table 3.13 shows the parameter levels corresponding to the three mixed-adoption cases; recall that factor levels are described in Tables 3.8-3.11. All three cases correspond to a wide availability of infrastructure, as indicated by Level 2 parameterization (Table 3.9). Moreover, the single difference in parameterization between cases 1 and 2 is the availability of incentives. However, case 2, in which incentives are not provided, shows that adoption of BE vehicles has instead been displaced by HFC and CNG adoption and a visible decrease in $CO_2$ emissions in 2028, as shown in Figure 3.19 (b). This indicates that case 2, as defined by the future parameter values, shows robustness to the removal of voucher incentives with respect to the capability to achieve a large reduction in cumulative emissions. Furthermore, cases 1 and 2 both show high adoption of HFC vehicles and correspond to the low cost assumption for hydrogen fuel of $2 per diesel gallon equivalent. This suggests that although voucher incentives may not be necessary, a fuel subsidy may be required in the future in order to achieve such a low cost for hydrogen fuel. It is cases 1 and 2, as shown in Figure 3.19 (d) and (e), that observe the highest reduction in total energy costs for all fleet types, as compared to the case 3 with mixed diesel, BE, and CNG adoption shown in Figure 3.19 (f).

Table 3.13. : Low $CO_2$ Point Parameters

| | Efficiency | Range | Payload Capacity | Cost of Fuel | Policies | Fuel/Charge Time | Infrastructure Availability | $CO_2$ Emissions Reduction |
|---|---|---|---|---|---|---|---|---|
| Case 1 | Level 1 | Level 1 | Level 3 | Level 6 | Level 1 | Level 1 | Level 2 | 25.3% |
| Case 2 | Level 1 | Level 1 | Level 3 | Level 6 | Level 2 | Level 1 | Level 2 | 25.8% |
| Case 3 | Level 2 | Level 2 | Level 2 | Level 3 | Level 2 | Level 4 | Level 2 | 25.9% |




(a) Mixed adoption case 1 (b) Mixed adoption case 2 (c) Mixed adoption case 3




(d) Fuel cost case 1 (e) Fuel cost case 2 (f) Fuel cost case 3

Figure 3.19. : Low $CO_2$ cases identified by the DOE study.

## 3.4 Risk Aversion to Emerging Technologies

There are several factors that can limit, and even hinder, the adoption of alternative and fuel efficient technologies. These factors are best indicated by the low adoption of natural gas powertrains, despite their availability in the Class 8 market for the last decade 2.5. The line-haul trucking sector has shown itself to be a slow adopter of revolutionary technologies in the past. Instead, fleet owners tend to opt for the well-known capabilities of conventional diesel vehicles [66]. Natural gas vehicles, primarily CNG, observed an increase in adoption after the cost of diesel fuel increased in 2011. However, their penetration level in the market was much lower than that of diesel vehicles. Furthermore, as the cost of diesel fuel declined and the cost advantage of operating natural gas vehicles disappeared, the sales of CNG vehicles declined. Less availability of natural gas vehicles across fleet-preferred manufacturers and the lack of fueling infrastructure may have been influential factors limiting their uptake. However, it is reasonable to hypothesize that a higher demand could itself entice manufacturers to make natural gas vehicles available in higher volumes, perhaps a more influential factor could be the market aversion exists to technologies that have not been as demonstrated in the field as the diesel baseline. In particular, new maintenance processes, new fueling safety requirements, and a lack of experience with high-pressure fuel systems [66] may have negatively influenced the perceived reliability of CNG powertrains and deterred fleets and their operators from adopting them. A decreased performance due to reliability issues may cause vehicle downtime and increase delivery times, ultimately affecting operational costs.

In the proposed fleet behavior model, reliability costs are taken into account in order to compute the fleet TCO on an annual basis (Equation 3.6). Here I explore the effects of perceived reliability on adoption of compressed natural gas by introducing variation in percent reliability, $B_q$, and downtime, $T_{d,q}$ for CNG powertrains and comparing the resulting adoption to historical data. Figure 3.20 shows the sensitivity of CNG adoption to variation in reliability and downtime, demonstrating that perceived reliability can be used as a factor to represent risk aversion to emerging technologies and therefore limit their projected uptake once they are introduced to the market.

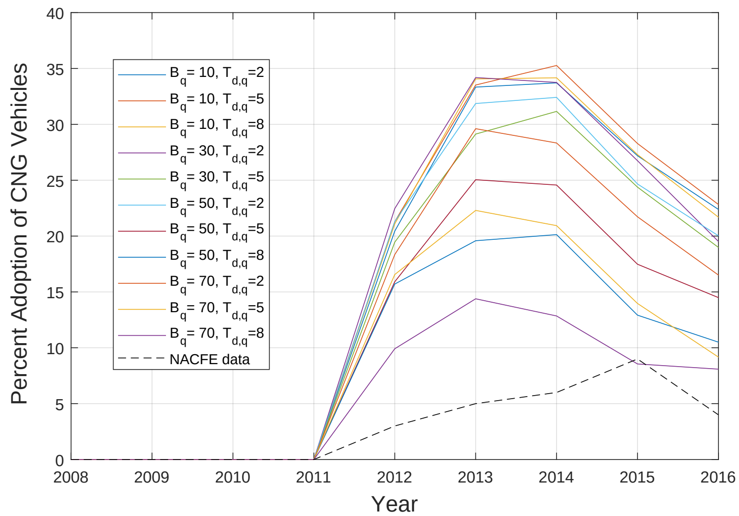
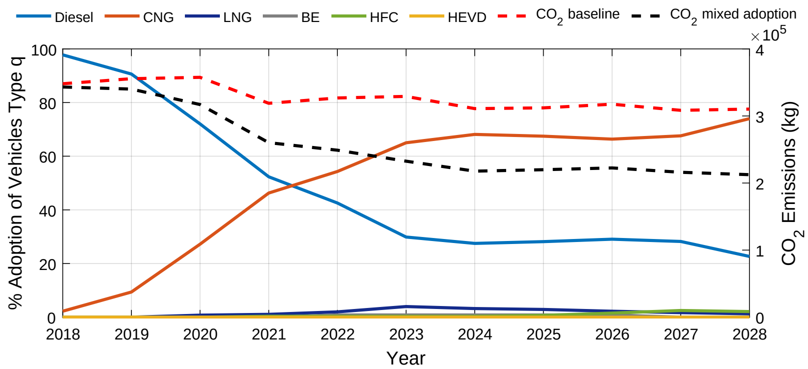
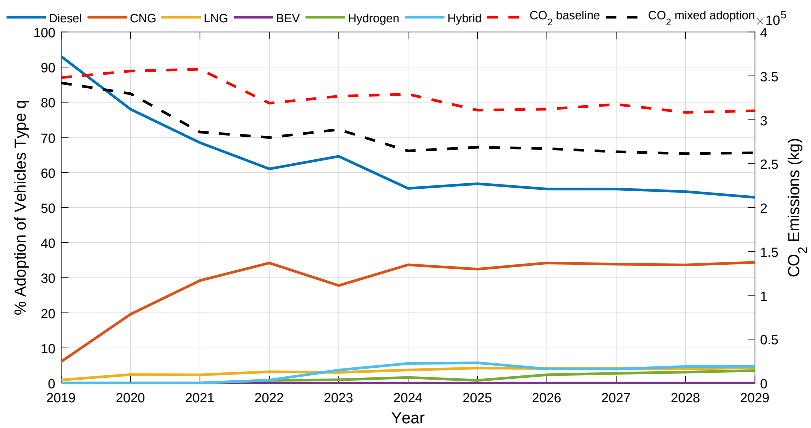



Figure 3.20. : Sensitivity of CNG adoption to variation in reliability and downtime.

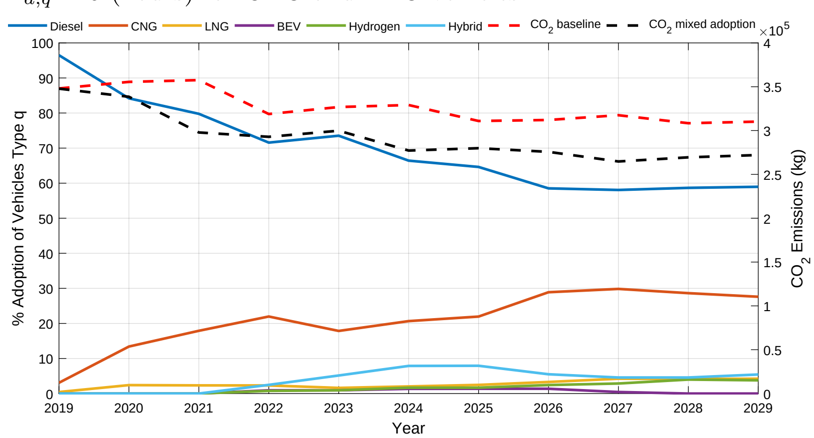
Selecting values of $B_q = 50$ and $T_{d,q} = 5$ for reliability and downtime causes adoption of CNG to achieve only a 34 percent adoption by 2028, observed in Figure 3.21a, as compared to the adoption observed in Figure 3.5. Further increasing the cost associated with perceived reliability, by increasing the values for these two parameters, causes adoption of CNG to achieve a maximum of 30% throughout the period, shown in Figure 3.21b. Given the lower effect of increasing $B_q$ from 50 to 70% and $T_{d,q}$ from 5 to 8 hours on CNG adoption, values of $B_q = 50$ and $T_{d,q} = 5$ are chosen for further studies. All other parameters were maintained the same as in Section 3.2.2.




(a) Reference adoption scenario.




(b) Resulting adoption scenario assuming $B_q = 50$ (percent) and $T_{d,q} = 5$ (hours) for CNG and LNG vehicles.




(c) Resulting adoption scenario assuming $B_q = 70$ (percent) and $T_{d,q} = 8$ (hours) for CNG and LNG vehicles.

Figure 3.21. : Powertrain adoption projections given introduction of autonomy levels. The black dotted line shows regional $CO_2$ emissions resulting from the projected adoption shown.

## 3.5 Summary

In this chapter, the model formulation was extended to predict the adoption and utilization of diesel and alternative powertrain technologies in the line-haul network modeled. This was achieved by taking into consideration the powertrain efficiency and performance characteristics as well as factors of the FTS—availability of fueling and charging infrastructure, fuel and electricity costs, and economic incentives—that influence the economic attractiveness of the technologies and the fleet adoption behaviors. The framework was then exercised to project adoption of diesel, low and zero emission alternative powertrain options and resulting $CO_2$ emissions across a line-haul network.

A powertrain adoption scenario demonstrated the potential for CNG vehicles to displace diesel by up to 80% by 2028, assuming current public policies and tax credit incentives, short term energy and vehicle cost projections, and limitations of infrastructure availability for alternative fuels remain in effect. Furthermore, the analysis demonstrated that the continuation of GHG Phase 2 regulations could cause a rapid reduction in $CO_2$ in both the baseline (98% diesel adoption) and a mixed adoption scenario by the year 2021. Furthermore, a sensitivity analysis quantified the influence of fuel costs, fueling and charging times, availability of infrastructure, and perceived reliability on adoption of low and zero emission powertrain technologies, including BE and HFC vehicles. Finally, the simulation analysis suggested that more than one future mixed-adoption scenario can be targeted in order to achieve a desirable reduction in emissions. Three adoption cases—a BE+HFC mix, primary HFC mix, and BE+CNG mix—were identified with similar low cumulative emission values, and an approximate reduction of 25% from the current line-haul market composition of 98% diesel vehicles.

This chapter focused on the introduction of emerging powertrain technologies to the line-haul network and their ability to reduce $CO_2$ emissions through their increased adoption and utilization. For this purpose, the influence of FTS factors, including infrastructure availability and policies, on alternative powertrain adoption was studied. The chapters that follow will focus on the introduction of various levels of vehicle autonomy, and the effect of these technologies on network-wide $CO_2$ emissions given combined adoption with alternative powertrain options.

# 4. VEHICLE AUTONOMY FOR FREIGHT TRANSPORTATION

Many stakeholders—manufacturers, policy-makers, and fleets—are involved in the development and introduction of autonomous vehicle technologies in the heavy-duty commercial vehicle sector. Automated trucks could enable energy savings, lower vehicle emissions, reduce traffic and congestion, increase road safety [67], and address the shortage of professional drivers in the freight industry [68]. Moreover, *vehicle autonomy, coupled with the emergence of low and zero emission powertrain options, could greatly impact emissions produced by the freight transportation system.*

Level 1 autonomous technologies [69], including advanced driver assist systems (ADAS), are already commercially available options on Class 8 trucks. These Level 1 features offer drivers assistance with control of steering or acceleration under limited conditions to reduce inefficient or unsafe driver behaviors [70]. Level 2 autonomous features partially automate driving tasks and are capable of controlling both steering and acceleration temporarily. The impact of Level 1 and 2 features result in on-road safety improvements and a limited increase in vehicle fuel efficiency. However, a skilled driver is still needed and must remain engaged and prepared to assume control of driving tasks at all times. As higher levels of autonomy are introduced, the driver's responsibilities and operation of the trucks may be significantly altered. Level 3, defined as conditional automation, enables the vehicle system to monitor the driving environment and control most driving functions, but may require drivers to take control in the event of an emergency [70]. Level 3 is believed to be unsafe as drivers may be quick to trust the autonomous system and unlikely to remain engaged in monitoring and intervention activities [68]. Level 4 autonomous technology, categorized as a high level of automation, enables the vehicle system to control all driving functions under certain conditions and limited environments without the need for the driver to monitor or assume control. Moreover, full automation, Level 5, is expected to handle all driving tasks under all conditions without the need for a driver present. With this level of autonomy, the vehicle can be guaranteed to maximize energy efficiency and safety for an extended period of time. Highly autonomous or driverless trucks could in turn have a disruptive impact on the role of truck drivers.

The timing of introduction, and rate of acceptance, of autonomous trucks is still uncertain [68]. However, their disruptive potential on the freight trucking sector is of great interest to the aforementioned stakeholders. As lower levels of autonomy are initially introduced, drivers may need incentives to utilize features that modify their driving behaviors. Higher levels of autonomy present the possibility of dramatically reducing driver costs for fleet owners and relaxing the driving time restrictions [71]. This would increase vehicle productivity and therefore deliver an economic benefit for freight fleet stakeholders [72]. Moreover, decreased downtime, improved fuel efficiency and driving range, and reduced operational costs of autonomous vehicles could enable the adoption of more costly low or zero emission powertrain technologies. A tool that can assist manufacturers and policy-makers to understand how the future state of the freight transportation system will affect the market penetration of autonomous trucking technologies and their interaction with powertrain adoption is necessary. Manufacturers and policy-makers can then envision the introduction of products, incentives and regulations to shape adoption, social impacts, and overall energy efficiency of the line-haul freight transportation system.

At present, a wide array of research studies are focused on eliminating the technological barriers for commercial readiness of automated heavy-duty trucks [7,73–77]. A majority of these studies are reasonably aimed on the design, improvement, and evaluation of autonomous vehicle control performance and robustness over specified drive cycles. While such research is necessary to develop the technology readiness of autonomous trucks, it does not address the effect that autonomous capability will have on the larger operations and energy efficiency of the freight transportation network nor the economic attractiveness to users in the sector.

Projecting the evolution of the freight transportation system with respect to energy costs, freight demand, availability of policies and incentives, infrastructure, and technology performance is a difficult task, as is the identification of a direct link between these factors, adoption, and the social and environmental impact of new technologies. Despite current barriers, researchers and industry stakeholders have made predictions about the commercial availability and uptake of autonomous trucks. Several studies explore the big-picture benefits and drawbacks of predefined adoption scenarios for autonomous vehicles in the transportation sector [68], but do not provide a quantitative understanding of how those adoption scenarios can be achieved. For example, the authors of [17] consider the potential impact of introduction of levels of automation on travel demand, congestion mitigation, highway speeds, crash avoidance, and GHG emissions from light-duty and heavy-duty vehicles in the U.S. by exploring illustrative, pre-defined scenarios and energy impact data published in the literature. In [70], the authors qualitatively explore the effects of large-scale introduction of automated road freight transport on professional truck drivers and make recommendations to help governments ensure a just transition. Researchers in [78] present a simulation study on resulting traffic stream behavior for pre-defined market penetration rates of connected and autonomous vehicles, suggesting substantial throughput increases under high penetration scenarios.

In this chapter, the model formulation is used to project the effects of autonomy features on heavy duty vehicle technology (powertrain and autonomy) *adoption and utilization* for multiple heterogeneous fleets operating in a regional freight transportation network. The focus here is to identify, through simulation, the technology characteristics, freight transportation system (FTS) factors, and vehicle autonomy assumptions that impact fleet operations and adoption behaviors. Consequently, the impact on total adoption of alternative, low emission powertrains and cumulative $CO_2$ emissions is captured across the regional fleets modeled. In Sections 2.2 and 2.3, a model of heterogeneous fleet vehicle purchasing behaviors and regional technology adoption over a line-haul freight transportation network was presented and validated.

This was done by modeling the FTS as a system-of-systems [33] and defining a representative set of fleets to capture the evolution of line-haul freight transportation system and the future economic attractiveness of emerging powertrain technologies. Here, I extend that framework to include the introduction of vehicle autonomy levels as a technology option in the heavy-duty Class 8 freight transportation sector. Autonomy is considered as the capability of the vehicle system to control its motion during highway operation with decreased driver input. Vehicle-to-vehicle, or vehicle-to-infrastructure connectivity and cooperation is therefore not modeled.

## 4.1 Extended Fleet TCO Optimization for Introduction of Autonomous Vehicles

In the previous chapters, the model formulation was limited to factors only pertaining to different powertrains and modeled constraints such as driver hours of service, vehicle range of travel, etc. Here, I briefly describe the variables, parameters, objective function, and constraints defined to construct the mixed-integer linear program and predict a single fleet's powertrain technology adoption and utilization behaviors. Please refer to Tables 3.2 and 3.3 for variables and parameters not defined in text.

The objective function represents the TCO criteria commonly used by fleet owners to select vehicles for purchase. Fuel consumption, repair and maintenance of a vehicle, and driver wages incur the highest percentage of total operational costs on a per mile basis over a vehicle's lifecycle [36]. In summary, the cost function $J$ is defined as the TCO and was computed in Section 3.1 as follows:

$$
\begin{aligned}
J = &\gamma \sum_{q} \sum_{(i,j)} x_{q,ij} [d_{ij} (\xi_{q,ij} C_{e,q} + C_{driver} + C_{M,q}) \\
&\gamma \sum_{q} \sum_{(i,j)} x_{q,ij} B_q T_{d,q} C_{delay,c} + \gamma \Phi_{CR} T_{CR} \sum_{(i,j) \in G} x_{q,ij} \\
&+ \gamma \Phi_{BS} (x_{q,n} S_f - \sum_{(i,j)} x_{q,ij} d_{ij} \xi_{q,ij} C_{e,q}) \\
&+ \sum_{q} x_{q,new} C_{p,q} - \sum_{q} x_{q,r} C_{r,q} \\
&+ x_{q,new} (\Phi_{CR} U_{CR} - B_{cap} C_{kWh} \Phi_{BS})
\end{aligned} \tag{4.1}
$$

where $x_{q,ij} = \sum_s \sum_n x^s_{qn,ij}$ and $G$ is the set of route links with wireless charging capability.

In the optimization problem, constraints are enforced on vehicle purchase, resale, and operation. Operational constraints are imposed on vehicle allocation over the routes based on cargo demand, vehicle capacity, hours of service limits, vehicle range, and availability of charging and fueling stations or on-road charging. Moreover, vehicle purchases are constrained by a user-defined fleet budget and the revenue created from the sale of vehicles being replaced. Vehicles are only maintained as part of the fleet until their maintenance costs are no longer optimal or their turnover age has been reached. The objective function, constraints, and associated models used to construct the MILP, used to predict a single fleet's technology adoption and utilization behaviors, is described in detail in Section 3.1.

### 4.1.1 Introduction of autonomy levels to MILP formulation

In this chapter, I introduce new variables, parameters (Table 4.1), and mathematical structure to the framework described in Chapter 3 to accommodate the introduction of autonomy levels. *By considering autonomy to be independent from the powertrain itself, I am able to capture the possibility of levels of autonomy to be vehicle agnostic.*

In Chapter 3, the cost of energy for daily operation of a heterogeneous fleet is used as a component to compute TCO, and is defined as

$$C_{ec,q} = \sum_{n} \sum_{(i,j)} x_{qn,ij} d_{ij} \xi_{q,ij} C_{e,q}, \quad \forall \ q. \tag{4.2}$$

Here, $C_{ec,q}$ is the cost of fuel consumed by vehicles of type $q$, i.e. diesel, natural gas, battery electric (BE), and hydrogen-powered vehicles. In order to compute the effect on energy consumption and costs due to the adoption of autonomous technologies, the fuel cost equation is modified as follows:

$$C_{ec,q} = \sum_{n} \sum_{(i,j)} x_{qn,ij} d_{ij} \xi_{q,ij} C_{e,q} (1 - p_a \Phi_{qn,a}), \quad \forall \ q \tag{4.3}$$

where $p_a$ represents the efficiency increase as indicated by the level of autonomy, and $\Phi_{qn,a}$ indicates if vehicle $n$ of type $q$ has autonomous capability. Here, the term $\sum_n \sum_{(i,j)} x_{qn,ij} d_{ij} \xi_{q,ij} C_{eq} \Phi_{qn,a}$ is non-linear, and therefore intermediate integer variables $y_{qn}$ and $z_{qn}$ are introduced, such that

$$y_{qn} = \sum_{(i,j)} x_{qn,ij} d_{ij} \xi_{q,ij} C_{e,q} \tag{4.4}$$

and

$$0 \leq z_{qn} \leq M \Phi_{qn} \tag{4.5a}$$

$$z_{qn} \leq y_{qn} \tag{4.5b}$$

$$z_{qn} \geq y_{qn} - M(1 - \Phi_{qn,a}), \tag{4.5c}$$

where $M$ is a sufficiently large number. Then, the energy cost (4.3) can be updated such that

$$C_{ec,q} = \sum_{n} \sum_{(i,j)} x_{qn,ij} d_{ij} \xi_{q,ij} C_{e,q} - p_a z_{qn}. \tag{4.6}$$

Table 4.1. : Extended Variable and Parameter Definition

| **Decision Variables** | **Description** |
|---|---|
| $\Phi_{qn,a}$ | Binary variable, indicates autonomous capability of vehicle $n$ of type $q$ |
| $y_{qn}$ | Intermediate variable used to linearize the cost of fuel equation |
| $z_{qn}$ | Intermediate variable used to linearize the cost of fuel equation |
| **Parameters** | **Description** |
| $\Delta\eta$ | Hours of service extension in hours |
| $p_a$ | Increase in vehicle efficiency, in %, given level of autonomy |
| $p_d$ | Increase in driver costs, in %, given level of autonomy |
| $U_a$ | Upcharge cost given level of autonomy |

Moreover, it is expected that the driver's responsibilities will be impacted by the introduction of higher levels of vehicle autonomy:

$$C_{wages} = \sum_{q} \sum_{n} \sum_{(i,j)} x_{qn,ij} d_{ij} C_{driver} (1 - p_d \Phi_{qn,a}). \tag{4.7}$$

Equation (4.7) also introduces a nonlinear term, which is linearized in a similar manner to (4.4)-(4.5). Other operational costs including maintenance costs, $C_M$, and costs associated with technology reliability, $C_R$, are computed as described by [79] such that

$$C_M = \sum_{n} \sum_{(i,j)} x_{qn,ij} d_{ij} C_{M,q}, \quad \forall\ q \tag{4.8}$$

$$C_R = \sum_{n} \sum_{(i,j)} x_{qn,ij} B_q T_{d,q} C_{delay,c}, \quad \forall\ q. \tag{4.9}$$

Next, it is assumed that an upcharge is added upon selection of autonomous capability for a purchased vehicle. Therefore, the purchasing cost is updated to include this upcharge, $U_a$, such that

$$c_{nv} = \sum_{q} x_{q,new} C_{p,q} + \sum_{q} x_{q,anew} U_a, \tag{4.10}$$

where $x_{q,anew}$ is the number of new autonomous vehicle purchases made in year $k$.

Higher levels of autonomy present the possibility of relaxing the driving time constraints as driver exhaustion and drowsiness is reduced. Therefore, a calibrated parameter, $\Delta\eta$ is added to extend the hours of service constraints, such that

$$\sum_{(i,j)} x^s_{qn,ij} t_{r,ij} + \leq h_{os} + \Delta\eta\Phi_{qn,a}, \tag{4.11}$$

and

$$\sum_{(i,j)} x^s_{qn,ij} t_{r,ij} + \Phi_{qn,c} t_{en,q} \leq \eta + \Delta\eta\Phi_{qn,a}. \tag{4.12}$$

Here, $\Delta\eta$ can be calibrated to zero for lower levels of autonomy where drivers must remain engaged throughout the period of operation. In such cases, the 11 hours of driving regulation ($h_{os}$) and 14 hours window of operation ($\eta$) will remain in effect.

## 4.2 Simulated Case Study and Sensitivity Analysis

In this section, 3 case scenarios are evaluated in which Levels 2, 4, and 5 of autonomy are introduced to the market in an individual and sequential manner. Level 3 may not be introduced to market by commercial vehicle manufacturers as it is assumed to have negative effects on traffic and safety [68], and is therefore not considered for this study. A design of experiments and sensitivity analysis are performed and used to quantify the effects of L5 autonomy factor variation on powertrain adoption projections.

### 4.2.1 Powertrain and Autonomy Adoption Scenarios

Here, levels 2, 4 and 5 of vehicle autonomy are introduced to the heavy-duty Class 8 vehicle market in order project the effects of autonomy on powertrain adoption, vehicle utilization, and $CO_2$ emissions between 2019 and 2035. For this purpose, the effects of vehicle autonomy are compared to a baseline case in which vehicle autonomy is *not* introduced to the market.

In Section 3.2, a representative regional network of line-haul highway corridors with pre-defined freight demand between six node pairs was defined. A set of active policies, incentives and regulations, and a representative set of 12 line-haul fleets operating in the region were also introduced. The same network is used for this study. Moreover, I assume that fueling and charging infrastructure is available on all six network nodes. Fueling and charging times are shown in Table 5.4. Six powertrain options (diesel, compressed and liquified natural gas, diesel-hybrid, battery electric, and hydrogen fuel cell) are considered, as indicated in Table 5.3. The vehicle efficiency, range, payload capacity, and purchase costs for the baseline, i.e. no autonomous capability, vehicles are given in Table 5.3. Fuel vehicle efficiencies for powertrain technologies are estimated in a diesel gallon equivalent based on fuel energy content, with the exception of battery electric (BE) vehicle efficiency expressed in kWh/mi. Moreover, the efficiencies of the baseline vehicle options are assumed to increase throughout the period of time based on EPA GHG Phase II estimates, as defined in Section 3.2.

Table 4.2. : Baseline FTS Parametrization

| Vehicle Type | Policy | Fueling Time (hr) |
|---|---|---|
| Diesel | GHG Phase II | 0.2 |
| CNG | 12% fuel tax rebate | 1.5 |
| | GHG Phase II | |
| LNG | 12% fuel tax rebate | 0.25 |
| | GHG Phase II | |
| HEVD | $20k voucher at purchase | 0.2 |
| BE | $45k voucher at purchase | 2 |
| HFC | $45k voucher at purchase | 0.25 |

Three levels of vehicle autonomy not yet commercially available are introduced in the simulation. These include Level 2 (L2), Level 4 (L4), and Level 5 (L5). Assumptions are made with respect to the year of introduction—the year autonomous vehicles of a specific level are available for purchase—and the upcharge costs of the added autonomous capability as shown in Table 5.5. Moreover, assumptions are made on the impact that each level of autonomy will have on vehicle efficiency, reliability, driver costs, and extension of the hours of service restrictions. The L2 package includes

Table 4.3. : Baseline Vehicle Parametrization

| Vehicle Type | Efficiency (mi/EN @55 mph) | Range (mi) | Payload Capacity (ton) | Vehicle Cost ($) |
|---|---|---|---|---|
| Diesel | 6.4 | 1000 | 25 | 145 |
| CNG | 5.5 | 600 | 23 | 172 |
| LNG | 5.7 | 1000 | 23 | 200 |
| HEVD | 6.88 | 1100 | 24 | 185 |
| BE | 0.42 | 450 | 23 | 220 |
| HFC | 11 | 450 | 24 | 250 |

Table 4.4. : Level of Autonomy Factors

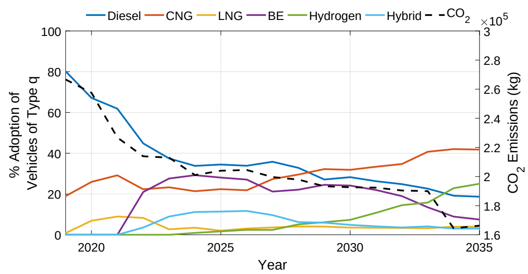
| Autonomy Level | Feature | Year of Intro | Upcharge Cost ($) | Efficiency Incr. (%) | Reliability Incr. (%) | Driver Cost Decr. (%) | HOS Extension (hrs) |
|---|---|---|---|---|---|---|---|
| Level 2 | ACC+LKA+AEB | 2025 | 15 | 5 | 10 | 10 | 0 |
| Level 4 | High automation | 2028 | 20 | 10 | 20 | 20 | 2 |
| Level 5 | Full automation | 2030 | 30 | 20 | 50 | 70 | Unlimited |

adaptive cruise control (ACC), lane keep assist (LKA), and automatic emergency braking (AEB). Since L2 capability only allows these features to be active under specific and limited circumstances, effects on vehicle reliability will be low compared to higher levels of autonomy [68]. However, a considerable benefit in fuel efficiency can be expected for L2 autonomy as several studies have demonstrated the capability of features, including ACC and acceleration and lateral assisted vehicle control, to reduce fuel consumption by 2% or more during highway operation [80]. As L2 vehicle drivers must remain engaged at all times, hours of service for L2 vehicles may not be extended; however, wages may vary if driver skill requirements are reduced [70].

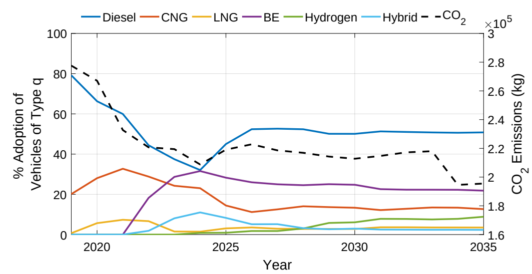
On the other hand, vehicle efficiency benefits could be much higher for L4 and L5 vehicles as inefficient driving behaviors are reduced or eliminated. Moreover, hours of service restrictions could be extended (L4) or eliminated (L5) as driver exhaustion may no longer be a concern. However, personnel costs, in the case of L4 and L5 autonomy, are not completely eliminated as operators may be needed for other tasks including loading or fueling. Table 5.5 summarizes the parametrization assumed for this case scenario analysis.

Following the assumptions and the model parameterization described above, I project adoption of diesel and alternative powertrain vehicles and $CO_2$ reduction over a 17 year period, shown in Figure 4.1, for 4 case scenarios: 1) No autonomy, 2) L2 versus Baseline, 3) L4 versus L2, and 4) L4 versus L5. Figure 4.1(a) shows the powertrain adoption projection for Case 1, in which no vehicle autonomy is introduced to the market. Figure 4.1(b) (Case 2) shows the effect on powertrain adoption and $CO_2$ emissions projections once L2 autonomy is introduced in 2025, providing fleet owners the option to purchase a vehicle with L2 features over one with no autonomy. Figure 4.1(c) shows powertrain adoption and $CO_2$ projections for Case 3 in which L4 autonomy is introduced to the market in 2028. In this case, it is assumed that L2 autonomy will observe a high market penetration upon introduction; therefore, all vehicles are modeled with a fuel efficiency increase of 5% after the year 2025. Fleet owners then have the option to purchase a L4 vehicle over a L2 baseline beginning in 2028, until 2035. Figure 4.1(d) shows powertrain adoption and $CO_2$ projections for Case 4 in which L5 autonomy is introduced to the market in the year 2030. It is assumed that all vehicles are at L4 in 2028. This is modeled by increasing vehicle efficiency by 10% in 2028. Fleet owners then have the option to purchase a L5 vehicle over a L4 baseline beginning in 2030, until 2035.

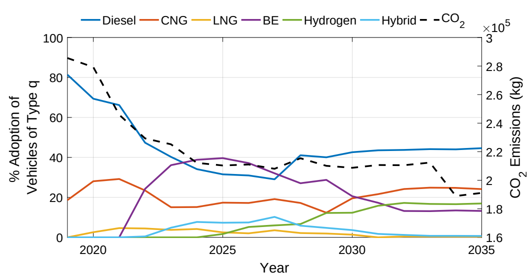
Case 2, shown in Figure 4.1(b), demonstrates that adoption of diesel vehicles increases after the year 2025, at the expense of a decrease in CNG adoption. Moreover, adoption of BE vehicles remains nearly stable once L2 autonomy has been introduced. On the other hand, Case 3 shown in Figure 4.1(c), causes an increase in diesel and CNG vehicle adoption, while BE vehicle adoption decreases after 2028. Finally, as with the previous cases, introduction of L5 autonomy, shown in Figure 4.1(d), increases adoption of diesel vehicles. In Case 4, however, adoption of BE vehicles decreases to zero after 2030, while adoption of CNG vehicles increases beyond that of diesel by 2035. In all cases, it is shown that *adoption of diesel vehicles increases upon* *introduction of the different levels of autonomy* as compared to a decreased adoption shown in Figure 4.1(a) in which autonomy is not introduced. This indicates the ratio of fuel efficiency and operational cost benefits to total purchase cost of adopting a diesel autonomous vehicle outweighs that of vehicles with alternative powertrain technologies, particularly as vehicle utilization (VMT) decreases once autonomy is adopted.



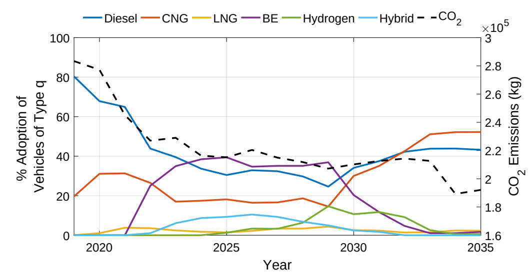

(a) Powertrain adoption projection given no introduction of vehicle autonomy.




(b) Powertrain adoption projection given introduction of L2 autonomy in 2025.




(c) Powertrain adoption projection given introduction of L4 autonomy in 2028.

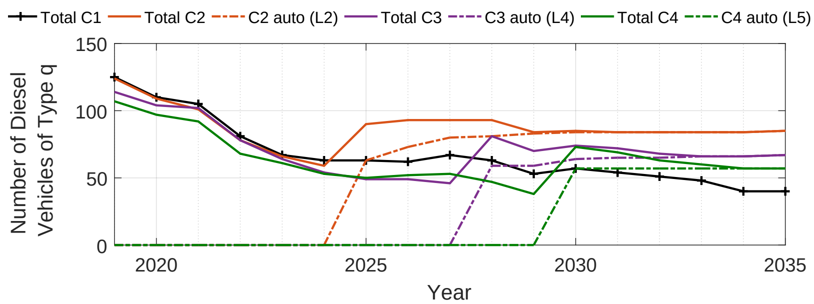



(d) Powertrain adoption projection given introduction of L5 autonomy in 2030.

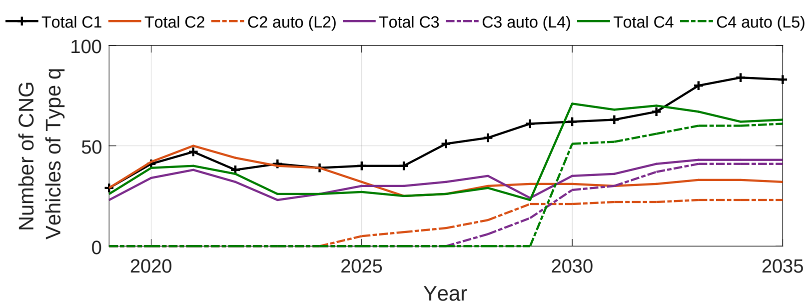
Figure 4.1. : Powertrain adoption projections given introduction of autonomy levels. The black dotted line shows regional $CO_2$ emissions resulting from the projected adoption shown.

Consequently, *the increase in diesel adoption due to introduction of vehicle autonomy causes an increase in $CO_2$ emissions in the regional network modeled* as compared with Case 1 shown in Figure 4.1(a). It is important to note here that the projections achieved in these case scenarios are a result of the assumptions made with respect to the future state of the FTS factors, the timed and progressive introduction of vehicle autonomy levels, and assumed cost and performance characteristics of powertrain and autonomous technologies. Variation in future factor values and assumptions for the state of the FTS could result in variation of the adoption projections. Nonetheless, the cases presented here demonstrate the proposed model's capability to identify the effects of introduction of different levels of autonomy on powertrain adoption under a given set of assumptions.

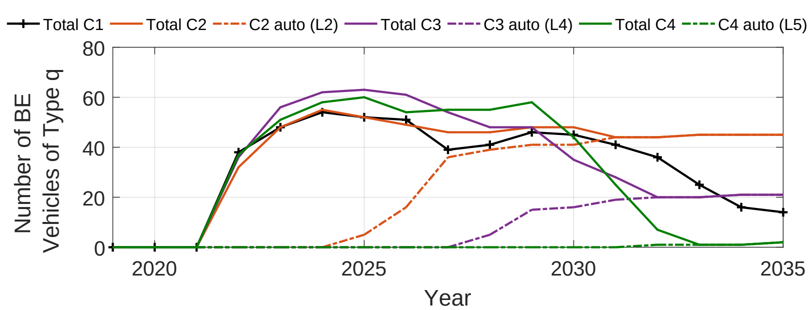
The total number of diesel, CNG, and BE vehicles used annually, and number of autonomous vehicles of each type, are shown in Figure 4.2 for each case. The analysis is focused on these 3 powertrain options as they were the most highly adopted throughout the period of evaluation. Figures 4.2(a)–4.2(c) demonstrate the growth in total number of diesel vehicle purchases once levels of autonomy are introduced, compared to Case 1 projected in black. The dotted curves in Figures 4.2(a)–4.2(c) highlight the adoption of the autonomy for each different powertrain option; only in Figure 4.2(b) do we see that even by 2035, there are still CNG powertrains without autonomy being used. Adoption of autonomous capability happens rapidly under the assumptions presented; nearly all vehicles have adopted the available level of autonomy merely 5 years after it is introduced to the market. In the case of L5 autonomy introduction, this implies that, by 2035, no drivers are required in the regional network modeled.




(a) Adoption projection of diesel powertrain option for cases 1-4 (C1–C4).

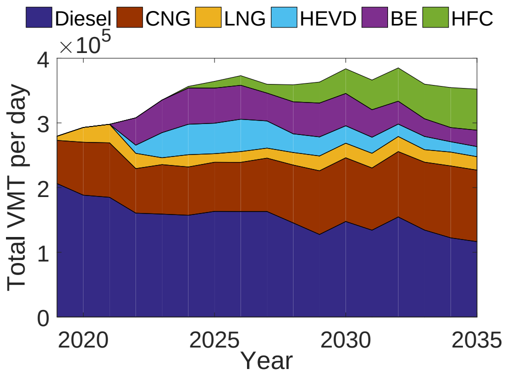



(b) Adoption projection of CNG powertrain option for cases 1-4 (C1–C4).

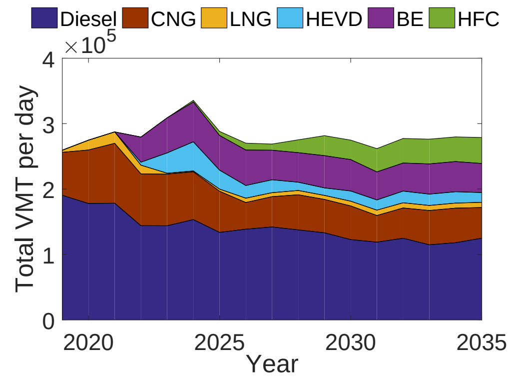



(c) Adoption projection of BE powertrain option for cases 1-4 (C1–C4).

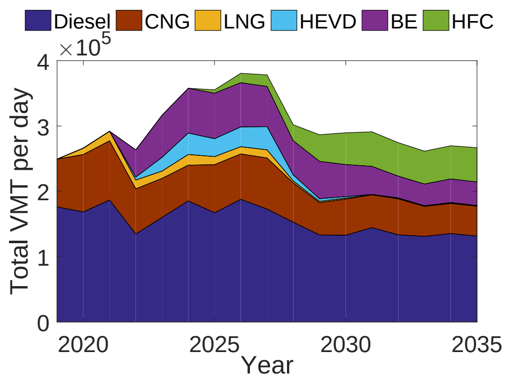
Figure 4.2. : Powertrain and autonomy adoption projections for diesel, CNG, and BE given introduction of autonomy levels.



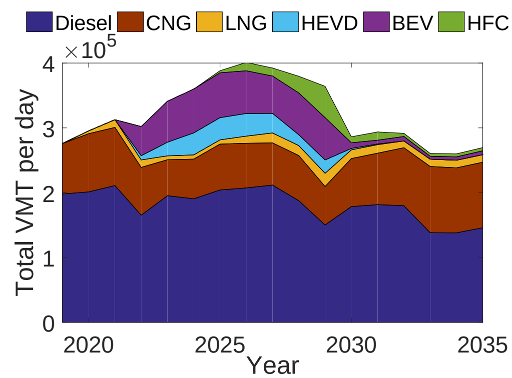

(a) VMT projection given no introduction of vehicle autonomy.




(b) VMT projection given introduction of L2 autonomy in 2025.




(c) VMT projection given introduction of L4 autonomy in 2028.




(d) VMT projection given introduction of L5 autonomy in 2030.

Figure 4.3. : VMT projections per powertrain given introduction of autonomy levels.

Figure 4.3 shows the total vehicle miles traveled per day for each type of vehicle powertrain option. This demonstrates the effect the introduction of vehicle autonomy levels could have, not only on vehicle technology adoption, but on overall vehicle utilization as well. Figures 4.3(a)–4.3(d) show that total VMT *decreases* once autonomy is introduced in each case scenario, when compared to Case 1. This indicates that vehicle autonomy has an impact on allocation of the vehicles over the network, resulting in *considerably less overall heavy-duty Class 8 vehicle traffic by 2035*.

### 4.2.2 Sensitivity Analysis

The results presented in the previous section assumed a specific set of values for vehicle autonomy factors. However, there is uncertainty associated with these assumptions since L2, L4, and L5 vehicles have not been commercially released. In this section, the proposed model is used to quantify the sensitivity of vehicle adoption projections to variation in L5 autonomy factor assumptions including upcharge costs, increase in vehicle efficiency, and impact on driver costs. A design of experiments (DOE) is performed, and exploratory values are introduced for each of the L5 factors selected for this study. Each experiment is defined by varying a single factor between a high and low value, while maintaining all other factors fixed at their nominal values. Table 4.5 shows the factor values evaluated. A similar DOE can be conducted to evaluate sensitivity of vehicle adoption projections for lower levels of autonomy or to introduce variation in other factors presented in Table 5.5.

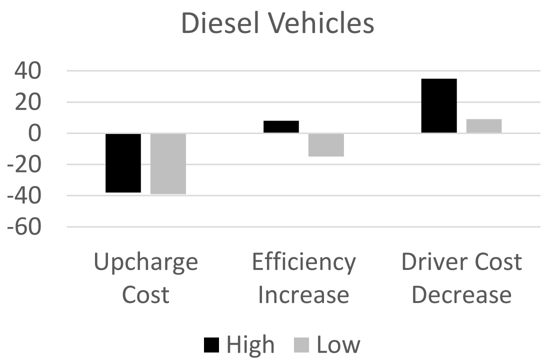
Table 4.5. : Level 5 Autonomy DOE Parameter Values

| Parameter | Nominal | High | Low |
|---|---|---|---|
| Upcharge Cost | \$30k | \$40k | \$20k |
| Efficiency Increase | 17% | 20% | 15% |
| Driver Cost Decrease | 70% | 100% | 50% |

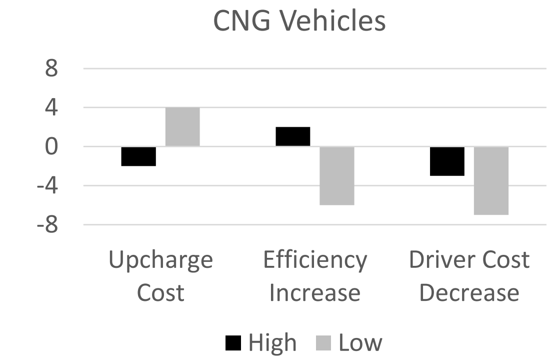
Figure 4.4 shows the effects of L5 factor variation on the total number of vehicles purchased, per powertrain option, from 2030–2035 (the period in which L5 autonomy is available). The figures demonstrate the deviation in the number of purchases per powertrain option, shown on the y-axes of Figures 4.4(a)–4.4(d), from those resulting from the evaluation of nominal values. Here, the reader can identify the most influential factors and the effects on adoption of each powertrain option. For example, as shown in Figure 4.4(a), the high factor value of 100% for ‘driver cost decrease’ results in the highest positive effect on adoption of diesel vehicles at the expense of CNG, LNG, and HFC vehicles. In other words, complete elimination of driver wages would be disruptive with respect to adoption of alternative powertrain options. On

the other hand, this assumption has no effect on the already low adoption of HEVD and BE vehicles as shown in Figures 4.4(d) and 4.4(e).

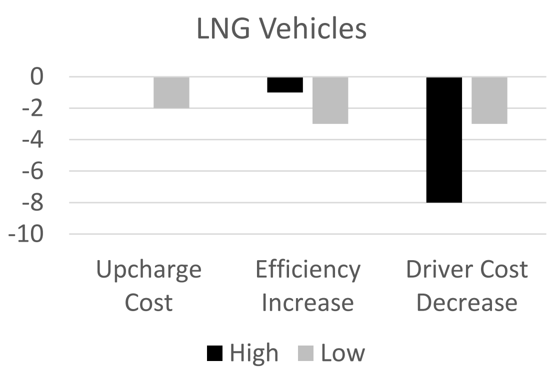
Moreover, diesel adoption shows the highest sensitivity to L5 autonomy factor variation as shown in Figures 4.4(a)–4.4(f). As an example, changes in upcharge and driver cost cause a fluctuation of approximately 40 diesel vehicle purchases from the nominal value. However, the total fluctuation in purchases of all other powertrains caused by varying these factors is much lower. This indicates that even as fewer diesel vehicles are being purchased, for example, they are not replaced by vehicles with alternative powertrain technologies. Instead, the total number of vehicle purchases during the last 5 years of the period is increasing or decreasing with the number of diesel vehicles adopted in the network. Since the freight demand is the same across all DOE experiments, the vehicle utilization or vehicle replacement periods must be fluctuating to account for the variation in total vehicle purchases. Finally, the introduction of L5 autonomy, given the factor variation assumed here, appears to have little effect in promoting the adoption of BE and HFC vehicles. The upcharge costs associated with the alternative powertrains are sufficiently high such that diesel autonomous vehicles become more cost effective than an alternative powertrain with an equivalent efficiency benefit. However, values introduced for upcharge cost, efficiency increase, and decrease in driver costs demonstrate a positive effect on the adoption of HEVD vehicles.



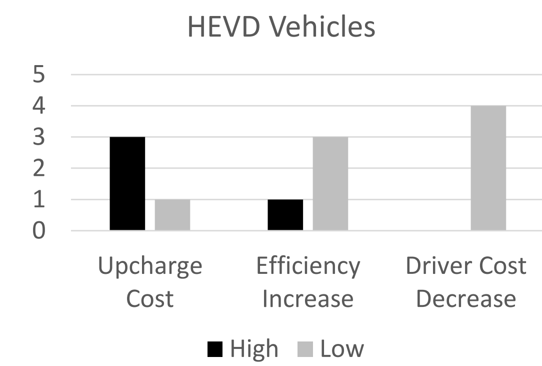

(a) Effect of factor variation on diesel purchases, shown as a differential with respect to 107 diesel vehicles purchased in the nominal case.



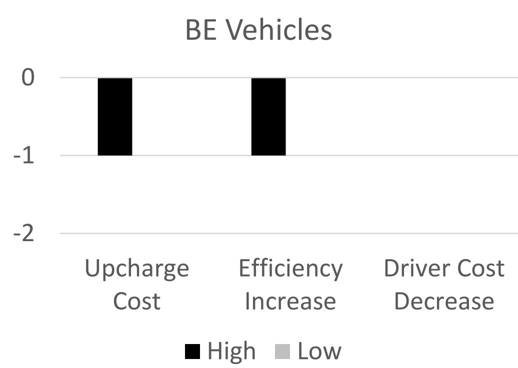

(b) Effect of factor variation on CNG purchases, shown as a differential with respect to 51 CNG vehicles purchased in the nominal case.



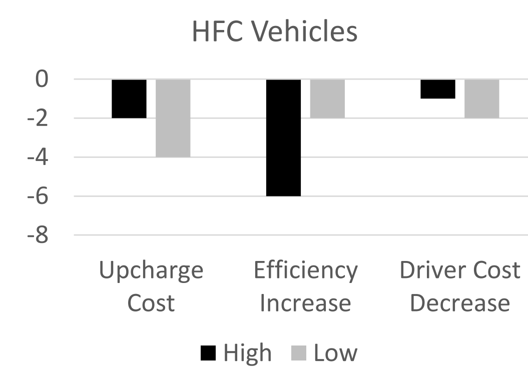

(c) Effect of factor variation on LNG purchases, shown as a differential with respect to 8 LNG vehicles purchased in the nominal case.




(d) Effect of factor variation on HEVD purchases, shown as a differential with respect to 0 HEVD vehicles purchased in the nominal case.




(e) Effect of factor variation on BE purchases, shown as a differential with respect to 3 BE vehicles purchased in the nominal case.




(f) Effect of factor variation on HFC purchases, shown as a differential with respect to 6 HFC vehicles purchased in the nominal case.

Figure 4.4. : Factor effect on number of vehicle purchases from 2030-2035 given introduction of L5 autonomy.

### 4.3 Summary

In this chapter, the model formulation was extended to predict how the introduction of different levels of autonomy affects fleet vehicle adoption and utilization in a regional freight transportation network. The constrained MILP was defined to represent the decision-making process for line-haul fleets selecting vehicles with different powertrain options and autonomous capability and allocating them on freight delivery routes to minimize TCO. The influence of FTS policies, network and infrastructure characteristics, route traffic, costs, and vehicle efficiency was considered.

The model was simulated to project powertrain adoption, utilization, and emissions from 2019–2035 given a set of assumptions for the impact different levels of autonomy may have on purchase costs, vehicle efficiency, driver wages, vehicle reliability, and hours of service regulations. A case scenario analysis showed that adoption of diesel vehicles increased upon introduction of levels 2, 4 and 5 of vehicle autonomy, causing an increase in $CO_2$ emissions in the network modeled. This result indicates that a more intensive set of policies incentivizing adoption of cleaner powertrain options or penalizing emissions must follow after introduction of vehicle autonomy to the market. Moreover, adoption of the different levels of vehicle autonomy followed rapidly after their introduction under the case scenarios presented.

In this chapter, model considerations were limited to levels 2, 4, and 5 of vehicle autonomy. Although vehicle platooning can be considered level 1 or 2 of autonomy, depending on the lateral and longitudinal control capabilities of the system, it was excluded from the analysis presented in this chapter as the operation of platooning vehicles differs from that of other autonomous vehicles. Adoption and utilization of intra-fleet vehicle platooning autonomy will be defined, formulated, and studied in the next chapter.

# 5. INTRA-FLEET 2-VEHICLE PLATOONING

Platooning vehicles must travel in a formation of 2 or more vehicles for the autonomous capability to be enabled and realize fuel efficiency benefits. As operation of platooning vehicles differs from that of other autonomous vehicles, the impact of platooning introduction on model formulation and future projection scenarios is presented independently in this dedicated chapter. Platooning vehicles make use of a cooperative adaptive cruise control approach [81] where the trailing vehicle safely follows a leading vehicle with a reduced distance while matching the acceleration profile. Vehicles traveling in a platoon formation are therefore expected to achieve significant fuel savings due to the reduction of aerodynamic drag. Turri et al. [76] demonstrate, by means of simulation, average fuel savings of up to 7% for a 2-vehicle platoon by introducing a topography look-ahead control approach. Authors in [7] and [81] demonstrate the robustness of a Class 8 2-vehicle platooning system, including implementation of vehicle-to-vehicle (V2V) communication and cooperative adaptive cruise control (CACC), to variation in vehicle speed, trailing distance, and mass, for fuel consumption certification cycles on a test track. Similarly, Alam et al. [77] demonstrate the capability of a Class 8 platooning system considering both a CACC and topography look-ahead approach to achieve fuel consumption savings across a 3-vehicle formation. These authors demonstrate a level of maturity of the technology and confidence in the fuel savings potential across leading and following vehicles in controlled conditions and experimental drive cycles. However, as platooning capability is still not yet commercially available in the Class 8 market, there is uncertainty with respect to the level of adoption and utilization this autonomous technology will achieve under real world scenarios. In particular, the fuel economy benefits and reduction in fleet-wide operational costs must be sufficient to overcome the need for allocation of more than one vehicle over the same route in order to increase adoption and utilization of intra-fleet vehicle platooning technology.

In this chapter, I describe the variables, parameters, objective function, and constraints defined to extend the mixed-integer linear program and predict a single fleet's powertrain technology adoption and utilization behaviors upon introduction of intra-fleet 2-vehicle platooning capability. Moreover, a case scenario is presented to project adoption and utilization of platooning and powertrain technologies in a regional network. Finally, a study on the effects of platooning fuel efficiency and freight demand on adoption and utilization of platooning vehicles is also presented.

## 5.1 Introduction of Platooning to MILP Formulation

In this chapter, new variables, parameters (Table 5.1), and mathematical structure are introduced to the framework to accommodate the introduction of intra-fleet 2-vehicle platoons—platoon formations are only allowed for vehicles belonging to the same fleet. In order to compute the effect on energy consumption and costs due to the adoption of platooning capability, the computation of the fuel cost, $C_{e,q}$ is modified as follows:

$$C_{ec,qij} = C_{eq}(\sum_n x_{qn,ij} - P_{q,ij}p_a)\xi_{q,ij}d_{ij} \quad \forall q,(i,j) \tag{5.1}$$

where $p_a$ represents the efficiency increase if the vehicle is traveling in a platoon, and $P_{q,ij}$ indicates the number of platoons per technology type $q$ traveling on link $(i,j)$. Moreover, $P_{q,ij}$ is computed such that

$$P_{q,ij} \leq \sum_n x_{qn,ij}\Phi_{qn,a} \quad \forall q,(i,j) \tag{5.2}$$

and

$$\sum_q P_{q,ij} = 2P_{ij} \quad \forall (i,j) \tag{5.3}$$

where $\Phi_{qn,a}$ is a binary variable representing the platooning capability of vehicle $x_{qn}$. Equation 5.4a) establishes the number of 2-vehicle platoons $P_{ij}$, regardless of powertrain technology type, to be lower than the total number of platoon-capable vehicles traveling on link $(i, j)$.

$$\sum_q \sum_n x_{qn,ij} \Phi_{qn,a} \geq 2P_{ij} \quad \forall (i, j) \tag{5.4a}$$

$$P_{ii} = 0, P_{ij} \geq 0. \tag{5.4b}$$

This enables platoon-capable vehicles to travel alone over any given link $(i, j)$ in regular operational mode without incurring any fuel efficiency benefits.

Next, it is assumed that an upcharge cost, $U_a$, is added upon selection of platooning capability for a purchased vehicle. Therefore, the purchasing cost is updated such that

$$c_{nv} = \sum_q x_{q,new} C_{p,q} + \sum_q x_{q,anew} U_a, \tag{5.5}$$

where $x_{q,anew}$ is the number of new platooning vehicle purchases made in year $k$.

Table 5.1. : Extended Variable and Parameter Definition

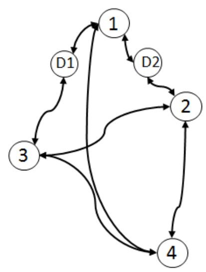
| **Decision Variables** | **Description** |
|---|---|
| $\Phi_{qn,a}$ | Binary variable, indicates platooning capability of vehicle $n$ of type $q$ |
| $P_{ij}$ | Number of platoons of all technology types traveling on link $(ij)$ |
| $P_{q,ij}$ | Number of vehicles of type $q$ traveling in a platoon formation on link $(i, j)$ |
| **Parameters** | **Description** |
| $p_a$ | Increase in vehicle efficiency, in % |
| $p_d$ | Increase in driver costs, in % |
| $U_a$ | Upcharge cost given platooning capability |

## 5.2 Simulated Platooning Case Studies and Analysis

In this section we introduce 2-vehicle platooning capability to the line-haul network across six powertrain options—diesel, compressed and liquefied natural gas, diesel-hybrid, battery electric, and hydrogen fuel cell. A nominal case scenario is presented in Section 5.2.1 in order to evaluate the combined adoption of powertrain technologies and platooning capable vehicles and effect on vehicle utilization and resulting $CO_2$ emissions in the network. Next, the impact of variation in fuel efficiency benefits for platooning vehicles is presented in Section 5.2.2, followed by a study on effects of traffic demand increase on platooning vehicle adoption and utilization in the network in Section 5.2.3. Finally, Section 5.2.4 presents the impact of a carbon tax, modeled as an increase in the cost of fuel and electricity, on adoption of low and zero emission powertrains and platooning vehicles.

### 5.2.1 Combined effects of platooning capability and powertrain options on technology adoption

In previous chapters, a representative regional network of line-haul highway corridors with predefined freight demand between six node pairs was introduced, as shown in Figure 5.1. Moreover, the freight demand satisfied by each fleet is assumed to increase between 0-2% annually, therefore causing an annual increase in freight demand over the network of study [79]. It is assumed that a representative set of 12 heterogeneous line-haul fleets operate in the region. Each fleet independently optimizes their total cost of ownership by selecting the number of vehicles, vehicle technology types, and routes over which each vehicle in the fleet is allocated to satisfy freight demand in the region. In Chapters 3 and 4, six powertrain options–diesel, compressed and liquified natural gas, diesel-hybrid electric, battery electric, and hydrogen fuel cell, as indicated in Table 5.3–and levels 1, 2, 4 and 5 of vehicle autonomy were introduced. The combined effects of powertrain technologies and autonomous capabilities on resulting technology adoption, vehicle utilization, and regional $CO_2$ emission trends were projected. This section focuses on the introduction of platooning vehicles, considered within level 2 autonomous capability. The vehicle efficiency, range, payload capacity, and purchase costs for the baseline vehicles, i.e. no autonomous capability, are given in Table 5.3. Vehicle fuel efficiencies for powertrain technologies are estimated in a diesel gallon equivalent based on fuel energy content, with the exception of battery electric (BE) vehicle efficiency expressed in kWh/mi. Moreover, the efficiencies of the baseline vehicle options are assumed to increase throughout the period of time considered based on EPA GHG Phase II estimates, as defined in Section 3.2. In Section 4.2, it was assumed that fueling and charging stations are available in all network nodes, this same assumption is applied in this section. Fueling and charging times are shown in Table 5.4. Moreover, policies, incentives, and regulations regarding the vehicle efficiency, tailpipe emissions, and utilization of diesel and alternative powertrain options are introduced as shown in Table 5.4. No further restrictions or incentives are considered with regard to vehicle autonomy.




Total Freight Demand Between Node Pairs (tons)

| | City 1 | City 2 | City 3 | City 4 | D1 | D2 |
|---|---|---|---|---|---|---|
| City 1 | 0 | 1880 | 1280 | 400 | 360 | 360 |
| City 2 | 2080 | 0 | 320 | 200 | 0 | 360 |
| City 3 | 1120 | 240 | 0 | 160 | 360 | 0 |
| City 4 | 80 | 200 | 120 | 0 | 0 | 0 |
| D1 | 360 | 0 | 360 | 0 | 0 | 0 |
| D2 | 360 | 360 | 0 | 0 | 0 | 0 |

Figure 5.1. : Representative line-haul network with 4 city nodes and 2 distribution centers. All direct routes between nodes are less than 500 miles.

Table 5.3. : Baseline Vehicle Parametrization

| Vehicle Type | Efficiency (mi/EN @55 mph) | Range (mi) | Payload Capacity (ton) | Vehicle Cost ($) |
|---|---|---|---|---|
| Diesel | 6.4 | 1000 | 25 | 145 |
| CNG | 5.5 | 600 | 23 | 172 |
| LNG | 5.7 | 1000 | 23 | 200 |
| HEVD | 6.88 | 1100 | 24 | 185 |
| BE | 0.42 | 450 | 23 | 220 |
| HFC | 11 | 450 | 24 | 250 |

In this chapter, as in chapter 4, level 2 of vehicle autonomy is introduced to the market. However, the focus here is placed on the introduction of platoon-capable autonomous features for vehicles of all powertrain options as aerodynamic drag reduction and collision mitigation are achieved equally [68]. It is also assumed that

Table 5.4. : Baseline FTS Parametrization

| Vehicle Type | Policy | Fueling Time (hr) |
|---|---|---|
| Diesel | GHG Phase II | 0.2 |
| CNG | 12% fuel tax rebate | 1.5 |
| | GHG Phase II | |
| LNG | 12% fuel tax rebate | 0.25 |
| | GHG Phase II | |
| HEVD | $20k voucher at purchase | 0.2 |
| BE | $45k voucher at purchase | 2 |
| HFC | $45k voucher at purchase | 0.25 |

platooning benefits with respect to increase in vehicle fuel efficiency and reliability are the same across all powertrains. Assumptions are also made with respect to the year of introduction—the year platooning vehicles are available for purchase—and the upcharge costs of the added autonomous capability. Drivers are required to remain actively engaged while driving non-fully autonomous vehicles. Therefore, it is not expected that hours of service will be extended upon introduction of platooning vehicles, nor will the driver costs be affected. Table 5.5 summarizes the parametrization assumed for platooning scenario analysis. Vehicle travel in a platoon provides reduction of aerodynamic drag, resulting in fuel efficiency benefits for both the front and following vehicles. Authors [7], [77], and [81] demonstrate 2-vehicle platoon fuel savings between 3.7%-10% as a function of operational factors including gap distance, steady-state speed, route grade, and gross vehicle weight. Accordingly, a nominal 7% fuel efficiency increase is assumed for each vehicle traveling in a platoon formation.

Table 5.5. : Platooning Parameters

| Year of Introduction | Upcharge Cost ($) | Efficiency Increase (%) | Reliability Increase (%) | Driver Cost Decrease (%) | Hours of Service Extension (hrs) |
|---|---|---|---|---|---|
| 2025 | 20k | 7 | 10 | 0 | 0 |

Adoption trends for the six powertrain technologies and platooning vehicles are demonstrated for the nominal case in Figure 5.2. Adoption is defined as the percent penetration of each technology across all 12 fleets modeled, computed as a function of vehicle purchases on an annual basis. Here, as a result of the introduction of platoon-capable autonomy and the assumptions listed in this section, diesel adoption decreases from nearly 80% in 2019 to approximately 25% in 2035. It can be noted that, while diesel adoption decreases monotonically between 2019-2025, it increases for one year after the introduction of platooning capability before again decreasing almost monotonically throughout the remaining time period considered. On the other hand, adoption of hydrogen vehicles is first observed in 2025, increasing monotonically and achieving 26% adoption in 2035. Moreover, as platooning vehicles reach 50% adoption in the network by the end of the period of study, a mixed adoption scenario results with respect to the powertrain options.

The penetration of platooning capability per powertrain option is shown in Figure 5.3. Here, the subfigures indicate the total number of vehicles of each powertrain technology purchased in the network, shown in black, and the number of those vehicles that have platooning capability, shown in blue. In this nominal case scenario, platooning adoption increases in the case of all powertrain options throughout the end of the period. It can be observed that although diesel adoption follows a decreasing trend, as shown in Figure 5.2, the absolute number of annual diesel vehicle purchases remains nearly stable after the introduction of platooning capability. Moreover, nearly 66% of diesel vehicles have platooning capability by 2035.

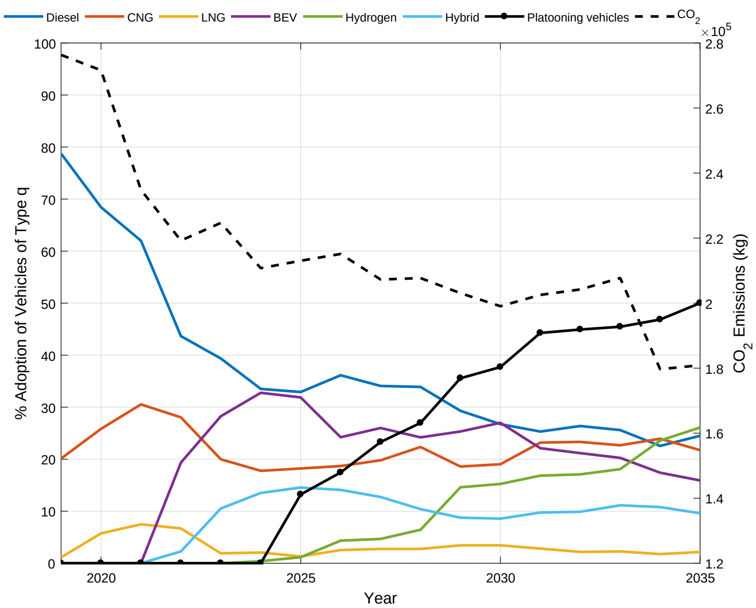



Figure 5.2. : Powertrain and platooning adoption trends throughout period of study given an assumption of 7% increase in fuel efficiency for platooning vehicles.

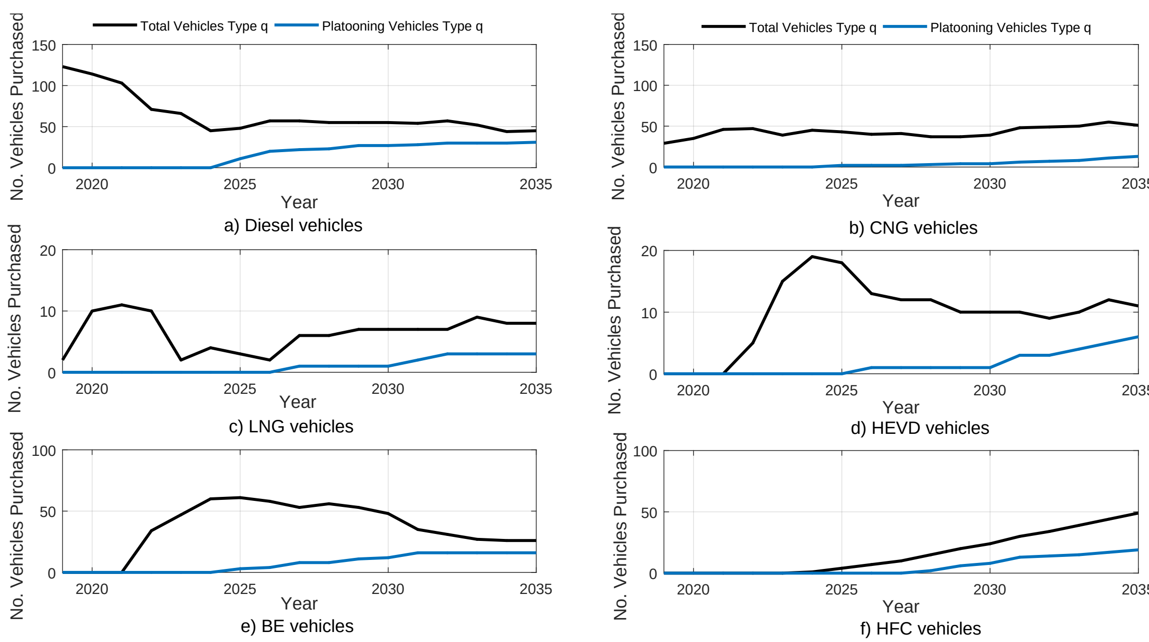



Figure 5.3. : Number of vehicles used per type throughout period of study given an assumption of 7% increase in fuel efficiency for platooning vehicles.

Finally, the allocation of 2-vehicle platoons on each route is shown in Figure 5.4 for this nominal case scenario. Here, the number of 2-vehicle platoons departing all

6 nodes is indicated for every year throughout the period of study. A large volume of platoons are allocated on route (1,2) departing from city 1, and route (2,1) departing from city 2, which correspond to the origin-destination node pairs with the highest freight demand in the network.

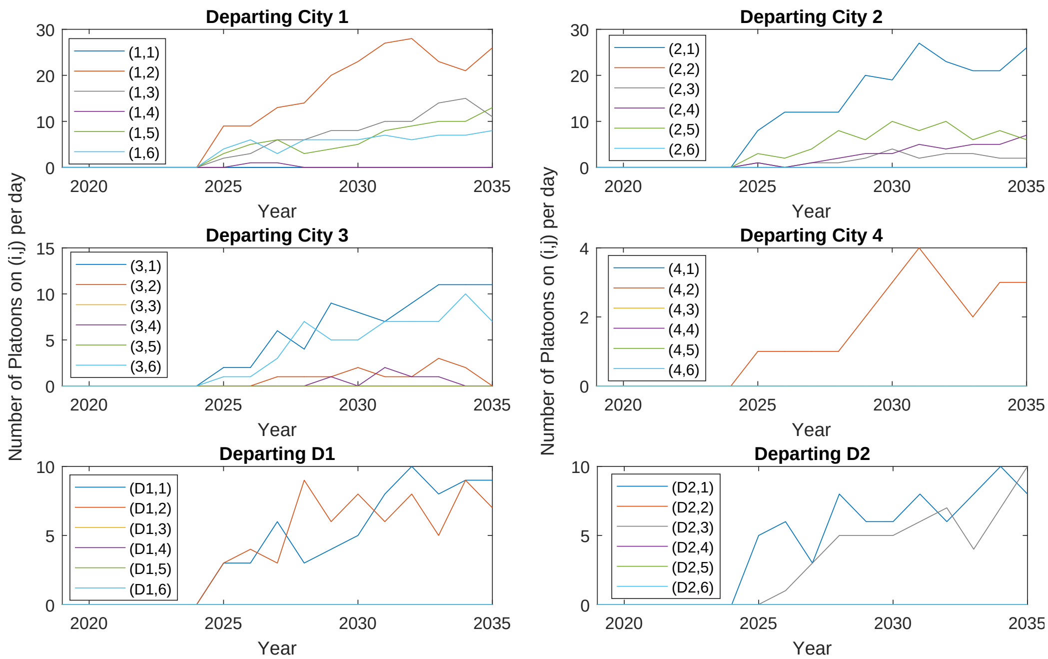
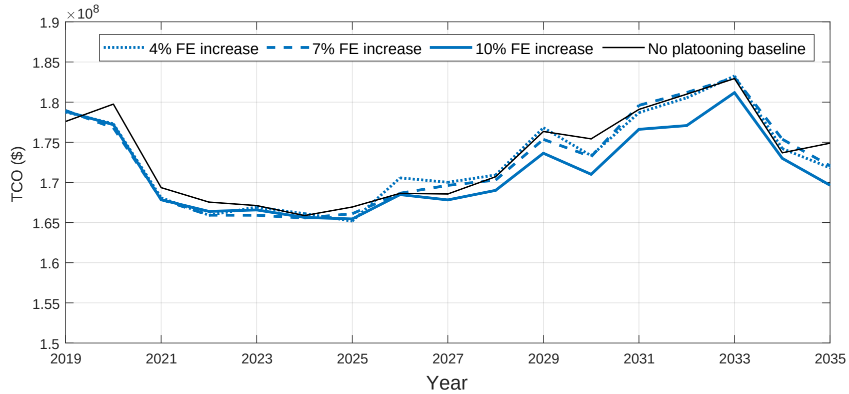



Figure 5.4. : Number of platoons traveling on route (i,j) throughout period of study given an assumption of 7% increase in fuel efficiency for platooning vehicles.

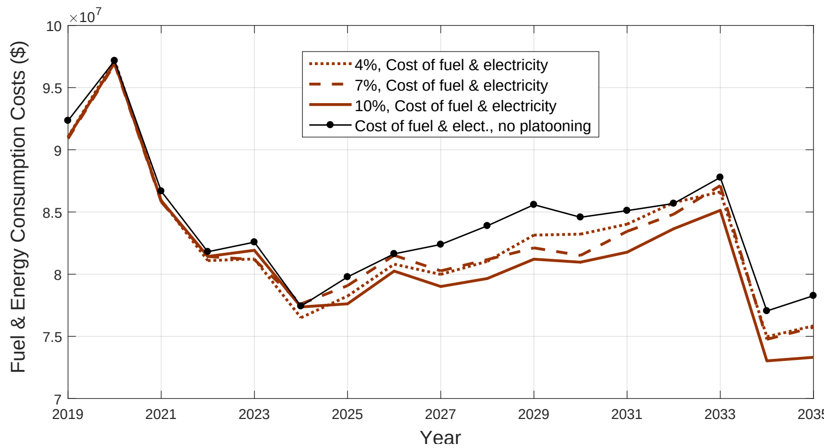
### 5.2.2 Effects of platooning vehicle fuel efficiency on technology adoption and utilization

Reduced air drag, and therefore increased fuel efficiency, is the most prominent benefit for the adoption of platooning-capable vehicles; other benefits including reduced congestion and improved safety. However, the fuel economy benefits and reduction in operational costs must be sufficient to overcome obstacles that hinder the allocation of 2-vehicle platoons over the same route. In order to understand the impact of fuel economy benefits on the adoption and utilization of platooning-capable vehicles of all powertrain technologies, I introduce variation in the fuel savings assumed.

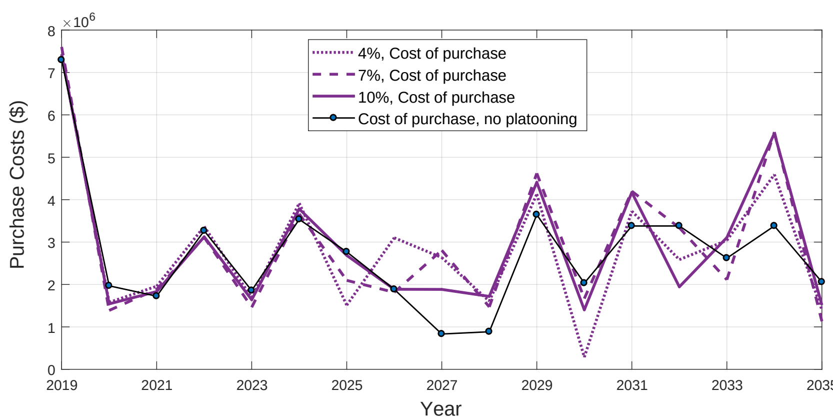
In a network where vehicle autonomy is not incentivized[AG]—purchase or upcharge costs are not subsidized in any way—and carbon output is not penalized, platooning capability must be economically attractive on its own for fleets to adopt and utilize their vehicles in a platoon formation. In other words, the fleet-wide fuel savings gained by the allocation of more than one vehicle over the same route must be enough to overcome the upcharge costs of the added autonomous capability. Figures 5.5(a)-5.5(c) show the network-wide total cost of ownership, purchasing costs, and fuel and energy consumption costs, respectively, for all 12 fleets operating in the network. Although the network-wide cost of purchase is higher for the platooning case scenarios (Figure 5.5(b)), as compared to the non-platooning baseline shown in black, Figure 5.5(c) indicates that energy consumption costs are significantly reduced as platooning capability is introduced to the market in 2025 for all fuel efficiency assumptions. Moreover, the lowest network-wide fuel and energy consumption costs are consistently achieved for the 10% fuel efficiency benefit scenario between 2025-2035. This considerable reduction in fuel costs results in a lower total cost of ownership for the high efficiency platooning scenario, as observed in Figure 5.5(a). The resulting adoption trends for powertrain technologies and platoon-capable vehicles are shown in Figure 5.6. Table 5.6 summarizes powertrain and platooning adoption and resulting emissions for the network in the year 2035 for the nominal case, a 4%, and 10% assumed fuel efficiency increase for platooning vehicles.




(a) TCO

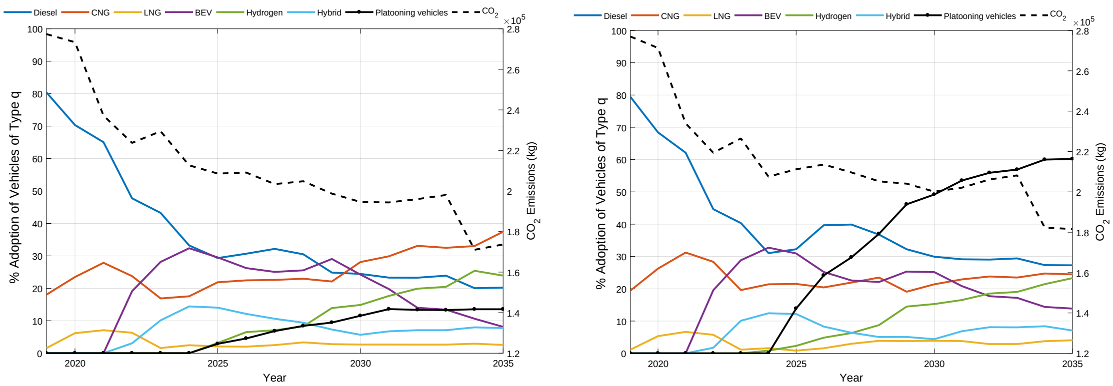



(b) Fuel and energy costs




(c) Cost of purchase

Figure 5.5. : Figure a) shows the network-wide total cost of ownership (TCO) as a function of fuel efficiency benefits for platooning vehicles. Figure b) shows the network-wide purchasing costs, after considering vehicle resale value and available incentives, as a function of fuel efficiency benefits. Figure c) shows network-wide total fueling and charging costs as a function of fuel efficiency benefits for platooning vehicles.




(a) 4% increase in fuel efficiency

(b) 10% increase in fuel efficiency

Figure 5.6. : Powertrain and platooning adoption trends throughout period of study given an assumption of 4% and 10% increase in fuel efficiency for platooning vehicles.

Table 5.6. : Powertrain and Platooning Adoption and Network Emissions in 2035

| Platoon Eff. Increase | Platoon Adoption (%) | Diesel Adoption (%) | CNG (%) | LNG (%) | Hybrid (%) | BEV (%) | Hydrogen (%) | $CO_2$ Emissions (kg) |
|---|---|---|---|---|---|---|---|---|
| 4% (Low) | 14 | 20 | 37.5 | 3 | 8 | 8 | 24 | 174,000 |
| 7% (Nominal) | 50 | 25 | 22 | 3 | 10 | 15 | 26 | 180,000 |
| 10% (High) | 60 | 27.5 | 25 | 4 | 7 | 14 | 23 | 182,000 |

Higher fuel efficiency benefits for platooning vehicles—10% increase—results in faster adoption and higher penetration of platooning vehicles in the network, as shown in Figure 5.6(b), as compared to the nominal and low efficiency case scenarios. Moreover, the summary of adoption of all technologies in the last year of the period of study, shown in Table 5.6, indicates that as fuel efficiency benefits increase, so does the adoption of platooning and diesel technologies, resulting in higher $CO_2$ emissions by 2035. This outcome demonstrates an undesired result, namely that the achievement of better fuel economy for platoon-capable vehicles translates into lower adoption of cleaner powertrain options. This could indicate that the introduction of highly efficient platoons to the line-haul network must be followed by policies designed to incentivize the adoption of low and zero emission powertrain technologies.

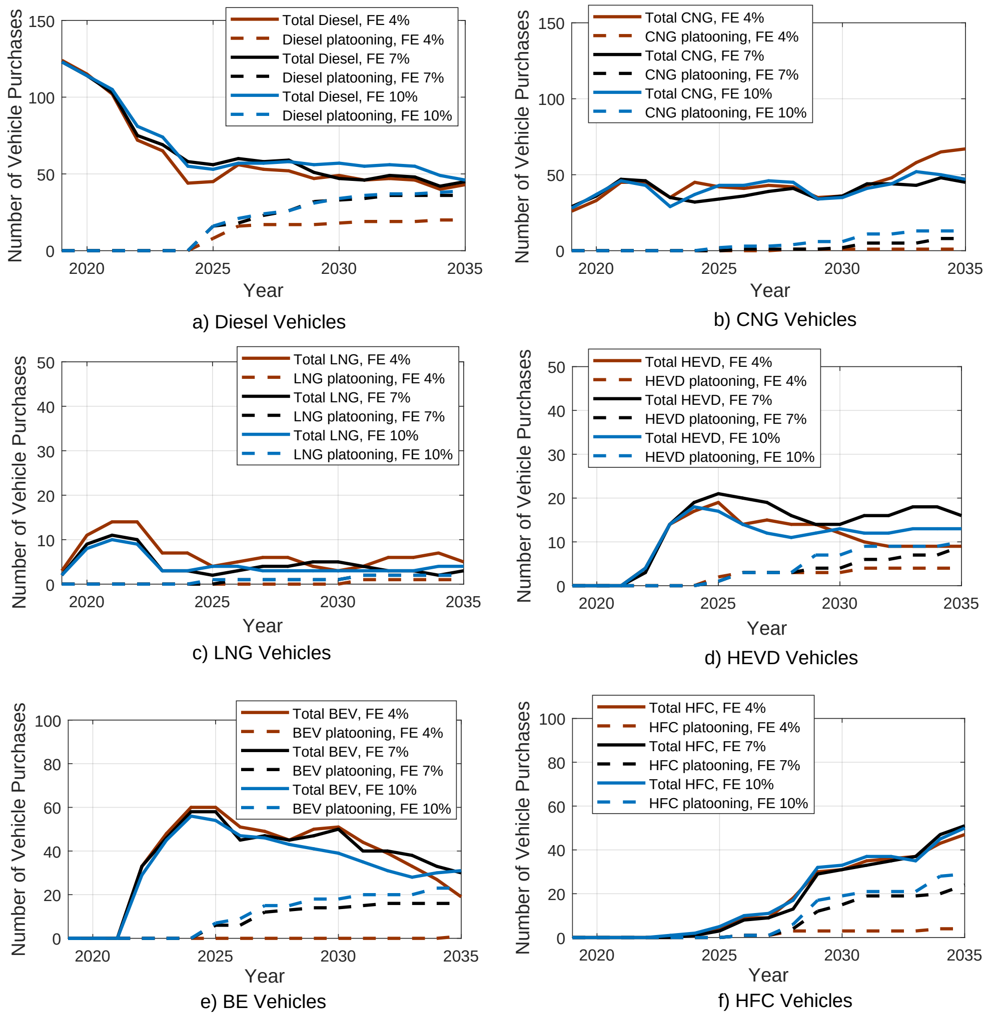



Figure 5.7. : Number of vehicles used per type throughout period of study given an assumption of 4%, 7%, and 10% increase in fuel efficiency for platooning vehicles.

Figure 5.7 shows the total number of purchases for all powertrain options, and the number of vehicles that are platoon-capable as variation in fuel economy benefits is introduced. A low fuel benefit assumption, 4%, results in low platoon-capable vehicle purchases for all powertrain options, and specifically no platooning adoption for BEV and HFC vehicles. In the case of CNG vehicles, shown in Figure 5.7(b), although there is nearly no adoption of CNG platooning vehicles by 2035 for the low fuel efficiency assumption case, overall CNG purchases increase for this case in 2032-2035. Moreover, approximately all diesel vehicles purchased are platoon-capable by the end of the period of study in the case of the nominal and high fuel efficiency assumptions.

Purchasing trends for BEV and HEVD vehicles appear to be negatively affected by the introduction of platooning capability in the year 2025 in all fuel efficiency scenarios, while purchasing trends for HFC vehicles continue to monotonically increase until 2035. Adoption of LNG vehicles begins to decrease before platooning is introduced in 2025 and otherwise maintains a low, yet steady, level of adoption after. It therefore can be assumed that the decrease in LNG adoption is instead caused by an uptake of BE and HEVD vehicles.

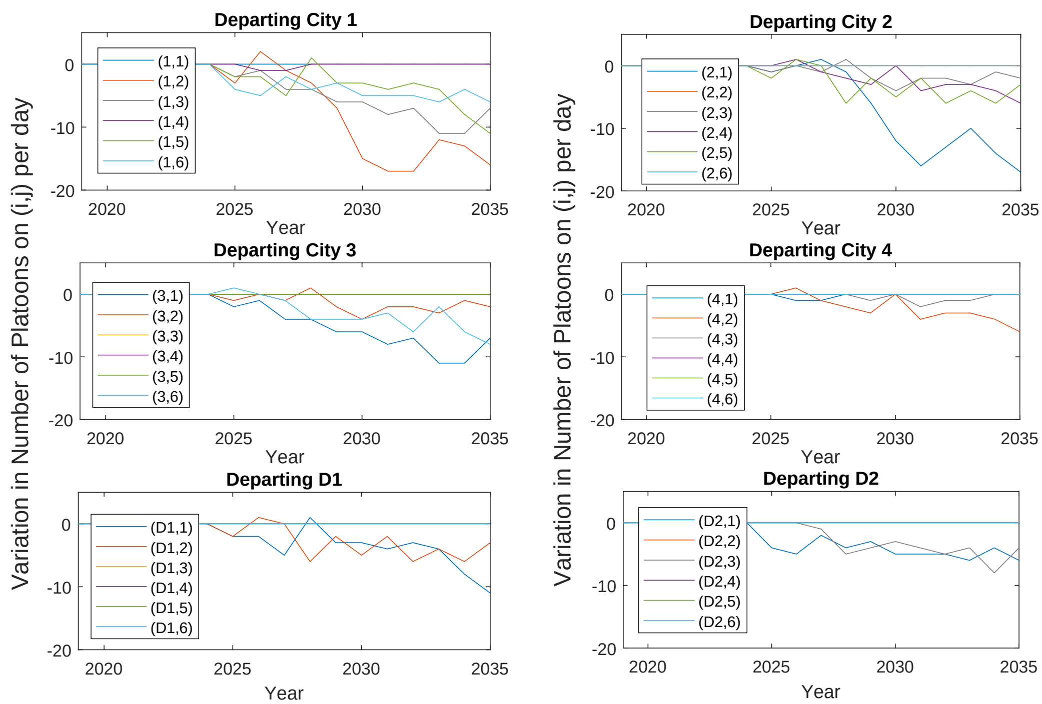



Figure 5.8. : Variation in number of platoons traveling on route (i,j) throughout period of study given an assumption of 4% increase in fuel efficiency for platooning vehicles, compared to a baseline of 7%.

A reduced fuel efficiency assumption—4% case—results in reduced allocation of platoons over all routes by 2035, as shown in Figure 5.8, when compared to the nominal case presented in Figure 5.4. Routes (1,2) and (2,1) show the highest reduction in platoon utilization, approximately a 50% reduction, as these routes observe the highest flow of freight and platoons in the nominal case. Platoon allocation is reduced by approximately 100% over route (3,1). An opposite result is observed for the high fuel economy case scenario, shown in Figure 5.9. Here, a higher volume of platoons is allocated on nearly every route, particularly on routes (1,2) and (2,1). However, an increase in fuel economy benefits, up to 10%, causes only an increase of approximately 25% of platoons allocated on these routes by the year 2035.

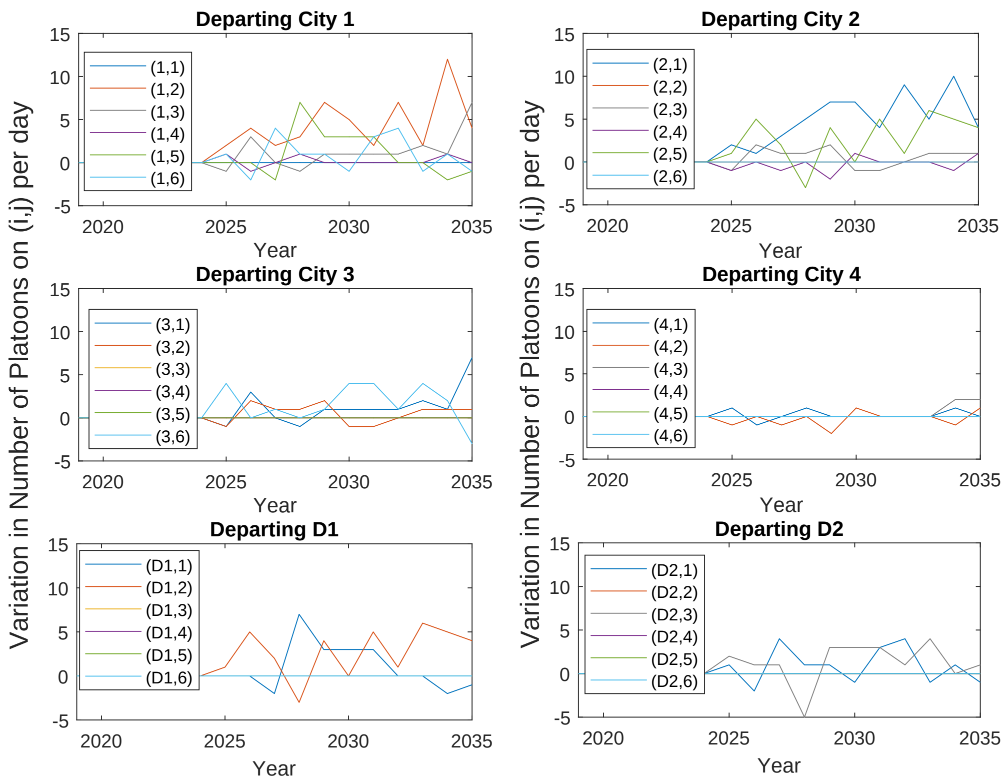



Figure 5.9. : Variation in number of platoons traveling on route (i,j) throughout period of study given an assumption of 10% increase in fuel efficiency for platooning vehicles, compared to a baseline of 7%.

This analysis shows the impact of platooning autonomy introduction on the adoption and utilization of different powertrain options, and therefore the resulting emissions, in a line-haul network. These results show that there is a high correlation between platooning capability, platooning efficiency, and adoption of powertrain technologies in the region. Moreover, for this type of network where adoption and utilization behaviors are purely based on economic attractiveness—carbon emissions are not penalized—high efficiency platooning results in higher $CO_2$ output due to the reduced network-wide fuel and energy consumption costs achieved in this scenario.

### 5.2.3 Effects of increased freight demand on platooning vehicle adoption and utilization

The need for a fleet to allocate more than one vehicle over a single route must exist for vehicle platooning to be economically attractive. Therefore it is hypothesized that an increase in freight demand over a single route can cause an increase in the adoption and allocation of platoons. In order to evaluate this hypothesis, the nominal total freight demand between city pairs (1, 2), (2,1), and (3,4), shown in Figure 5.1, was incremented independently for the year 2019. Each fleet will accommodate an additional annual increase in freight demand according to their parametrization, shown in Table 3.5.

Figures 5.10-5.12 show the resulting variation in total number of trips and platooning vehicles allocated over each direct route between nodes where freight demand is increased. For this study, freight demand is increased between the three selected city pairs such that a resulting variation in vehicle trips can be observed over the direct routes. Figure 5.10(a) shows the resulting variation in overall vehicle trips and platooning vehicles allocated on route (1,2) as freight demand increases from 1880 to 2500 tons between cities 1 and 2. Here, it is shown that the increase in freight demand results in more vehicles allocated on this direct route, specifically an increase between 45 to 150 trips, between 2020-2035. However, the variation in platooning vehicles is only positive between 2028-2030 and 2033-2035, reaching a maximum value of 18. Moreover, Figure 5.10(b) shows that although a higher number of platooning vehicles are allocated over the route during those years, the percent utilization of platooning vehicles is lower on this route than the nominal freight scenario. That is, the number of allocated platoons does not increase proportionally to the number of increasing trips. Therefore, a majority of the vehicles allocated to satisfy the increase in freight demand are of non-platooning capability or traveling as a single vehicle. Figure 5.11 shows a similar result for the case where freight demand increases from city 2 to city 1 from 2080 to 2500 tons. Similar to the previous case, although more platooning vehicles are allocated between 2027-2028 and 2033-2035, the percent utilization of platoons over the direct route is still lower than the nominal case. Here, again, a higher number of non-platooning vehicles are allocated on route (2,1) to satisfy the freight demand.

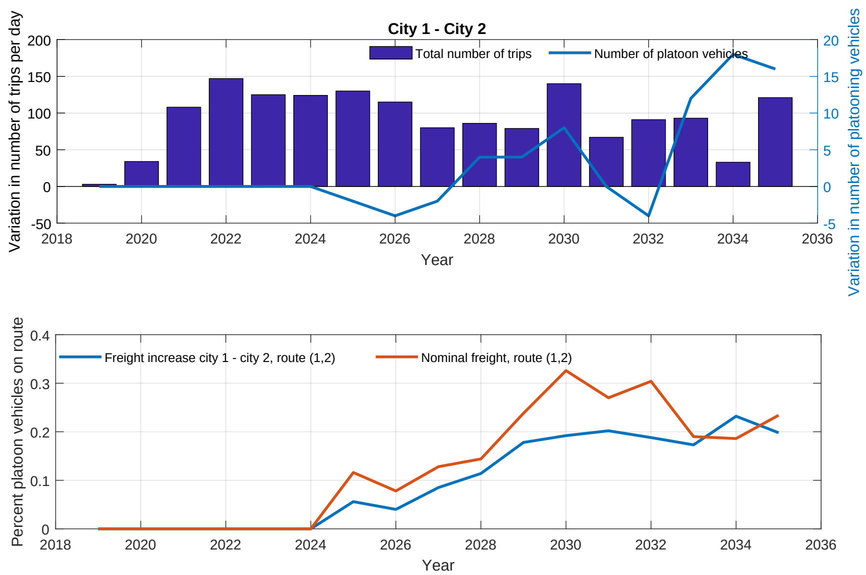



Figure 5.10. : Variation in number of vehicle trips given an increase in freight demand from city 1 to city 4.

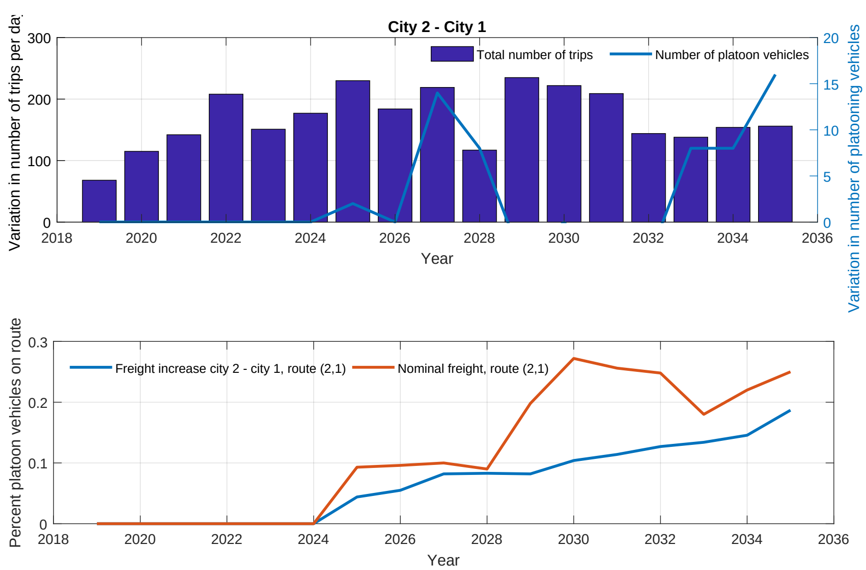



Figure 5.11. : Variation in number of vehicle trips and platoons given an increase in freight demand from city 2 to city 1.

The increase in freight demand from city 3 to city 4 shows a different outcome, as observed in Figure 5.12. The allocation of platooning vehicles on the direct route (3,4) is originally low in the nominal case, with 4 or less platooning vehicles allocated to the route as freight demand is initially low (Figure 5.1). Here, as freight demand is increased from 160 to 450 tons, between 4 and 8 more platooning vehicles are allocated in the periods between 2026-2028 and 2030-2035. This results in a higher platooning utilization on route (3,4), between 10-20%, once platooning capability is introduced, except for the year 2029.

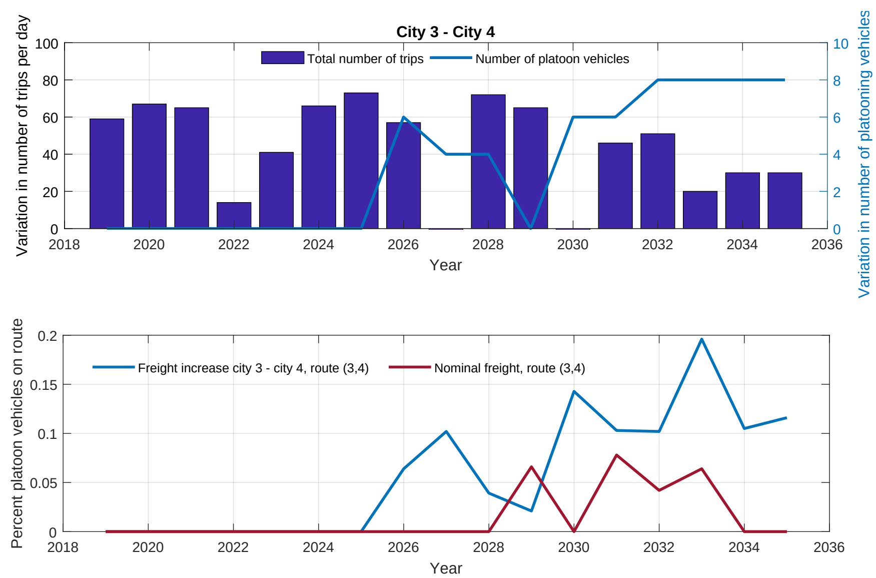



Figure 5.12. : Variation in number of vehicle trips given an increase in freight demand from city 3 to city 4.

Routes $(1,2)$ and $(2,1)$ originally observe the highest allocation of vehicle trips as freight demand is high between these city nodes. Moreover, as fleets originate in cities 1 and 2, most vehicles must be allocated to these two routes to start or end their daily operation, therefore contributing to the high number of trips. In the nominal freight demand scenario, these routes also observe the highest number of platoon trips. Surprisingly, however, although the increase in freight demand between these city nodes results in a much higher number of vehicle trips on routes $(1,2)$ and $(2,1)$, the increase in number of platoons is relatively low. This indicates the number of allocated platoons does not increase proportionally to the number of vehicle trips resulting from an increase in freight demand. Interestingly, the opposite effect is observed when freight demand is increased from city 3 to city 4. Although trip allocation is originally low given that nominal freight demand is low on this route, an increase in freight demand between these cities results in a higher percentage of platooning *utilization* on this direct route. These results suggest that the relationship between freight demand and platoon utilization is not obvious. Here, only intra-fleet platooning capability is evaluated, but different platooning utilization results may be observed for inter-fleet platooning capability. Therefore, this relationship warrants additional study and evaluation.

### 5.2.4 Effects of Carbon Tax on Network $CO_2$ Emissions

Policies to de-carbonize transportation must focus on reducing or eliminating both tailpipe and well-to-tank emissions. This means that any carbon-pricing policies must not only increase the adoption of low and zero emission vehicles, but the upstream emissions during production and transportation of the fuel or electricity consumed must also be reduced. Hybrid, fully electric and hydrogen fuel cell vehicles are considered low and zero emission vehicles as they reduce or completely eliminate *tailpipe* emissions [13]. However, regions like the U.S. Midwest are currently highly dependent on coal as a source of electricity production, and hydrogen fuel is primarily sourced from natural gas reforming [51]. A carbon tax for the U.S. has been proposed as an effective approach to complement the number of federal, state, and local policies already in effect to reduce carbon output in the transportation sector [82–84]. A carbon tax would assign a social cost to carbon emissions and impose a fee on fuels or energy sources, including coal, natural gas, and oil produced domestically or imported, based on how much carbon they emit. This approach would help to reduce "upstream" carbon emissions, that is the well-to-tank $CO_2$ produced before the fuel is burned by the freight transportation vehicle. Moreover, fuel and electricity suppliers

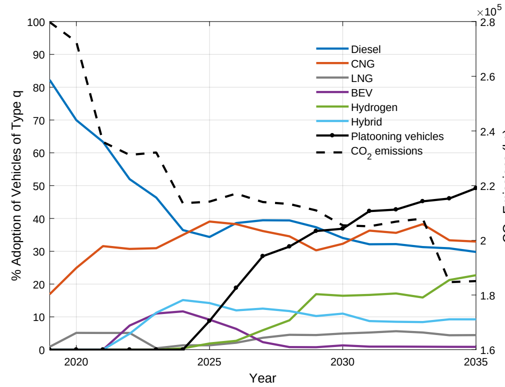
Table 5.7. : Well-to-Wheel $CO_2$ emissions for various fuel types [51]

| Vehicle | Well-to-tank | Tank-to-Wheel | Units |
|---|---|---|---|
| Diesel | 9.45 | 10.16 | kg $CO_2$/gal |
| CNG | 2.23 | 7.11 | kg $CO_2$/dge |
| LNG | 2.56 | 7.73 | kg $CO_2$/dge |
| HEVD | 9.45 | 10.16 | kg $CO_2$/gal |
| BE | 0.63 | 0 | kg $CO_2$/kWh |
| HFC | 17.6 | 0 | kg $CO_2$/dge |

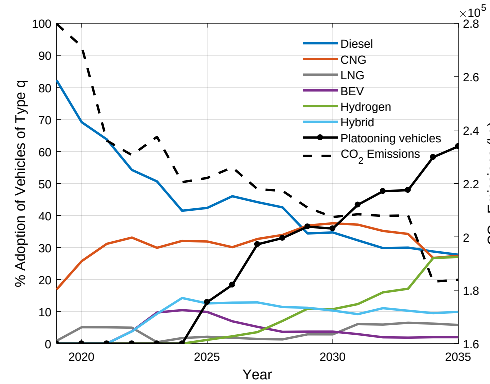
would be free to pass the added cost of the tax "downstream" to consumers at the pump or point of distribution. This policy could incentivize freight transportation fleets to drive fewer miles and to adopt cleaner vehicle technologies. The carbon tax could be increased or modulated as needed based on the market response and the resulting emission trends over a period of time.

In 2018, the Congressional Budget Office produced a study evaluating the economic impact of a carbon tax including a \$25/metric ton of $CO_2$ and \$50/metric ton of $CO_2$ rate and their likelihood to achieve the GHG emissions reduction targeted under the International Paris Agreement [84]. Authors in [85] found that a constant tax rate of \$43/metric ton of $CO_2$ imposed in 2019 would be enough to achieve the Paris Agreement target set for 2025. Here, we present a study to evaluate the impact of a carbon tax on technology adoption and resulting emissions under the assumption that the cost of the tax will be passed to consumers at the pump or point of charging. For this purpose, we introduce a carbon tax between \$15 to \$120 per metric ton of $CO_2$, taking into account the well-to-wheel emissions created during production, transportation, and combustion of the various fuels and electricity as shown in Table 5.7. The carbon tax is introduced in the year 2025 and is assumed constant throughout the period of study. A 7% increase in fuel efficiency is assumed for vehicles traveling in a platoon.

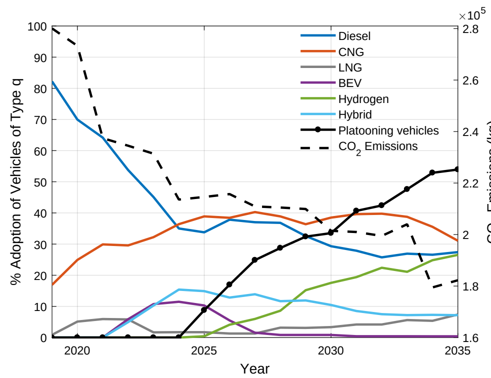
The first scenario evaluated assumes well-to-tank $CO_2$ emissions for BE vehicles based on the U.S. electricity mix [51]. Figures 5.13(a)-(d) show the resulting adoption of the different powertrain technologies and platooning vehicles, as well as network-wide $CO_2$ emissions for four carbon tax values introduced to the network. Table 5.8 summarizes the increase in fuel and electricity costs based on the carbon tax assumed, the resulting cumulative emissions throughout the period of study, and the emissions produced in 2035, the last year in the period of study. The figures show that the carbon tax, in all instances, does not negatively affect adoption of platooning-capable vehicles. However, the highest adoption of platooning-capable vehicles is observed in the \$30 and \$45 per metric ton of $CO_2$ scenarios shown in Figures 5.13(b)-(c). Moreover, these two carbon tax scenarios result in the highest reduction in cumulative and end-of-period emissions due to lower adoption of diesel vehicles, while a tax of \$60/metric ton of $CO_2$ unexpectedly results in the *highest* cumulative and end-of-period emissions. These results indicate that a carbon tax between \$30-\$45 per metric ton of $CO_2$ may be ideal for the network considered here. However, it is important to note that in this case, all powertrain options, not only those using petroleum fuels, are affected by the carbon tax, which in turn is reflected as an increase in their cost of operation. In other words, a high carbon tax may be more effective in achieving a transition to cleaner vehicle technologies if the source of energy has lower well-to-tank emissions.



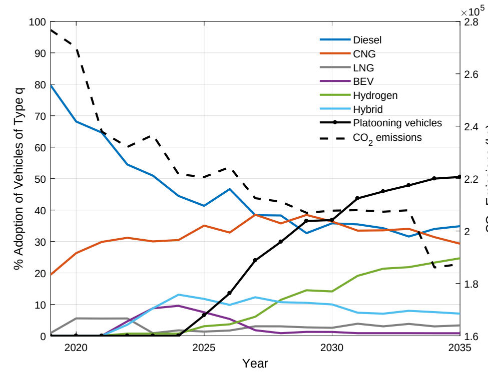

(a) Carbon tax of \$15 per ton of $CO_2$.




(b) Carbon tax of \$30 per ton of $CO_2$.




(c) Carbon tax of \$45 per ton of $CO_2$.



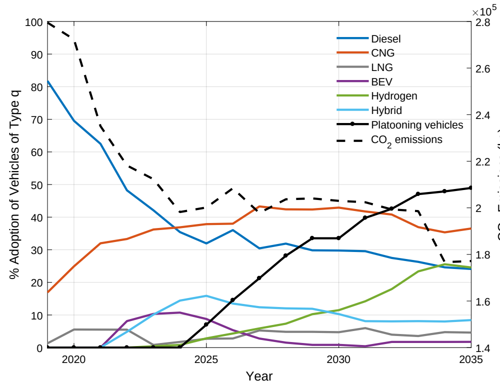

(d) Carbon tax of \$60 per ton of $CO_2$.

Figure 5.13. : Technology adoption and network emission trends given carbon tax assumptions. Note that right-hand y-axis provides scale for $CO_2$ emissions.

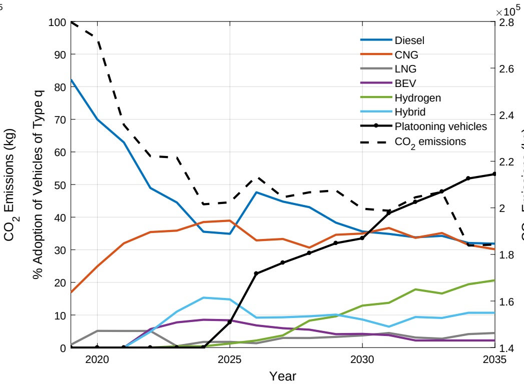
Table 5.8. : Carbon tax parameters and resulting network emissions

| Carbon Tax (\$/ton $CO_2$) | Diesel Cost Incr. (\$/gal) | CNG Cost Incr. (\$/dge) | LNG Cost Incr. (\$/dge) | Electricity Cost Incr. (\$/kWh) | Hydrogen Cost Incr. (\$/kg) | Cumulative Emissions (ton) | Emissions 2035 (ton) |
|---|---|---|---|---|---|---|---|
| 15 | 0.17 | 0.13 | 0.16 | 0.0095 | 0.26 | 3,729,900 | 185,090 |
| 30 | 0.34 | 0.26 | 0.32 | 0.019 | 0.52 | 3,717,000 | 183,040 |
| 45 | 0.51 | 0.39 | 0.48 | 0.0285 | 0.78 | 3,699,600 | 182,250 |
| 60 | 0.68 | 0.52 | 0.64 | 0.038 | 1.04 | 3,755,300 | 187,380 |

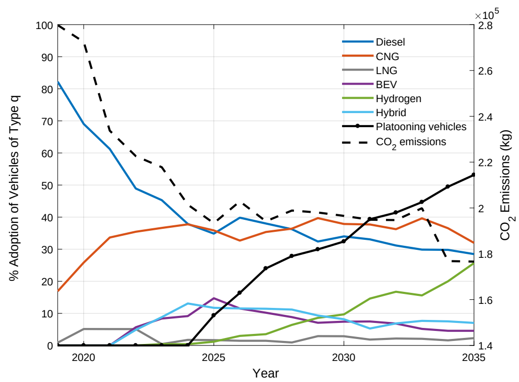
In the second scenario, we assume electricity is sourced from clean sources in the region of study, thereby eliminating well-to-tank emissions for BE vehicles. Here, five different levels are introduced for the carbon tax. Table 5.9 summarizes the increase in fuel and electricity costs based on the carbon tax values assumed, the resulting cumulative emissions throughout the period of study, and the emissions produced in the year 2035. The cost of electricity does not increase over the period of study, and therefore, operational costs of BE vehicles are not affected by the carbon tax imposed. As expected, given that there is no well-to-tank penalty associated with powertrains driven by electricity, adoption of BE vehicles increases with the introduction of higher carbon taxes to the network, as shown by Figures 5.14(a)-(e). Both cumulative and end-of-period emissions decrease with higher carbon taxes, reaching the lowest value with an imposed tax of \$120/metric ton of $CO_2$. This is approximately a 15% reduction from the baseline scenario (Figure 5.2) in which no carbon tax is introduced. Like the first scenario, introduction of the carbon tax does not negatively affect adoption of platoon-capable vehicles.



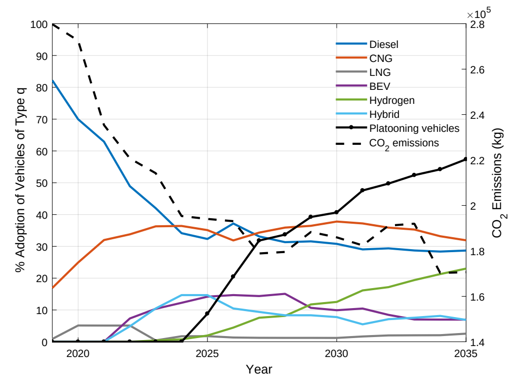

(a) Carbon tax of \$15 per ton of $CO_2$.



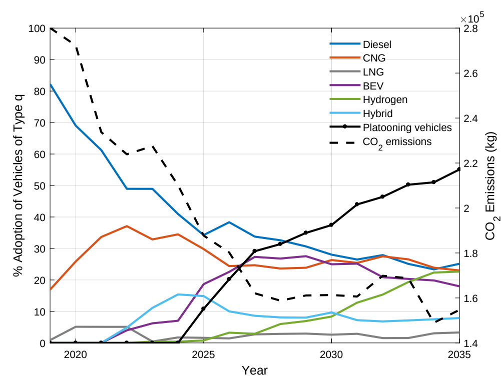

(b) Carbon tax of \$30 per ton of $CO_2$.




(c) Carbon tax of \$45 per ton of $CO_2$.




(d) Carbon tax of \$60 per ton of $CO_2$.




(e) Carbon tax of \$120 per ton of $CO_2$.

Figure 5.14. : Technology adoption and network emission trends assuming zero-carbon output for production of electricity.

This analysis suggests that a carbon tax alone, without any other policies focused on reducing the upstream emissions released during production and distribution of fuel or electricity, may not be enough to cause a transition to cleaner vehicle technologies. As such, the carbon tax alone would not be enough to counteract the increase in

Table 5.9. : Carbon tax parameters and emissions for zero-carbon output for production of electricity

| Carbon Tax ($/ton $CO_2$) | Diesel Cost Incr. ($/gal) | CNG Cost Incr. ($/dge) | LNG Cost Incr. ($/dge) | Electricity Cost Incr. ($/kWh) | Hydrogen Cost Incr. ($/kg) | Cumulative Emissions (ton) | Emissions 2035 (ton) |
|---|---|---|---|---|---|---|---|
| 15 | 0.17 | 0.13 | 0.16 | 0 | 0.26 | 3,586,700 | 177,160 |
| 30 | 0.34 | 0.26 | 0.32 | 0 | 0.52 | 3,645,700 | 184,230 |
| 45 | 0.51 | 0.39 | 0.48 | 0 | 0.78 | 3,554,600 | 176,590 |
| 60 | 0.68 | 0.52 | 0.64 | 0 | 1.04 | 3,444,300 | 170,640 |
| 120 | 1.36 | 1.04 | 1.28 | 0 | 2.08 | 3,261,800 | 154,700 |

diesel adoption, and therefore $CO_2$ emissions, observed upon introduction of higher efficiency vehicle platooning.

## 5.3 Summary

In this chapter, the MILP formulation was extended to capture the particular operational behavior of platooning autonomous vehicles as they achieve fuel savings while traveling in formation. Moreover, the framework was used to project adoption and utilization of powertrain technologies and vehicle platooning capability, and resulting $CO_2$ emissions, upon introduction of this autonomous feature to the regional network. The impact of fuel efficiency variation and increase in freight demand on adoption and utilization of platooning vehicles was also studied.

The studies in this chapter demonstrate that higher fuel efficiency benefits for platooning vehicles result in faster adoption and higher penetration and utilization of platooning capability. Moreover, as fuel efficiency benefits increase, so does the adoption of diesel powertrain technology, resulting in higher $CO_2$ emissions in 2035. Additionally, approximately all diesel vehicles adopted by 2035 are platoon-capable in the high fuel efficiency case scenarios. These results indicate that for this type of regional network where carbon emissions are not penalized, policies incentivizing adoption of low and zero emission powertrain options may be necessary upon introduction of platooning technology to the market. Finally, the analysis in this chapter indicates that platooning utilization does not increase proportionally to vehicle traffic resulting from an increase in freight demand between city nodes. Therefore,the impact of higher platooning efficiency on platooning utilization is more pronounced than the effect observed given an increase in freight demand.

# 6. CONCLUSIONS

## 6.1 Summary of Research Contributions

Projecting the technology adoption trajectories that result in targeted reductions in emissions in a region is a complex task. New technologies introduced to the market can cause significant changes to the way fleets operate their vehicles since their performance will differ from the well-known diesel baseline. Moreover, fuel prices, introduction of supporting infrastructure for alternative fuels and electric vehicles, and active and new regulatory policies and incentives will affect the economic attractiveness of emerging technologies. Ultimately, adoption behaviors of Class 8 fleets will respond to dynamic changes in these critical freight transportation system factors. A simulation framework that can be used to project future scenarios and predict the effects on mixed technology adoption trajectories is necessary.

In this thesis, I presented the development of a parametrized model of the decision utilities (total cost of ownership) and behaviors for a fleet to emulate their selection process based on the operational and acquisition costs of the vehicles. This parametrized fleet behavioral model was used to project a mixed fleet composition, including multiple types of powertrains and other vehicle technologies. More importantly, I modeled the effects of the evolving freight transportation environment on vehicle route allocation and operational costs. I developed parametrized models of the FTS components (network of cities and highway routes, vehicle performance, fuel costs, and active regional policies) that capture their time-varying characteristics. Finally, I integrated the FTS component models to represent the environment of inputs and constraints influencing the adoption behaviors of a set of 12 heterogeneous fleets operating in a regional network. This simulation framework was calibrated and validated against historical data, demonstrating its capability to project adoption trends of Class 8 vehicle technologies.

I used this simulation framework to project adoption trajectories for diesel conventional, diesel electric hybrid, CNG, LNG, battery electric, and hydrogen fuel cell heavy-duty Class 8 vehicles and resulting $CO_2$ emissions in a line-haul network. Moreover, the framework was also used to predict how the introduction of different levels of autonomy, including intra-fleet 2-vehicle platooning, affects fleet adoption and utilization of low and zero emission technologies. I achieved this by extending the validated framework to include the effects of new technologies on purchase and operation costs, while maintaining the structure of the MILP and integrated framework. I also performed a design of experiments to determine factor variation effects on adoption and utilization trends of powertrain options and levels of vehicle autonomy, therefore quantifying the response in network-wide emissions. The studies and analysis presented in this thesis demonstrated that the framework, which predicts both adoption and utilization, can empower stakeholders with a deeper understanding of how and why the introduction of new technologies and evolution of the FTS factors impacts the broader freight transportation network. This in turn renders the framework a more effective tool for policymaking and strategic decision-making for a variety of stakeholders.

## 6.2 Future Research Direction

Future research could further develop this framework to concurrently model regional freight transportation to determine penetration of powertrain technologies for Class 6, Class 7, and Class 8 vehicles. These vehicles are commonly operated over shorter routes and closer to urban areas. This would then allow future research to project adoption in a regional network that would not only focus on Class 8 vehicles and highway operation, but also on applications that operate on drive cycles with higher variation in vehicle speed and vehicle performance. The same policies, fuel and energy costs, well-to-tank emissions, and location of fueling and charging stations would influence adoption and operation of all vehicles (Class 6 to Class 8). *This extended formulation would then increase the breadth of the scope*, without the need to add more factors with respect to policies and economic considerations in the ROPE matrix. Extending the formulation for this purpose would require adding more nodes and links to the network in order to discretize the routes into a finite number of segments with different parametrization and represent urban road links of varying traffic characteristics and vehicle speeds. An increase in number of nodes and links would increase computational requirements by raising the number of decision variables regarding vehicle travel on link $(i, j)$. Therefore, future work should focus on reducing the complexity of the MILP formulation by defining traffic assignment in terms of path travel rather than link travel [35].

Moreover, network discretization will enable future researchers to project the effects of shorter route distances and varying traffic flow speeds on adoption and utilization of those vehicle architectures with limited range and those that benefit from operation at lower speeds (e.g. battery electric vehicles). For this purpose, this phase of future research could implement advanced macroscopic traffic models—Lighthill-Whitham model and others [86]— calibrated to explore different traffic streams over urban and rural highways and arterial streets. The framework could then be used to identify if any niches in the market exist; for example, higher utilization of BEVs closer to the city vs. higher utilization of diesel or LNG on longer line-haul routes. This level of discretization may show an effect on regional–line-haul and urban–fleet composition and vehicle utilization, therefore resulting in different $CO_2$ emission trajectories. Furthermore, this will allow future researchers to consider the emergence of a higher number of distribution hubs and fueling or charging stations on those nodes introduced. Again, an effect on adoption and utilization of vehicles with shorter range may emerge, as these vehicles will be able to deliver freight over shorter urban routes and benefit from the close availability of fueling or charging stations.

Another future research direction could focus on developing the framework to minimize the reduction in $CO_2$ emissions by optimizing the policies active in different regions of the U.S., including voucher incentives and carbon taxes. In this extended framework, fleets would still optimize their total cost of ownership at the lower level of the framework. However, at a higher level, the voucher amount offered per vehicle and the carbon tax per kilogram of $CO_2$ produced would be defined as decision variables, instead of user inputs. This would create a closed-loop approach by optimizing incentives and penalties to achieve minimum carbon emissions in the network. The studies I presented in this thesis are representative of a network in the U.S. Midwest. Network traffic, freight demand between nodes, route distance, traffic speeds, policies, and well-to-tank emissions, among other factors, are dependent on the region or state where the network is located. The enhanced framework could then be used to project expected adoption and emissions across different regions in the country, and identify the networks that would benefit the most from the introduction of new programs incentivizing adoption of low and zero emission technologies, such as the programs already active in the state of California. Moreover, a map of optimal carbon tax values and incentives could be differentiated per region or state by using this enhanced framework.

Finally, another future research direction can introduce parametric uncertainty to the model and identify how innovation factors—technology performance and policies—can be designed, adapted, and controlled to minimize the uncertainty of desired emission outcomes. Some influential parameters come with a high degree of uncertainty, and it is difficult to identify how likely it is that the scenarios assumed in this thesis will happen. Therefore, future research can introduce uncertainty to those parameters that have shown volatility in the past (e.g. fuel prices) or which values are uncertain but expected to have a direct effect on economic attractiveness of vehicles (e.g. vehicle purchase costs and battery costs). Future researchers could then perform a Monte Carlo analysis to quantify uncertainty in vehicle adoption and resulting $CO_2$ emissions outcomes. This approach will further help policymakers identify the likelihood of projected outcomes in the regional segment—line-haul and urban—of the freight transportation system.

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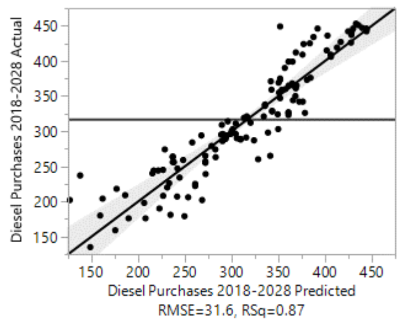
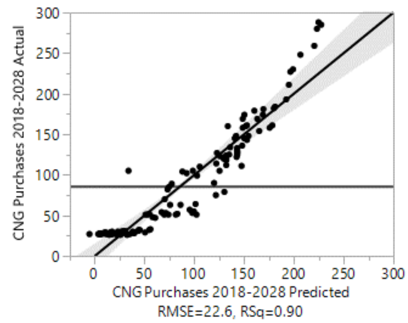
APPENDIX

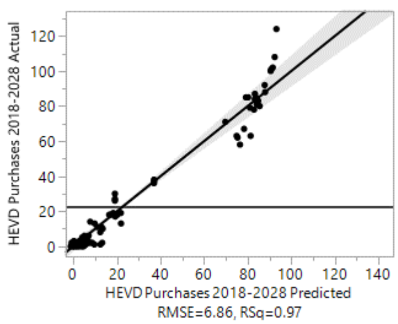
Figures 1 and 2 support the sensitivity analysis presented in Section 3.2.2. The quality of fit for the regression models computed in Section 3.2.2 are shown in Figure 1, indicating root mean square error and coefficient of determination ($R^2$) values for predicted vehicle purchases. Figure 2 shows the variation in vehicle purchases given the factor levels introduced in the sensitivity study.



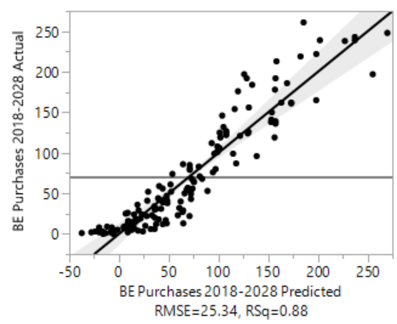

(a) Diesel Baseline



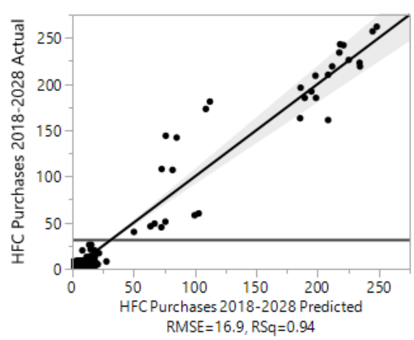

(b) CNG




(c) HEVD

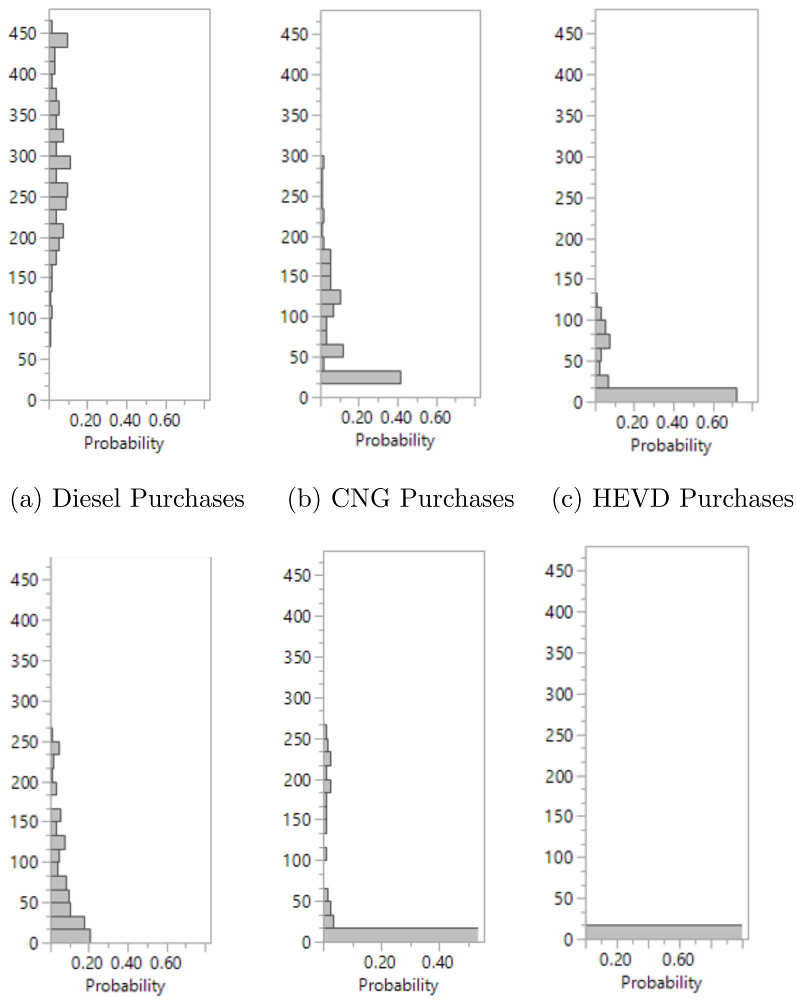



(d) BE




(e) HFC

Figure 1. : Summary of regression fit showing mean of response, RMSE, and $R^2$ for predicted vehicle purchases throughout period of study.



(a) Diesel Purchases (b) CNG Purchases (c) HEVD Purchases

(d) BE Purchases (e) HFC Purchases (f) LNG Purchases

Figure 2. : Histograms showing distribution of vehicles purchased throughout 11-year period as a result of the DOE factor variation.