U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

SMART Mobility

Multi-Modal Freight Capstone Report

July 2020

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Foreword

The U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative, managed by the Energy Efficient Mobility Systems Program of the Office of Energy Efficiency and Renewable Energy, Vehicle Technologies Office, dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The first three-year research phase of SMART Mobility occurred from 2017 through 2019, and included five research pillars: Connected and Automated Vehicles, Mobility Decision Science, Multi-Modal Freight, Urban Science, and Advanced Fueling Infrastructure. A sixth research thrust integrated aspects of all five pillars to develop a SMART Mobility Modeling Workflow to evaluate new transportation technologies and services at scale.

This report summarizes the work of the Multi-Modal Freight Pillar. The Multi Modal Freight Pillar's objective is to assess the effectiveness of emerging freight movement technologies and understand the impacts of the growing trends in consumer spending and e-commerce on parcel movement considering mobility, energy, and productivity. For information about the other Pillars and about the SMART Mobility Modeling Workflow, please refer to the relevant pillar's Capstone Report.

Acknowledgments

This material is based upon work supported by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy (EERE), specifically the Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program.

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This work was authored for the U.S. Department of Energy (DOE), by Lawrence Berkeley National Laboratory under Contract No. DE-AC02-05CH11231, Argonne National Laboratory under Contract No. DE-AC02-06CH11357, Idaho National Laboratory under Contract No. DE-AC07-05ID14517, National Renewable Energy Laboratory under Contract No. DE-AC36-08GO28308, and Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725. Funding provided by U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Vehicle Technologies Office.

Nomenclature or List of Acronyms

AEO	Annual Energy Outlook
BAU	business-as-usual
BEV	battery electric vehicle
CAV	connected and automated vehicle
CBD	Central Business District
CBP	US Census County Business Patterns
CMAP	Chicago Metropolitan Agency for Planning
DOE	US Department of Energy
DOT	US Department of Transportation
DTA	dynamic traffic assignment
EIA	US Energy Information Administration
EERE	Energy Efficiency and Renewable Energy
EPA	US Environmental Protection Agency
ESS	energy storage system
EV	electric vehicle
F-MEP	freight mobility energy productivity
FAF	Freight Analysis Framework
FHWA	Federal Highway Administration
GHG	greenhouse gas
GIS	geographic information system
HDT	heavy-duty truck
HEV	hybrid electric vehicle
HPMS	Highway Performance Monitoring System
LDV	light-duty vehicle
mbpd	million barrels per day
MD/HD	medium-duty/heavy-duty
MDT	medium-duty truck

MEP	mobility energy productivity
MMF	multimodal freight
MSA	metropolitan statistical area
NREL	National Renewable Energy Laboratory
NPV	net present value
OD	origin-destination
PHEV	plug-in hybrid electric vehicle
SMART	Systems and Modeling for Accelerated Research in Transportation
SU	single-unit
SUV	sport utility vehicle
TAZ	traffic analysis zone
TNC	Transportation Network Company
UPS	United Parcel Service
VHT	vehicle hours traveled
VIUS	Vehicle Inventory Use Survey
VMT	vehicle miles traveled
VTO	US Department of Energy Vehicle Technologies Office

Executive Summary

The US Department of Energy (DOE) Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium comprises five focused research and development areas:

1. Connected and automated vehicles
2. Mobility decision science
3. Urban science
4. Advanced fueling infrastructure
5. Multimodal freight (MMF)

Each of these “pillars” allow focused research in distinct transportation energy–related fields. Advancements and coordination between each of these areas is required to increase efficiency in transportation at the system level. Though all focus areas must work together to ensure that transportation as a system is improved, projections from multiple sources—which highlight the future increase in transportation energy consumption—identify MMF as a critical part of the SMART Mobility Consortium. Integration of new and appropriate technologies into the commercial vehicle space provides a safe way to reduce petroleum consumption and solidify national energy security while reducing congestion and providing benefits to industry, consumers, and commercial fleets.

The SMART Mobility MMF pillar objective is to assess the effectiveness of emerging freight movement technologies and understand the impacts of the growing trends in consumer spending and e-commerce on parcel movement considering mobility, energy, and productivity. This assessment is accomplished by using available data sets and modeling tools to understand trends in freight movement and the associated impact of alternative technologies in the medium-duty/heavy-duty (MD/HD) space. These trends are necessary to develop relationships and metrics and to improve existing tools, delivery strategies, and requirements to elevate the DOE’s traditional transportation energy focus to a new systems-level perspective for freight efficiency. The MMF pillar is structured into three focus areas as described below.

1. **Intracity last-mile delivery.** Last-mile freight delivery modes will impact infrastructure and energy demands, as well as fleet productivity. Alternative and disruptive delivery technologies have the promise to greatly improve mobility, productivity, and energy efficiency.

2. **Intercity freight movement.** Freight optimization techniques and shifts in delivery modes from region to region may have significant national-level impact on energy use, infrastructure, and fleet logistics strategies.

3. **Regional transportation system impacts of freight (including long haul, last-mile delivery, and other regional freight movements).** The full transportation picture of the energy and mobility impact of inter- and intracity freight movement must be understood using data-driven agent-based system simulation in a way that also considers interactions with passenger movement.

Disruptive technologies such as powertrain electrification, drone delivery, parcel lockers, and even shared delivery pods may factor into reducing energy consumption for delivery, but the question remains of how these technologies will impact congestion or total transportation system efficiency. By analyzing important components and/or alternatives to each generalized system, the MMF pillar research can identify opportunities available through various technology adoptions and expand understanding of the integral relationships of the many facets of freight mobility.

The electrification of commercial vehicle powertrains will undoubtedly increase freight energy efficiency. To determine the appropriate level of electrification for a wide range of payloads and duty cycles, additional data collection and understanding the relevance of existing data will be required. Additionally, reliable forecasts for production applications and market penetration of advanced technologies are required for accurate subsystem performance. Critical elements in the deployment of full electrification of MD/HD vehicles include in-depth knowledge of the electric infrastructure requirements, capabilities, costs, and security, as well as the impact to the onboard energy storage system, particularly at high charge rates and environmental extremes. Electrification will add to the list of options for fleet procurement agents but will also add to the complexity of their decisions as each technology brings variations in service, maintenance, infrastructure and life cycle costs.

The SMART Mobility Consortium performed research and development in various urban decision and transportation areas, which resulted in a number of freight-related foundational projections:

1. Freight mobility requirements will continue to grow and significantly influence transportation systems and related energy consumption. The EIA (U.S. Energy Information Administration) predicts energy consumption for freight mobility to rise nearly 10% by 2050, whereas the consumption for the light duty vehicle (LDV) sector is projected to decrease by 2050.

2. Increasing commodity flows and, in particular, e-commerce will have a substantial impact on overall vehicle miles traveled and transportation energy consumption. SMART Mobility research results indicate that e-commerce deliveries will not directly replace all shopping trips, but instead may substitute or supplement shopping trips depending on the type of good purchased.

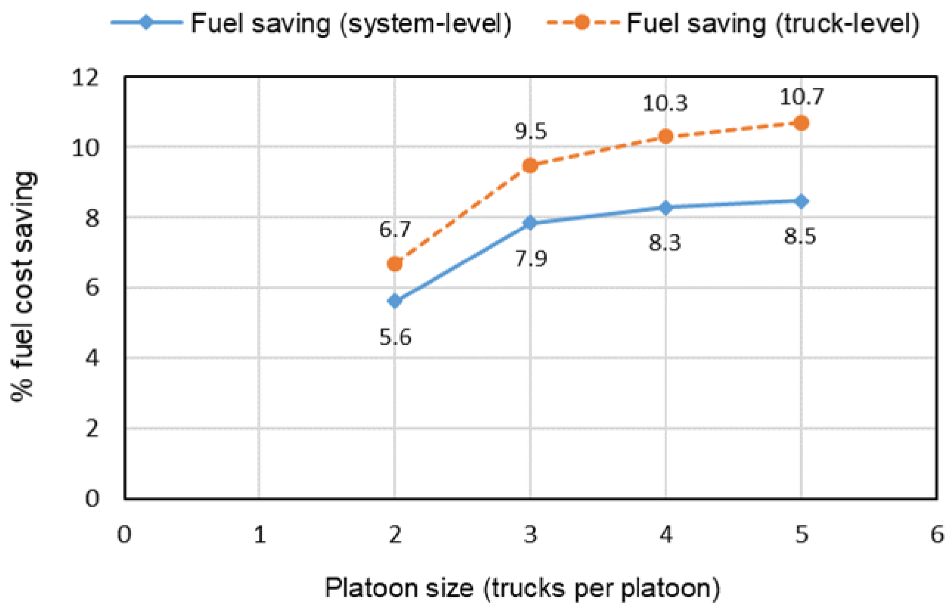
3. Development and implementation of improved vehicle technologies and delivery approaches will be required to mitigate fuel consumption increases in the commercial vehicle sector and corresponding congestion impacts affecting all traffic. Targeted R&D and the development of new metrics for system performance evaluation will allow the commercial vehicle industry to understand and quantify the impact of new technologies and approaches.

This report summarizes the findings from each focus area of the MMF pillar. These findings will help to form a detailed picture of sectors of MMF operations and provide guidance for future R&D selection. Elements of this work bridge across tasks (and pillars) to anchor the perspective for future work in freight and goods movement energy research.

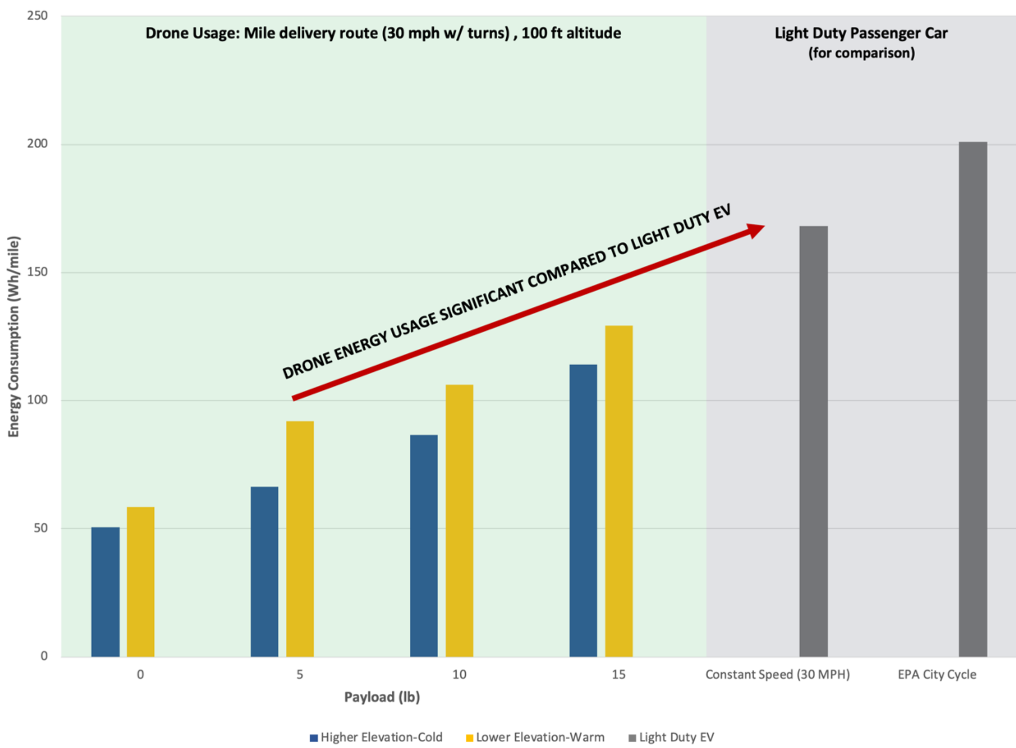
A complete list of findings from the MMF research can be found in the summary of this report with the key insights from this pillar's research shown below.

- **Electrification.** Assuming adequate charging infrastructure and no payload limitations, full electrification of freight moved under 300 miles could be accomplished by electrifying 11-15% of the Class 7–8 truck fleet, and could potentially reduce energy consumption in this segment by 11%, or 0.45 quads, relative to US Energy Information Administration (EIA) AEO 2017 reference case.
  - This potential reduction in Class 7 & 8 fleet energy equates to over 32,000 metric tons of carbon dioxide emissions reduction annually.
  - A case study showed electrification may require a change in the operations of the traditional hub and spoke model and sufficient access to chargers with power capacity substantially greater than 350 kW.
- **Platooning.** The SMART Mobility Consortium analyzed commodity flows and traffic data from the U.S. Department of Transportation and Federal Highway Administration that indicate nearly 60% of interstate and highway roads may be platoonable, based on average highway speeds and the availability of nearby trucks to form a platoon. By applying results from track-based testing of platooning technologies, researchers estimate that deploying 2- and 3-truck platoons on these road segments could reduce Class 7–8 truck diesel fuel consumption by 1–2 billion gallons annually—approximately 6%–8% of the fuel consumption in this segment. Energy savings from platooning are impacted by speed, the gap between

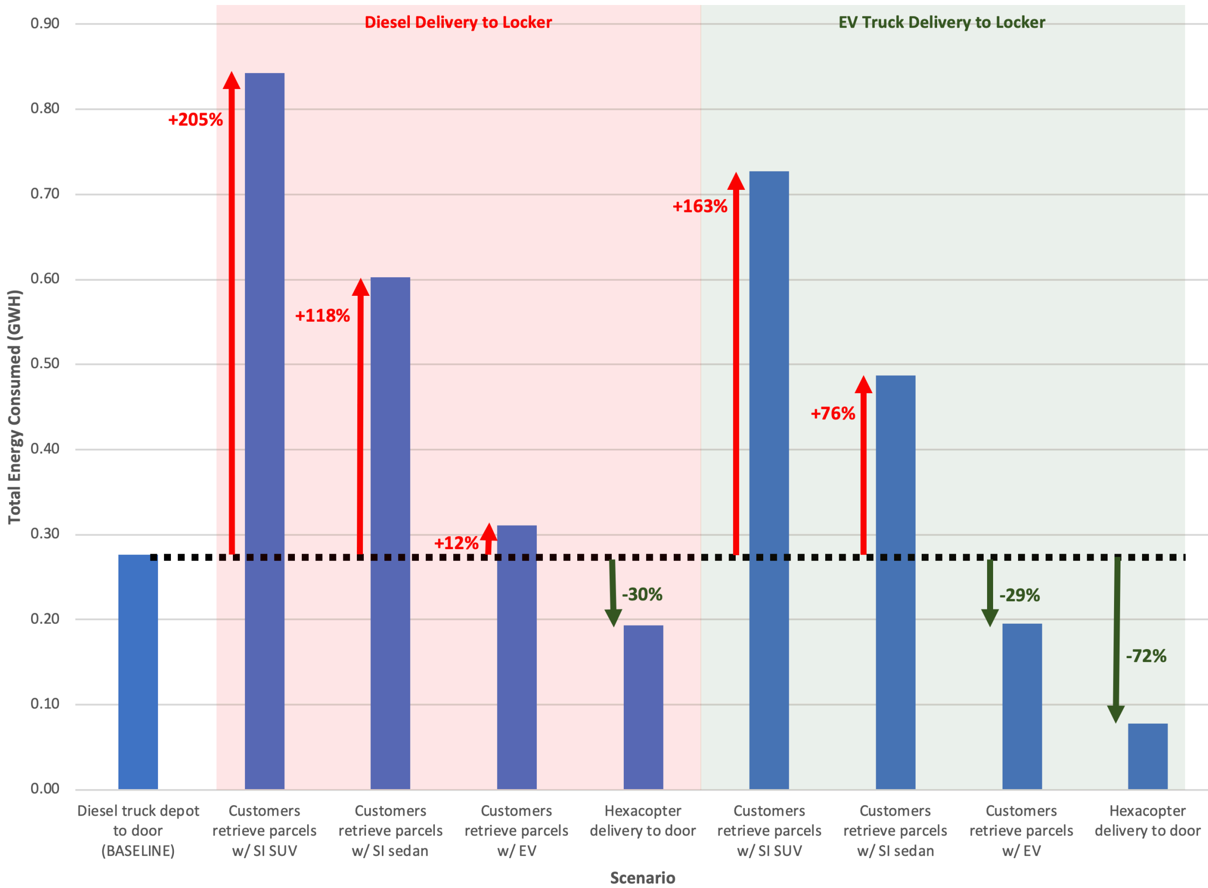
trucks, and the number of trucks in the platoon. Additionally, real-world operational constraints may limit the actual fuel savings of truck platooning.



- **Drones**. Experimental research determined that airborne drone energy consumption is comparable to light-duty electric vehicles and is very sensitive to payload, mission profiles, and operating conditions.
    - Although drones do not save energy on a payload-per-mile basis relative to land-based conventional modes, they may offer operational efficiency gains by reducing the total number of miles through straight-line delivery routing, and by eliminating traffic effects (delays due to signaling, congestion, accidents, remote parallel deployment, etc.).
    - Drone delivery provides operational flexibility, including time-critical parcel delivery.



- **E-commerce**
    - Although e-commerce is expected to generate a large increase in last-mile delivery, results from a case study in the greater Chicago metropolitan area indicate an overall net reduction in vehicle miles traveled (34%–56%) and energy use (29%–54%), because one additional delivery trip increases the truck route by an average of 0.4 miles, compared to an average 7–8 miles one-way for an individual's shopping trip. While this case study assumes a direct substitution of deliveries for shopping trips, consumer behavior studies done as part of the SMART Mobility WholeTraveler survey of the San Francisco Bay area suggest that a delivery replaces a household vehicle shopping trip approximately 50% of the time.
    - Research also shows that alternative delivery approaches, such as parcel lockers, have the potential for energy savings for parcel delivery fleets. However, the impact of implementing parcel lockers on the total energy use of parcel delivery strongly depends heavily on consumer transportation choice as shown in the graphic below.
        - The research shows interactions in which energy-savings implications for one group (fleets) can lead to possible energy increases for the transportation system overall.
        - Continued research and development of powertrain electrification and other vehicle efficiency technologies applicable to both passenger and commercial vehicles will maximize the benefits of these alternative goods delivery approaches.


Diesel Delivery to Locker
EV Truck Delivery to Locker
Total Energy Consumed (GWH)
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
+205%
+118%
+12%
-30%
+163%
+76%
-29%
-72%
Diesel truck depot to door (BASELINE)
Customers retrieve parcels w/ SI SUV
Customers retrieve parcels w/ SI sedan
Customers retrieve parcels w/ EV
Hexacopter delivery to door
Customers retrieve parcels w/ SI SUV
Customers retrieve parcels w/ SI sedan
Customers retrieve parcels w/ EV
Hexacopter delivery to door
Scenario

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1 Introduction

1.1 Overview

1.1.1 Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium

The US Department of Energy's (DOE) Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The SMART Mobility Consortium operates under the management of the Office for Energy Efficiency and Renewable Energy (EERE) and consists of five pillars of research:

- **Connected and automated vehicles (CAVs)**: Identifying the energy, technology, and usage implications of connectivity and automation and identifying efficient CAV solutions
- **Mobility decision science (MDS)**: Understanding the human role in the mobility system, including travel decision-making and technology adoption in the context of future mobility
- **Multimodal freight (MMF)**: Evaluating the evolution of freight movement and understanding the impacts of new modes for long-distance goods transport and last-mile package delivery
- **Urban science (US)**: Understanding the linkages between transportation networks and the built environment and identifying the potential to enhance access to economic opportunity
- **Advanced fueling infrastructure (AFI)**: Understanding the costs, benefits, and requirements for fueling/charging infrastructure to support future energy-efficient mobility systems

The SMART Mobility Consortium creates tools and generates knowledge about how future mobility systems may evolve and identifies ways to improve their mobility energy productivity. The consortium also identifies R&D gaps that the DOE Energy Efficient Mobility Systems Program may address through its advanced research portfolio and generates insights that will be shared with mobility stakeholders.

Unlike in the light-duty vehicle (LDV) transportation sector, significant optimization in the area of freight energy efficiency requires advancement in multiple vehicle types because freight movement is the combination and integration of complex operating and vehicle systems. The science of moving freight poses challenges beyond the typical personal usage of an LDV, with the complexity of the commercial motor vehicle space and the limited resources for R&D, given the multilayered structure of the commercial motor vehicle industry and large number of uses for each vehicle and/or powertrain architecture. A deeper understanding of the complexity in this transportation space allows for the research to go beyond the surface level benefit of reduced aerodynamic load from platooning two or more vehicles, to uncovering the impact of scheduling control of platooned vehicles or the vehicle-to-vehicle communications required to ensure safe operation in platooning mode. This understanding will contribute to improving freight mobility, which is an important factor in the nation's economy and quality of life.

1.1.2 Multimodal Freight Pillar

The objective of the MMF pillar is to assess the effectiveness of emerging freight movement technologies and understand the impacts of the growing trends in consumer spending and e-commerce on parcel movement with respect to mobility, energy, and productivity. To accomplish this objective, the MMF pillar has been divided into three distinct focus areas:

1. **Intracity last-mile delivery.** Last-mile freight delivery modes will impact infrastructure and energy demands, as well as fleet productivity. Alternative and disruptive delivery technologies have the potential to greatly improve mobility, productivity, and energy efficiency.

2. **Intercity freight movement.** Freight optimization techniques and shifts in delivery modes from region to region may significantly impact national-level energy use, infrastructure, and fleet logistics strategies.

3. **Regional transportation system impacts of freight (including long haul, last-mile delivery, and other regional freight movements).** The full picture of the energy and mobility impact of inter- and intracity freight movements must be understood. This picture also includes interactions with passenger movements using a fully integrated, data driven agent-based transportation system simulation.

1.2 Why is Multimodal Freight Important?

The importance of an efficient MMF system to the economic health of the United States is usually understated, and the complexity of the system is typically misunderstood. The scope of technologies required for efficient freight movement reaches from logistics to advanced powertrain technologies to CAVs to refueling/recharging infrastructure, and this list only covers direct on-road vehicle-related technologies. The MMF pillar uses large data sets and modeling tools to recognize trends, develop relationships and metrics to quantify energy use in this sector, and improve the process by which potential technology impacts can be more accurately predicted.

1.2.1 Significance of Freight in Energy

Typical reports of energy use in the transportation sector focus on the changes in LDV consumption and the future projected reduction in LDV energy use, even with increasing vehicle miles traveled (VMT). As shown in Figure 1, US transportation of freight by all modes consumed energy equivalent to 4.4 million barrels of oil per day (mbpd) in 2018 and accounted for 33% of total US transportation energy. The EIA projects this to grow to 4.7 mbpd and 39% by 2050 because of increases in economic productivity and efficiency gains in LDVs (EIA, 2019). Commercial trucks alone account for 24% of transportation sector energy use and are expected to account for 29% by 2050 (EIA, 2019). A portion of the freight energy use and associated emissions can be potentially reduced by vehicle electrification, connection and automation (e.g., platooning), and shifts to more efficient modes.

The monetary value of the total commodity flow from the Freight Analysis Framework Version 4 (FAF^4) is projected to grow dramatically from $17.7 trillion in 2012 to $37.0 trillion in 2045 (US DOT, 2018). As shown in Figure 2b, truck freight's share—which is the main focus of this study—in the total annual FAF commodity flow in tons is dominant in all years at nearly 64%. The monetary value of the FAF^4 commodity flow shipped by truck increases from $12.2 trillion in 2012 to $24.0 trillion in 2045. Based on these projections, truck freight will represent an increasing challenge to the nation from an energy perspective. Therefore, the MMF pillar focuses its research efforts to make the truck freight transportation system more efficient.

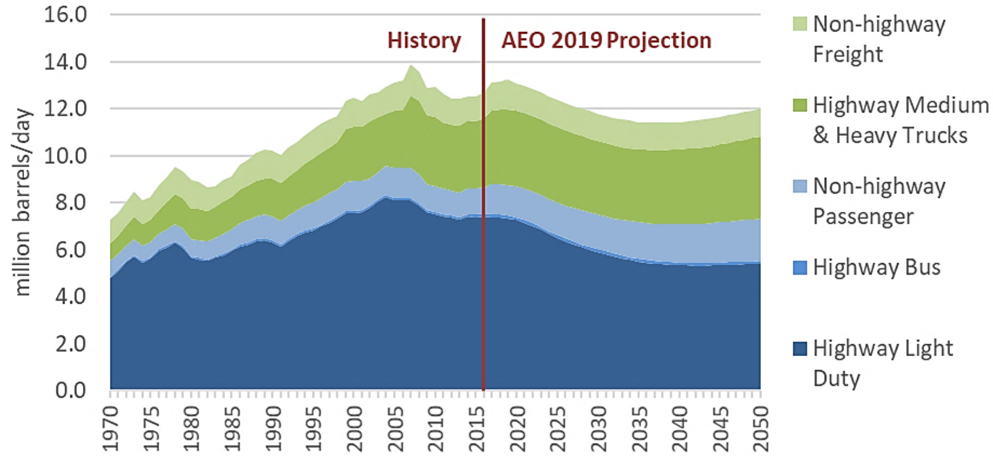


Figure 1. US transportation energy consumption. Light-duty includes cars and trucks under 10,000 lb gross vehicle weight rating and motorcycles. Medium and heavy trucks include all trucks over 10,000 lb gross vehicle weight rating. Non-highway modes include rail, air, water, and pipeline. Data sources: Davis & Boundy, 2019 (history), EIA, 2019 (projection).

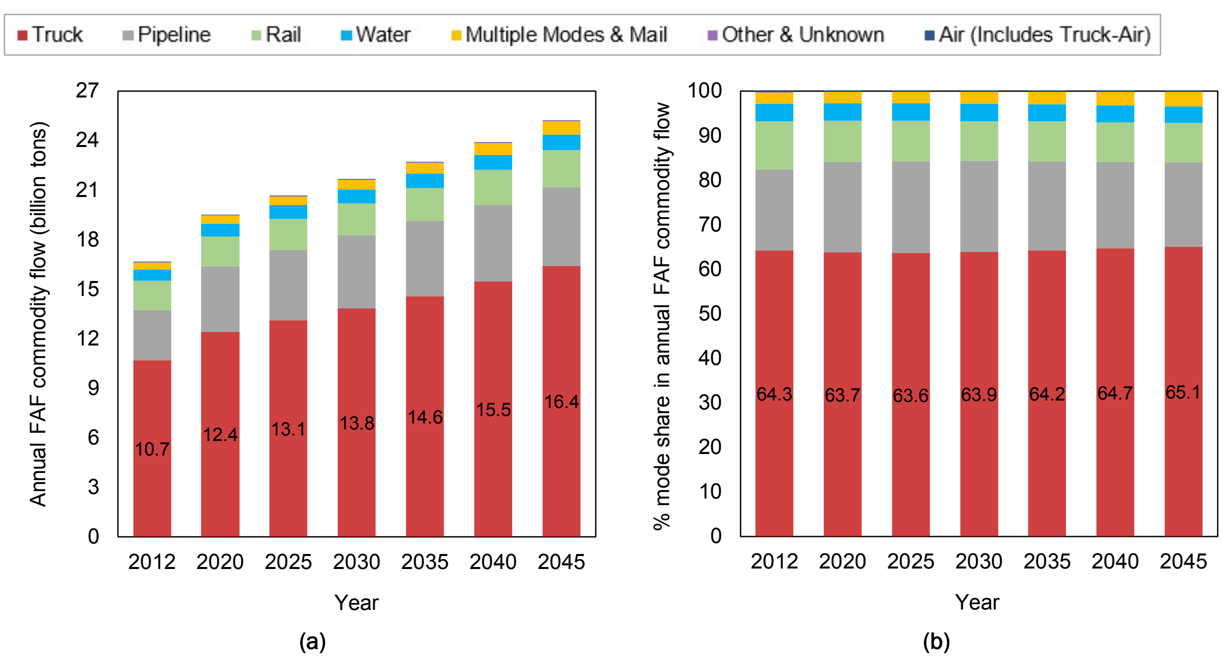


Figure 2. Share of (a) billion tons and (b) percent mode share in the annual Freight Analysis Framework (FAF) Version 4 commodity flow from 2012 to 2045.

1.2.2 Significance of Future Technology and Approaches

In the context of MMF system operation, the introduction and adoption of vehicle electrification technologies must be carefully planned and validated prior to deployment or policy implementation. Safety considerations, efficiency, reliability, vehicle availability, and capability combine to form a value equation to meet customer expectations. When compared with similar technologies deployed in the LDV industry, the technology cost offset was incentivized by government vehicle subsidies and infrastructure development to accelerate the adoption of LDV electrification. Currently, MD/HD fleets shoulder the burden of introducing and maintaining vehicle electrification and infrastructure in the MMF industry.

Full electric vehicle (EV) commercial vehicle requirements from infrastructure through energy storage systems (ESSs) and even tire construction/wear impact studies are absent for this segment of the transportation industry.

The development of high-power electrified driveline components suitable for use in MD/HD vehicles is a maturing technology, and high-energy grid distribution is a developing services space. Energy and power transfer providing fast reliable changing for commercial vehicles may have a grid impact similar to the projected autonomous vehicles impact on total LDV energy consumption, which could make heavy-duty EVs increase electrical energy use and raise general electricity cost, thus impacting LDV electrification adoption.

1.3 Scope for Multimodal Freight Pillar

1.3.1 Freight Issues and Technologies

The issues of freight mobility and the various technologies, which have applications to improve freight system productivity and reduce the energy consumption of the system, range from established transportation technologies from other sectors to undeveloped communications and autonomous/automated vehicle technologies. Vehicle electrification in the freight industry provides a viable path to substantially reduce energy consumption, but onboard energy storage and charging infrastructure costs could become significant. Alternative delivery modes, such as parcel lockers, can also provide gains in freight energy efficiency for the fleet operator but may have negative impacts on the transportation system when considering increased consumer trips and vehicle choice.

1.3.2 Freight Mobility Energy Productivity Metric

Since freight movement is vital to economic health and quality of life, it is important to understand the impact of emerging technologies and trends on the freight movement system's productivity. Productivity is generally defined as output (or benefit) per unit of input (or cost). Measuring system impacts with a productivity metric will help public and private stakeholders make informed decisions, depending on their objectives, regarding technology development and deployment, freight establishment location, transport mode selection, infrastructure planning and investment, and regional development. Consistent with the DOE mission[1], an effective metric measures freight mobility per unit of inputs, including economic cost, energy, and time (at a minimum).

Developing a holistic metric is challenging due to the complex nature of the freight and logistics system and a well-known lack of data and transparency. However, an extensive body of literature discusses performance measurement of freight transportation systems for application to regional planning, project development, and analysis; see, for example, (FHWA, 2017). While this literature provides a large set of potential performance measures, each of these measures is unidimensional and, in isolation, fails to reflect multidimensional goals or trade-offs among the measures. Although the literature also provides complex analysis methodologies to simultaneously consider multiple metrics, it does not provide a concise approach for combining them. Further, the literature does not consider energy productivity or provide an approach to analyze geographic variation.

This project introduces the freight mobility energy productivity (F-MEP) metric as a concise, scalable measure of system quality that is nationally generalizable, geographically based, and useful for assessing current systems as well as comparing regions and alternative future scenarios. Separate formulations were developed for inter- and intracity freight movement to account for differences in scale, scope, data availability, and system architecture.

[1] The mission of the Department of Energy is to ensure America's security and prosperity by addressing its energy, environmental and nuclear challenges through transformative science and technology solutions. The vision of the US DOE's Office of Energy Efficiency and Renewable Energy is a strong and prosperous America powered by clean, affordable, and secure energy.

1.4 Overall Research Questions

Because of the vast research scope in MMF optimization, the MMF pillar researchers focused on three specific aspects of freight mobility for this project. First, an intracity approach dealt with the movement of freight within a single metropolitan area (i.e., last-mile delivery) using new delivery technologies. Second, an intercity approach focused on city to city freight energy. Finally, regional impacts of freight (including long haul, last-mile delivery, and other regional freight movements) on the overall transportation system. This approach sought to answer the following research questions:

- What is the baseline for freight energy use (inter- and intracity) from a SMART Mobility perspective?
- How is MEP defined for freight, and what is the baseline F-MEP for a given region?
- How is F-MEP impacted by disruptive technologies such as
  - Platooning
  - Connectivity and automation
  - Electrification
  - Drones.
- What effect do/will e-commerce trends have on F-MEP from a "shopping to shipping" perspective?
  - Freight effects on congestion and overall traffic movement, especially considering some new delivery modes
  - Purchase behavior and shipping preference motivating new modes, and how to characterize shipping behavior based on consumer buying.

2 Research Findings

2.1 Intracity Last-Mile Parcel Delivery

2.1.1 Introduction

Increases in the volume of freight deliveries have been driven by a relatively recent shift in consumer preferences to purchase an increasing number of goods online rather than in physical stores. This shift is often referred to as "shopping to shipping," and it has the potential to impact the mobility, efficiency, and productivity of regional transportation systems regarding the last-mile portion of intracity deliveries.

The National Household Travel Survey reflected a doubling of the number of online shopping orders from 2009 to 2017, and the trend is expected to increase more rapidly in the future (McGuckin & Fucci, 2018). This trend toward online shopping is already visible for some consumer goods. For example, results from the WholeTraveler survey conducted as part of SMART Mobility indicate that there are as many deliveries of clothing items purchased online as there are shopping trips to retail locations to purchase clothing, as shown in Figure 3 (Spurlock, Todd-Blick, Wong-Parodi, & Walker, 2020). However, deliveries represent a much smaller portion of other types of purchased items, such as groceries and prepared meals.

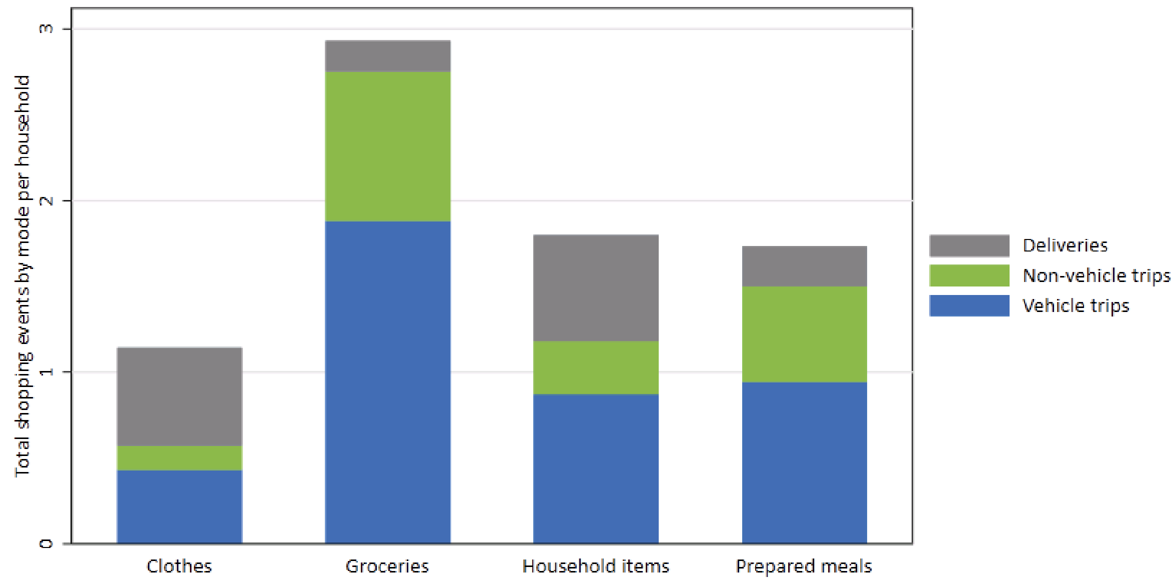


Figure 3. Shopping events per household in a typical week by vehicle, non-vehicle, or delivery. Source: WholeTraveler survey of San Francisco–area residents (N = 1012).

Although it is commonly assumed that an increase in the number of e-commerce deliveries will replace passenger vehicle trips, that is not always the case. The WholeTraveler survey for the San Francisco metropolitan statistical area (MSA) found that a delivery replaced a vehicle-based shopping trip approximately half of the time, while it either supplemented a shopping trip or replaced a non-vehicle shopping trip the other half of the time, as shown in Figure 4 (Spurlock, Todd-Blick, Wong-Parodi, & Walker, 2020).

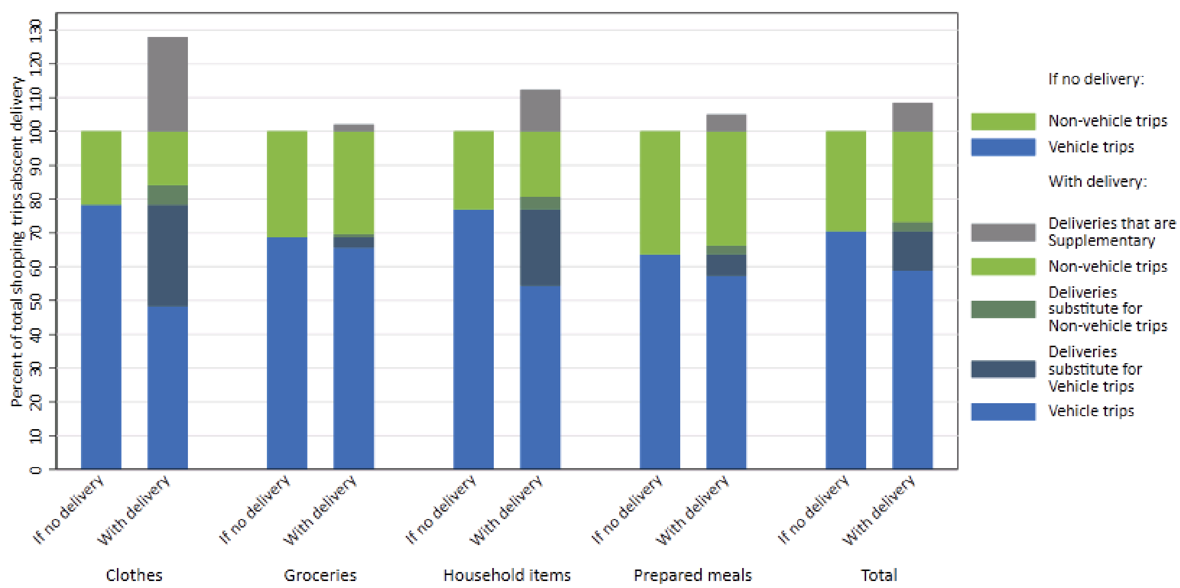


Figure 4. The overall degree of substitution and supplementation of delivery for household shopping trips in the WholeTraveler survey.

The complex relationship between e-commerce and passenger movement has implications for the freight sector, especially for local or last-mile delivery typically performed by medium-duty trucks or vans. This increase in delivery vehicles could lead to an increase in traffic on local roads, impacting congestion, especially in large metropolitan areas. It also has implications for parking and the use of curb space. More importantly, because these vehicles primarily rely upon the use of fossil fuels, depending on vehicle technology, passenger and commercial fleet composition, and packaging logistics there may be impacts to energy consumption and emissions.

Shippers and carriers alike are interested in finding new and improved ways to cut costs associated with moving freight, including saving time and resources. Although many companies have their own systems, including advanced optimization software, to help in the decision-making process, room for improvement always exists. Current research—such as the work being performed by the SMART Mobility Consortium, which examines innovative ways to move freight more efficiently—can help companies by providing a menu of potentially viable options for their consideration.

2.1.2 Objectives

Intracity last-mile delivery research primarily focuses on energy reduction strategies and technologies for moving freight within an urban context. Intracity freight is typically confined to the city limits or perimeter highway of an urban area and has many interactions that long-haul freight does not, such as

- Interactions with personal vehicles and transit, leading to increased urban congestion on secondary roadways
- Limited amount of available parking and curb space
- Complex and circuitous intracity freight routes
- Many stops and starts in large residential areas.

These scenarios present an opportunity for improving mobility, efficiency, and productivity, which is the primary focuses of this work. Thus, the MMF pillar researchers sought to explore options for reducing transportation-related energy usage involved in intracity last-mile parcel delivery through modeling, simulation, and testing.

Research is needed for intracity freight that takes a system-level approach, covering the many interactions within the entire transportation system, and addressing the future problems associated with a growing population and changing consumer demand. Research results can provide cost-savings benefits to the private sector, and can also be useful for public entities responsible for making decisions related to zoning; growth and development of business and residential areas; transportation and infrastructure planning; and linking all the systems together in a way that both maximizes the utility for residents and respects the environment.

2.1.3 Approach

2.1.3.1 *How research questions were addressed*

This research focused on the microscale, with efforts concentrating on two MSAs: Columbus, Ohio and Chicago, Illinois. Columbus was initially chosen because it received the US Department of Transportation (DOT) SMART City Challenge and the Vulcan grant, and Chicago was chosen because of ongoing development of POLARIS, the agent-based model developed by Argonne National Laboratory using Chicago as one of the first modeling areas. Although this particular research focused on localized, intracity freight, the findings were integrated with intercity (region to region, or long-haul) freight into the SMART Mobility workflow to understand the large-scale MSA-wide effects on the overall transportation network. The work evaluated the potential energy and mobility impacts to intracity freight movement by the introduction of new delivery modes (in this case, drones, parcel lockers, electrification, small vehicle fleets, and ground-based delivery robots) and through the incorporation of innovative multimodal, last-mile configurations to meet increasing freight demand brought about by rising e-commerce trends. This work considered current technology and did not consider any future improvements in energy efficiency of modes in this analysis.

The approach to answering these various research questions involved several high-level steps:

1. Investigation of the detailed energy use of different modes, and methods of introducing these modes, to evaluate the energy-, time-, and cost-saving potential of these new modes
2. Consideration of the demand and applicability of these new delivery technologies, including coordination with industry to investigate how to approach the current problems and assess the baseline needs
3. Estimation of energy usage for the baseline and new technologies during microscale simulations to better understand small-scale impacts
4. Investigation of system-level impacts by
    a. Estimating overall existing and projected parcel delivery demand for Chicago
    b. Understanding existing and projected fleet ownership size at major parcel distribution hubs
    c. Modeling projected delivery routes based on results from POLARIS
    d. Evaluating energy and mobility impacts by incorporating the scenarios tested in the microscale simulations.

2.1.3.2 *Scenarios*

Alternative delivery modes such as drones, EVs, and delivery robots are changing how people and goods move within the transportation network, and further evaluation of these modes will identify the extent of the changes. A series of scenarios for this research explored energy profiles of different modes and the impacts that these modes have on the existing transportation system. To conduct this research, the MMF pillar researchers collaborated with industry partners to better understand delivery demand, as well as the applicability of new modes to meet current and future demand. Researchers modeled these new modes and technologies within different contexts and made certain assumptions during the development of these scenarios.

To evaluate the energy-saving potential of new delivery modes, the assumption was made that currently, the status quo for intracity freight delivery is by truck, which means that the majority of parcels are brought into distribution centers by Class 8 trucks, and deliveries are made to homes and businesses by smaller trucks, such as Class 6. After the decision that trucks would be used for the baseline cases, scenarios using new modes needed to be chosen to compare energy usage estimates. These scenarios would be modeled to represent tours, which represent the path a vehicle makes from an origin to a series of temporary destinations and back to the origin. Traffic analysis zone (TAZ)–level data, common in transportation modeling, was used for the modeling. Table 1 describes the scenarios analyzed for the preliminary study of Columbus, Ohio. Table 2 outlines the scenarios addressed for the full analysis of the Chicago MSA. In both cities, standard and EV Class 6 trucks were evaluated, along with EV vans and sedans, parcel lockers, and hexacopter drones. The study in Chicago included additional scenarios involving another drone model (quadcopter), delivery robots, and multiple types of passenger vehicles to expand upon the scenario involving customer retrieval of parcels from lockers.

Table 1. Scenarios for preliminary study of Columbus, Ohio.

ID	Scenario
Baseline	Class 6 Truck: Depot to door
Alt1	Class 6 EV: Depot to door
Alt2	Class 6 Truck: Depot to store; EV van to door
Alt3	Class 6 Truck: Depot to store; EV car to door
Alt4	Class 6 Truck: Depot to lockers
Alt5	Class 6 EV: Depot to lockers
Alt6	Class 6 Truck: Depot to lockers; drone to door

EV = electric vehicle

Table 2. Scenarios for full study of Chicago, Illinois.

ID	Scenario
Baseline	Diesel truck depot to door
Alt 1	EV truck depot to door
Alt 2	EV vans depot to door
Alt 3	Diesel truck to lockers; quadcopter locker to door
Alt 4	EV truck to lockers; quadcopter locker to door
Alt 5	Diesel truck to lockers; hexacopter locker to door
Alt 6	EV truck to lockers; hexacopter locker to door
Alt 7	Diesel truck to lockers; bot to door
Alt 8	EV truck to lockers; bot to door
Alt 9	Diesel truck to lockers; customers retrieve parcels
Alt 10	EV truck to lockers; customers retrieve parcels
Alt 11	Diesel truck to lockers; customers drive Toyota Camry to retrieve parcels
Alt 12	Diesel truck to lockers; customers drive Ford Explorer to retrieve parcels
Alt 13	Diesel truck to lockers; customers drive Nissan Leaf to retrieve parcels
Alt 14	EV truck to lockers; customers drive Toyota Camry to retrieve parcels
Alt 15	EV truck to lockers; customers drive Ford Explorer to retrieve parcels
Alt 16	EV truck to lockers; customers drive Nissan Leaf to retrieve parcels

EV = electric vehicle

2.1.3.3 *Scenario critical assumptions*

In general, the baseline and alternative scenarios were modeled in three tour configurations:

1. A tour from the depot to an urban TAZ located near the city center (this location was chosen because it was located in a densely developed urban area), returning to the depot

2. A full tour from the depot, making all stops within multiple TAZs, returning to the depot

3. A tour from the depot to a suburban TAZ with estimated delivery stops (based on estimations obtained from a freight delivery demand estimation model), returning to the depot.

The researchers chose these three configurations to evaluate the energy-saving potential for the different locations within the study area, which varied in street network configuration and density, level of connectivity, and distance from the depot. The following summary describes the high-level assumptions for each data set and city.

Columbus, Ohio

- United Parcel Service (UPS) depots: 1
- Trucks in the sample: 20
- Average daily mileage per vehicle: 30 mi
- Average number of stops per vehicle tour: 120
- Average daily number of deliveries for sample fleet: 2,400.

Chicago, Illinois

- UPS
    - Depots in the entire Chicago MSA: 13; service areas: 13
    - Average fleet size per depot: 75 trucks
    - Average daily mileage per vehicle: 66 mi (tour size is 120 stops per vehicle; depot–stops–depot)
    - Number of e-commerce deliveries per day: 117,711 (based on percentage of e-commerce shopping, market shares, and estimates from delivery demand estimation model and POLARIS).
- Federal Express (FedEx):
    - Depots in the entire Chicago MSA: 10; service areas: 10
    - Average fleet size per depot: 55 trucks
    - Average daily mileage per vehicle: 67 mi (tour size is 120 stops per vehicle; depot-stops-depot)
    - Number of e-commerce deliveries per day: 66,408 (based on percentage of e-commerce shopping, market shares, and estimates from delivery demand estimation model and POLARIS).

2.1.3.4 *Modeling approach adopted/tools developed*

For Columbus, Ohio, truck delivery tours were modeled using actual GPS traces from the Columbus UPS depot fleet. These data, which were processed to obtain stopping locations based primarily on timestamps and engine speed, were used along with socioeconomic data from the Mid-Ohio Regional Planning Commission to develop a freight delivery demand estimation model for freight deliveries as a function of the number of households, office jobs, retail jobs, and other jobs within a TAZ. Establishing this model was necessary to estimate average daily numbers of UPS parcel deliveries per TAZ in the Columbus MSA. Once these estimates were obtained, three TAZs were chosen from the study area to be used as preliminary case studies and subjected to the six alternative scenarios outlined in Table 1. For the final Columbus results, overall estimates were obtained for the UPS fleet covering the entire Columbus MSA.

For Chicago, Illinois, UPS GPS data were not available. However, the freight delivery demand estimation model developed in Columbus was applied and UPS delivery estimates per TAZ were obtained for the Chicago MSA. As with Columbus, three TAZs were chosen as case studies and subjected to the 17 scenarios outlined in Table 2.

In the final results for Chicago, daily average fleet-wide energy estimates were obtained for the entire Chicago MSA for both UPS and FedEx, using estimates and current market shares for the two companies.

2.1.3.5 *Data collected*

For this research, GPS data for a representative subset of UPS Class 6 delivery fleet from the Columbus, Ohio UPS depot were obtained by National Renewable Energy Laboratory (NREL). These data were used to develop the freight delivery demand estimation model used in both Columbus and Chicago. To gain an understanding of the energy consumption rates of typical drones, experimental testing of quadcopter and hexacopter drones was performed at Idaho National Laboratory. The testing was conducted in a variety of climates, altitudes, and elevations, at various speeds and payloads, while considering varying atmospheric conditions. NREL's FleetDNA MD/HD database and the DOE's FuelEconomy.gov (maintained by Oak Ridge National Laboratory) were the sources for average energy consumption estimates for standard modes (trucks, vans, passenger vehicles, and so on), as shown in Table 3.

Table 3. Energy use (kWh/mi) for each scenario.

ID	Scenario	Energy Intensity (kWh/mi)
Baseline	Diesel truck depot to door	4.29
Alt 1	EV truck depot to door	1
Alt 2	EV vans depot to door	0.56
Alt 4	Diesel truck to lockers; quadcopter locker to door	0.1
Alt 5	EV truck to lockers; quadcopter locker to door	0.1
Alt 6	Diesel truck to lockers; hexacopter locker to door	0.22
Alt 7	EV truck to lockers; hexacopter locker to door	0.22
Alt 8	Diesel truck to lockers; bot to door	2
Alt 9	EV truck to lockers; bot to door	2
Alt 10	Diesel truck to lockers; customers retrieve parcels	4.29
Alt 11	EV truck to lockers; customers retrieve parcels	1
Alt 12	Diesel truck to lockers; customers drive sedan to retrieve parcels	0.96
Alt 13	Diesel truck to lockers; customers drive SUV to retrieve parcels	1.47
Alt 14	Diesel truck to lockers; customers drive EV to retrieve parcels	0.34
Alt 15	EV truck to lockers; customers drive sedan to retrieve parcels	0.96
Alt 16	EV truck to lockers; customers drive SUV to retrieve parcels	1.47
Alt 17	EV truck to lockers; customers drive EV to retrieve parcels	0.34

SUV = sports utility vehicle; EV = electric vehicle

2.1.4 Results/Findings

2.1.4.1 *Drone energy consumption*

To understand the relative energy needs for drone delivery, the research team selected and tested a typical delivery drone system—a hexacopter drone with varying payloads that would represent different sizes of packages. During testing, detailed data logs on each of the drones recorded the energy consumption during flight. To better characterize each element of the flight and understand the impacts of different variables, the tests were repeated in different settings considering different variables. Each test was performed without a payload, and then tested with payloads of 5, 10, and 15 lb. The tests were performed in a high-altitude, low-temperature setting, as well as a low-altitude, high-temperature setting. An additional set of tests was performed at a high-altitude, high-temperature setting, in which the drone was connected to external, calibrated instruments to help refine the energy modeling and confirm the log measurements.

One set of tests involved recording energy use while the hexacopter was ascending, hovering, and descending with each of the different payloads. The results showed that the energy used during different elements of the flights did not vary as significantly, so an average value energy value was used across the entire flight test. Figure 5 shows that the energy usage increased significantly as payload increased. Each additional 5 lb of payload increased the energy draw by approximately 30% across all tests. The results also show that higher ambient temperatures also increased energy use significantly, and seemed to have a greater impact than the altitude differences.

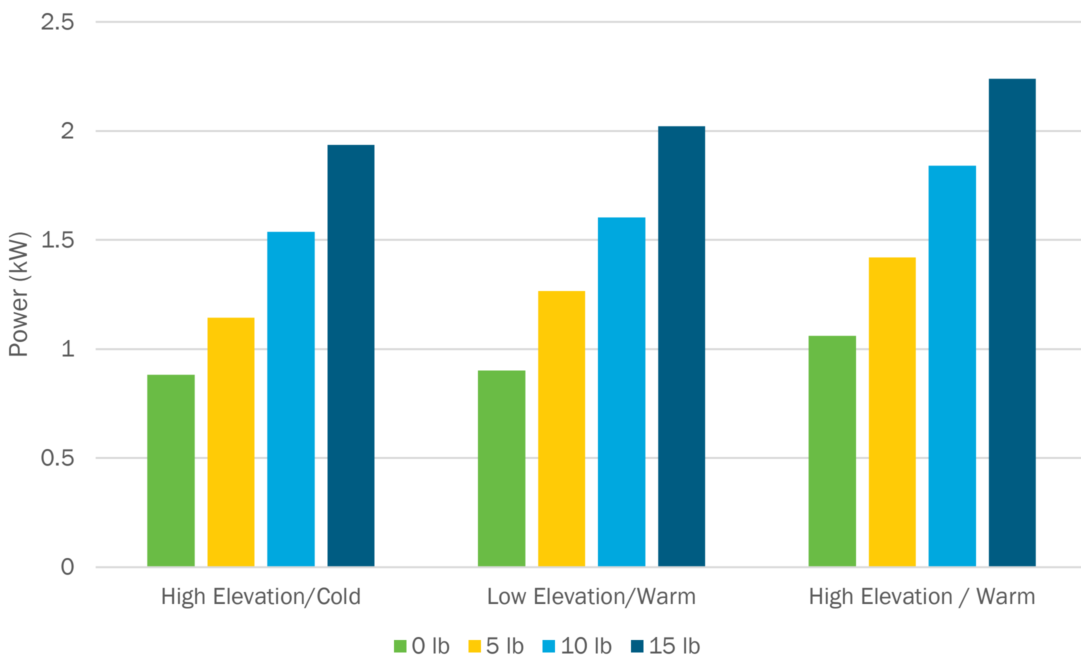


Figure 5. Average drone energy use for a 1-mi trip by payload at varying altitudes and temperature. Higher payload and higher temperature significantly increased energy use.

Further, to truly estimate the practical energy use of drones, the MMF pillar researchers also completed tests involving a 1-mi delivery route which included 6 turns with the drone flying at 30 mph and at 100 ft for each payload. This type of operation could simulate a typical delivery route over the road network. During these tests, total energy usage was again evaluated using the logs and divided into ascent, flight period, and descent. The energy use was again found to be relatively consistent across the entire flight. As shown in Figure 6, the total energy to complete the 1-mi route at larger payloads was significant. Figure 6 also shows a comparison of energy estimates per mile for an electric passenger car, which has a much higher carrying capacity than a drone. At higher weights, a drone carrying a single package consumes more than half the average energy of a passenger car. Additionally, drone tests at 17 mph showed even more energy consumed, as the drone was in the air longer.

The significant energy needs of the drone compared with ground vehicles are due primarily to the basic operating characteristics. The drone must continuously use energy to remain in flight and combat gravity, and it must move both vertically as well as translationally, whereas the passenger car only consumes appreciable energy when it is under powered driving modes.

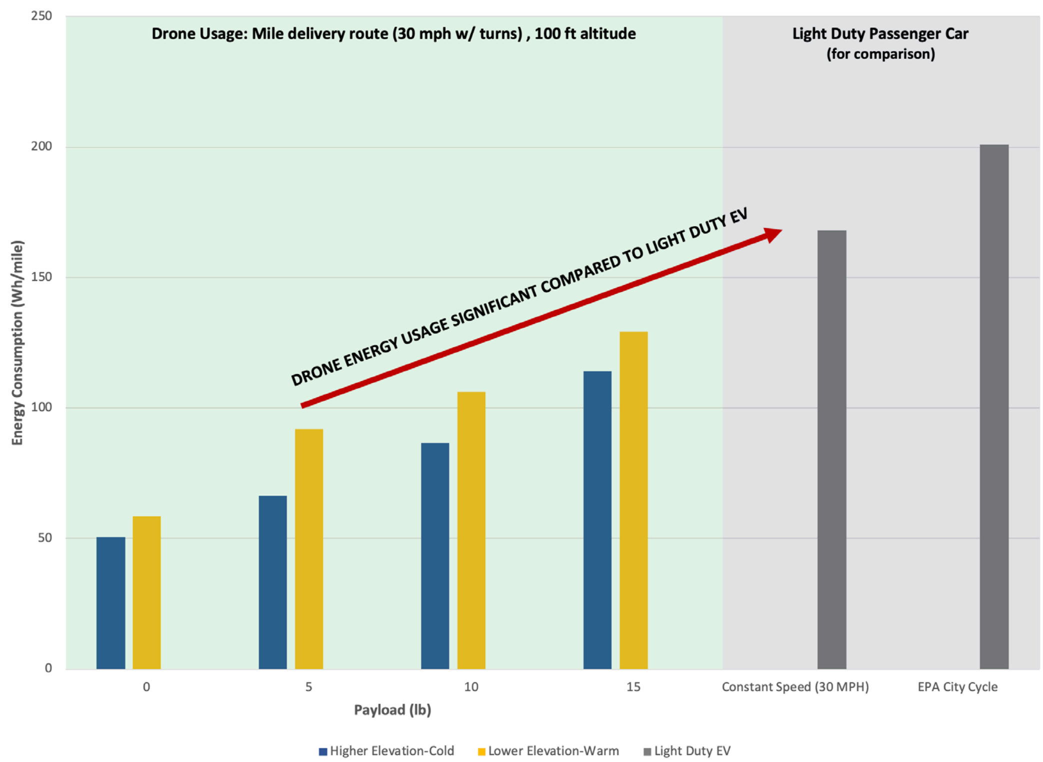


Figure 6. Experimental drone energy consumption results for a 1-mi route indicates significant energy use compared with electric vehicle (EV) passenger cars.

The researchers' findings indicate that drones are not as efficient as EV cars for moving multiple goods. However, there are advantages in which drones will likely be effective. They use less energy for delivering light, single packages. In this context, drones have the potential to use less energy and move faster than vehicles in urban areas by avoiding the congestion of road traffic. Drones may also be useful in reducing costs of personnel for business and provide some fast deliveries. However, the researchers' findings have indicated that how drones are used, and their operating profiles, can have significant energy and cost impacts and that many elements need to be considered by drone operators for deliveries.

2.1.4.2 *Results for Columbus, Ohio*

2.1.4.2.1 **Freight delivery demand estimation model**

The GPS data sample available to the team was relatively small and only covered a portion of the city of Columbus and surrounding Franklin County, Ohio. Therefore, the research team created an estimation model to generate additional scenarios for areas of Columbus and Franklin County where data were lacking.

A simple multiple linear regression model was created using delivery stop counts per TAZ as the dependent variable. The model further assumed that TAZs with higher populations (more residents and more employees), more jobs (all categories), and proximity to areas of interest such as the Ohio State University, the Central Business District (CBD), local parcel delivery distribution stores, and I-270, would likely be explanatory variables for the model. Socioeconomic data per TAZ (income, age, school enrollment, and so on) were obtained from the Mid-Ohio Regional Planning Commission, along with data regarding employment by business type. Locational and proximity variables were also developed in the Geographic Information System GIS. Based on the resulting model (Eq. 1), the researchers found that the number of households and employment in various sectors appeared to be appropriate indicators of delivery demand within Columbus TAZs.

Once the estimation model was developed, estimated delivery stop counts were obtained for TAZs where GPS data were lacking, as depicted in Figure 7. These results, along with the assumed delivery counts from the GPS data, provided counts for all TAZs within Franklin County. These counts were the basis for developing the alternative scenarios to model in the GIS.

$$\hat{Y} = 16.325 + .039\beta 1 + .041\beta 2 + .179\beta 3 + .033\beta 4 \quad (1)$$

$\hat{Y}$ = Estimated number of deliveries per TAZ for July 2017
$\beta 1$ = Total number of households per TAZ
$\beta 2$ = Total number of office jobs per TAZ
$\beta 3$ = Total number of retail jobs per TAZ
$\beta 4$ = Total number of other jobs per TAZ

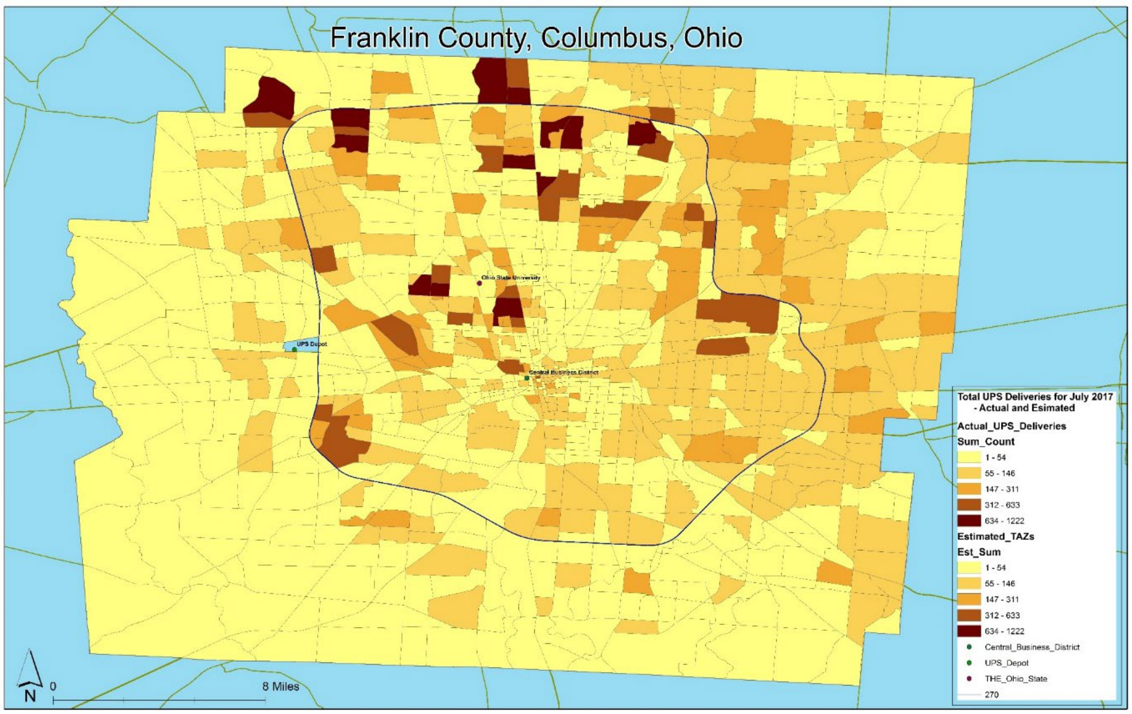


Figure 7. Traffic analysis zone (TAZ)–level delivery estimates for Columbus, Ohio.

2.1.4.2.2 **Scenario results**

Initially, three case studies were modeled using the six scenarios developed: an urban TAZ, a complete tour involving multiple TAZs, and a suburban TAZ. This setup was initially made to better examine locational attributes inherent to different areas within Columbus. After the three case studies were examined in-depth, a final model was developed, which considered energy use involved in completion of all tours made by the sample fleet.

The initial tour configuration involving the use of an urban TAZ for Columbus, Ohio was considered, although it did not represent the energy usage involved in completion of a full vehicle tour. However, it did represent the potential reduction in energy usage made by incorporating fully electric Class 6 trucks in delivery routes where the majority of the truck's mileage is within the distance from the depot to the TAZ. Because the TAZ chosen for the configuration was in a densely developed area, the majority of mileage was in the stem (depot to TAZ) rather than in the distance traversed during deliveries. The results also suggest that incorporating the use of parcel lockers only resulted in a minimal reduction in energy usage, which was also likely due to the TAZ being in a densely developed location where there was connectivity within the street network. The researchers found that the overall distance traveled by the truck was not significantly reduced by incorporating a parcel locker. The placement of parcel lockers in relation to the depots becomes critical with respect to full tour energy usage since the length of the stem portion of the tour can dominate delivery vehicle VMT.

The full tour results from the preliminary analysis of Columbus, Ohio are shown in Figure 8. The results from the model using the full tour are such that scenario Alt5, using the fully electric Class 6 truck, making deliveries to an optimal or centralized parcel locker location, required significantly lower energy usage than any of the other scenarios. Both scenarios involving the use of the fully electric Class 6 truck resulted in substantially lower energy usage, which is not surprising, considering that the kilowatt per hour per mile (kWh/mi) estimates are approximately 1 kWh/mi, compared with approximately 4.3 kWh/mi for the baseline case.

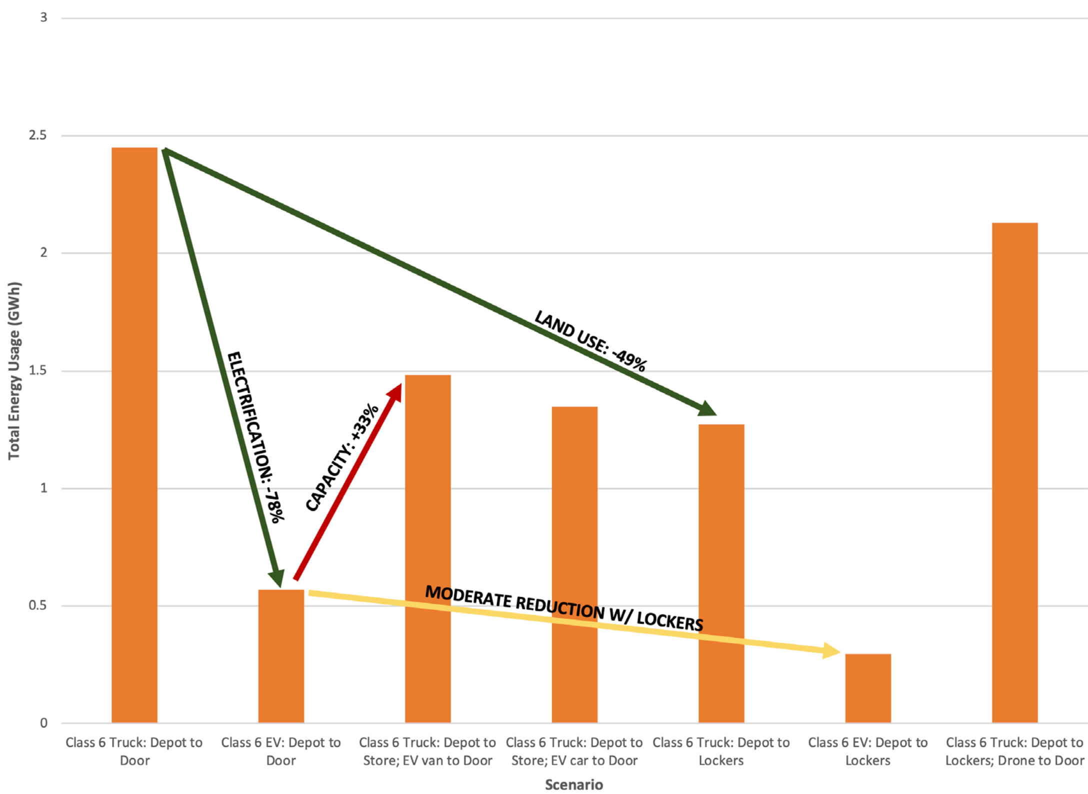


Figure 8. Energy usage per mode for full tour scenario.

The two scenarios incorporating the use of the fully electric delivery van and the electric passenger vehicle were similar in energy usage estimates since both vehicle types have similar energy consumption characteristics. However, although each of these delivery vehicles had substantially lower energy consumption characteristics compared with the larger Class 6 EV, they suffered from a corresponding loss of capacity. Therefore, more of these vehicles were required to make the same number of deliveries that a smaller Class 6 EV fleet could accomplish.

Finally, the energy usage estimates for scenario Alt6, using drones to make all deliveries, were unsurprisingly the second highest estimate of all the scenarios. These results were based on the bookend drone usage scenario, which required the drone to make single deliveries (origin to destination) while carrying a single parcel, rather than making multiple deliveries before returning to the delivery truck (which could either be at the origin location or en-route to the final delivery location). An example of this scenario is depicted in Figure 9. A more efficient use of drones would result in lower energy estimates. The energy estimate was also solely based on one drone model.

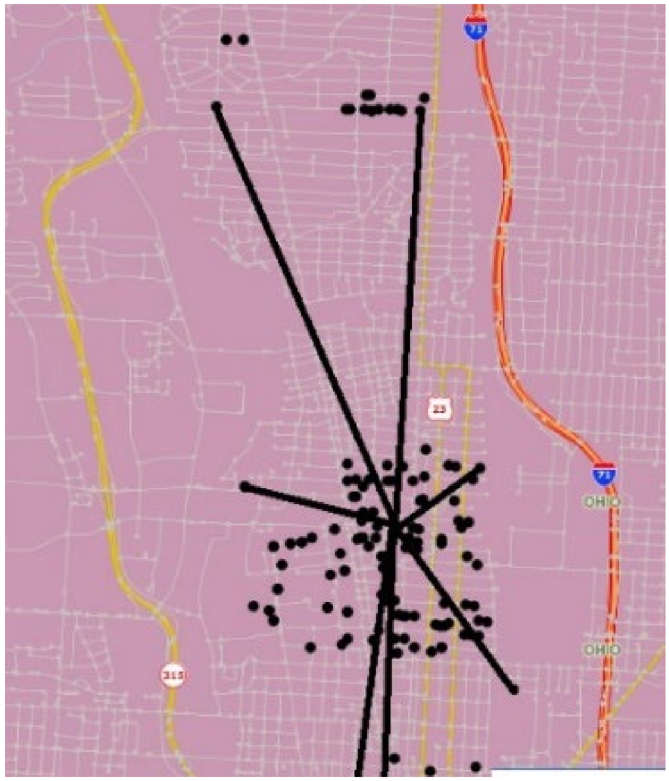


Figure 9. Example of drone delivery scenario (single-parcel delivery).

The results from the model using the configuration with the suburban TAZ, as with the urban TAZ, do not necessarily represent the energy usage involved in completing a full tour. However, they do represent the potential reduction in energy usage by incorporating the use of fully electric Class 6 trucks in delivery routes where the majority of mileage is in the stem portion. Also, they demonstrate the potential reduction in energy usage by incorporating the use of parcel lockers, primarily because of a different approach to land use in suburban areas, which typically contain subdivisions with cul-de-sacs and fewer through-streets. The placement of parcel lockers at the entrance to a subdivision increases operational efficiency since the delivery truck avoids the need to turn around in the cul-de-sacs, which ultimately reduces the overall VMT of the tour. By combining the usage of fully electric Class 6 trucks with parcel lockers, the potential exists to further reduce energy usage in suburban locations.

In the final Columbus model, energy estimates for the UPS fleet were estimated for the entire Columbus MSA. The results from the final model were in line with those found in the case studies. The results suggest that electrification will reduce energy usage, which is attributed to the longer stem portions of the Columbus tours. Additionally, electrification coupled with land use changes (parcel lockers) resulted in the greatest reduction in energy usage compared with the baseline. However, modes to lockers were not considered and will need to be considered in the future. The slight reduction in energy usage from the baseline in the drone scenarios is likely attributed to the lower density and less demand found in Columbus vs. larger, denser urban areas such as Chicago.

The two key outcomes of the Columbus research are the (1) development of a freight estimation model that can be further generalized to other areas (e.g., Chicago), and (2) understanding that truck electrification and storage lockers can reduce energy use in intracity delivery. These two key findings were crucial in the next phase of the study involving Chicago.

2.1.4.3 *Results for Chicago, Illinois*

2.1.4.3.1 **Freight delivery demand estimation model**

The initial modeling work performed in Chicago used a UPS freight delivery demand estimation model and census-level data from the Chicago Metropolitan Agency for Planning (CMAP) to estimate UPS parcel deliveries in the Chicago MSA at the TAZ level (destinations) as shown in Eq. 2. This modeling was done to provide an initial estimate of parcel deliveries for use in the POLARIS model for Chicago. Since only UPS data were considered for the modeling work performed in Columbus, only UPS data were considered in the initial modeling work performed in Chicago. Because of a lack of GPS data for the Chicago MSA, the Columbus delivery demand estimation model was adjusted to represent delivery demand for Chicago using data obtained from the CMAP as shown in Figure 10.

$$\hat{Y} = 24.2276 + .043127\beta 1 + .028473\beta 2 + .179\beta 3 \quad (2)$$

$\hat{Y}$ = Estimated number of household and business deliveries per TAZ

$\beta 1$ = Total number of households per TAZ

$\beta 2$ = Total number of retail jobs per TAZ

$\beta 3$ = Total number of all jobs per TAZ (including office, service, and others)

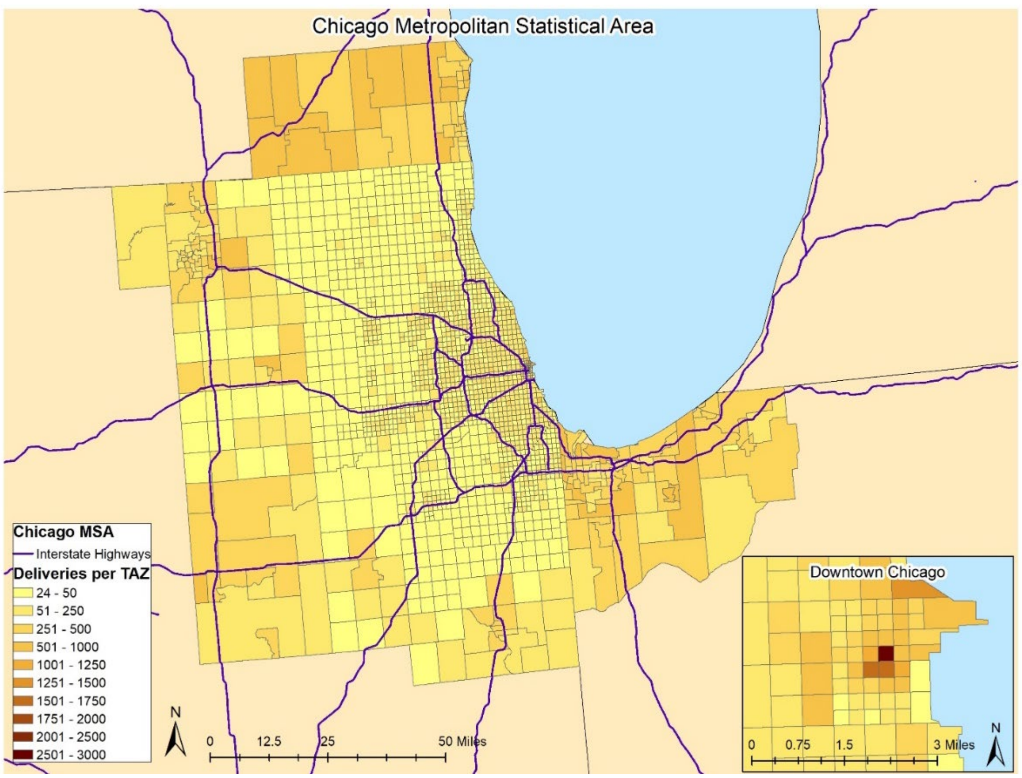


Figure 10. Traffic analysis zone (TAZ)–level delivery estimates for Chicago, Illinois.

Once UPS delivery estimates for residences and businesses were established for all TAZs within the Chicago MSA, all UPS depots and stores were located throughout the region. These locations were necessary for scenario development and to provide origin-destination (OD) pairs to Argonne National Laboratory to be used as input for POLARIS to represent displaced passenger vehicle shopping trips.

2.1.4.3.2 **Scenario results**

The final model for Chicago provided fleet-level average daily energy estimates for both UPS and FedEx. Five-day average total shopping estimates per TAZ were obtained from POLARIS. These estimates were then altered to only include the current percentage of shopping through e-commerce to capture parcel delivery. Current market shares for UPS and FedEx were obtained and applied to the estimates. Using these estimates, delivery locations were estimated, and fleet-level energy usage was estimated for the baseline and the 17 alternative scenarios.

Figure 11 shows the effect of alternative technologies on the average daily fleet-wide energy usage for Chicago from a fleet operator perspective. The impact of electrification of the existing Class 6 fleet was substantial as shown by a 77% reduction in energy used. The result agrees with what was found in the Columbus study in this report. However, the effect of land use (parcel lockers, in this case) was much more pronounced for the Chicago study than for the preliminary Columbus analysis.

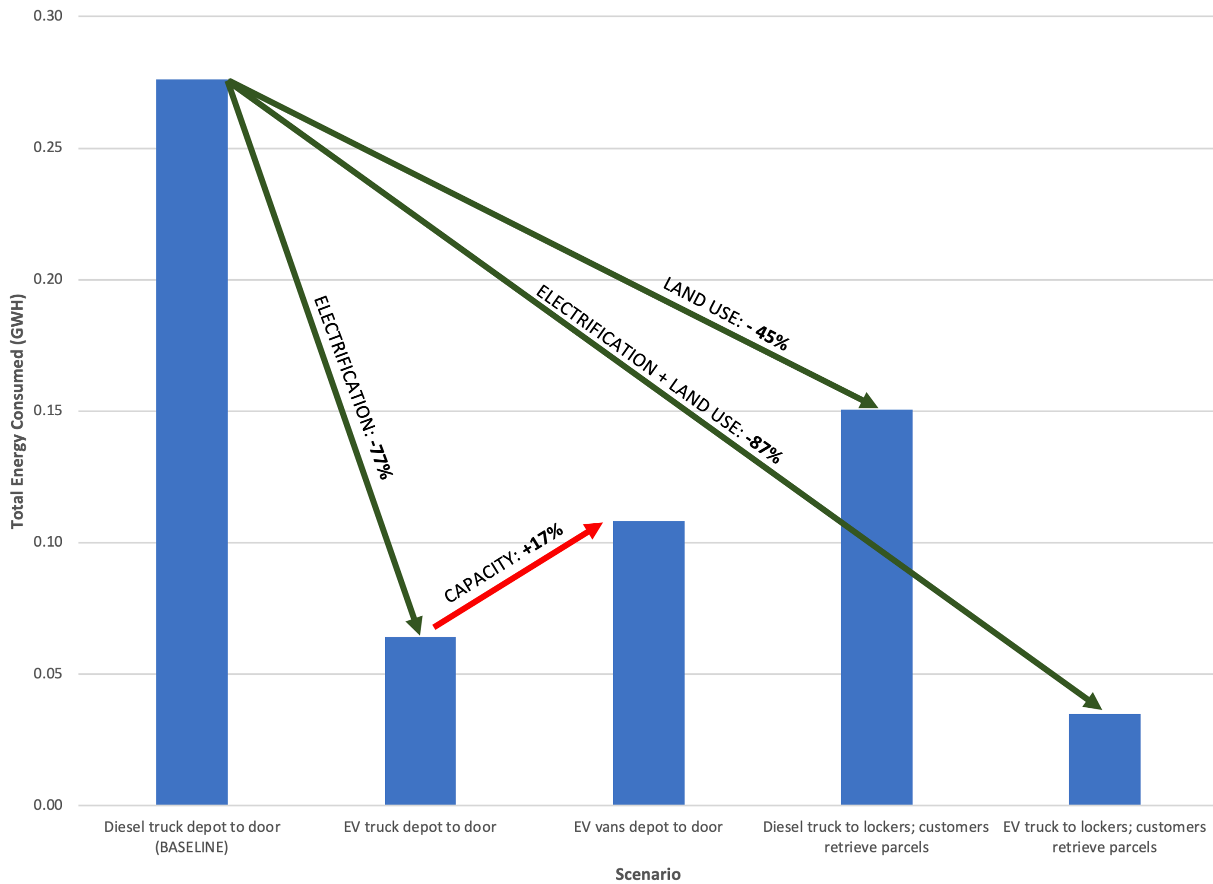


Figure 11. Effect of alternative technologies on average daily fleet-wide energy usage for Chicago, Illinois.

In this case, retaining the conventional fleet of diesel trucks and moving to a more aggregated delivery system substantially reduced energy usage. However, the full economics of electrification and land use were not studied. For electrification, further work must be done to fully understand the impact of fleet vehicle electrification (conversion or outright purchase), and the associated charging infrastructure requirements for the fleet. At the same time, the siting, permitting, and construction of parcel lockers need a deeper study to understand the true business case and a better comparison with the electrification case. However, electrification and land use can evidently substantially reduce the overall energy usage for the fleet operator. The scenario in which smaller electrified vehicles (vans) were used in place of the Class 6 vehicles is notable. While overall net energy usage was reduced from the baseline, a 17% increase in energy existed from the Class 6 EV case. Even though the energy consumption rate was much lower for the EV vans, more physical vehicles were required to meet the delivery demands of the Chicago area. Therefore, capacity was a detriment in this case, and vehicle energy consumption rates must not be studied alone when considering fleet composition and mission.

Figure 12 represents a graphical summary of the total energy usage for a full tour considering delivery to parcel lockers and consumer pick up from the parcel locker back to their homes. This study was meant to be an extreme case and did not consider combined trips (picking up a parcel from the lockers on the way to another destination). Additionally, the study broke out various modes for passenger movement and did not consider an integrated fleet composition of sedans, sport utility vehicles (SUVs), and battery EVs (BEVs). The researchers showed that parcel lockers can potentially substantially reduce energy usage for the delivery fleet. However, Figure 12 reveals a few key takeaways:

1. Conventional means of personal transportation (gasoline sedans and SUVs) have the potential to significantly raise the total energy usage per tour by as much as 76–205%. Each scenario in the figure assumes a 100% penetration of the passenger movement mode. However, even a more representative mix would significantly increase energy usage over the baseline. The increase in SUV sales and the proclivity of automakers to produce more SUVs and less sedans will exacerbate the problem.

2. An increase in market penetration of passenger BEVs and parcel lockers will have a positive effect on delivered goods because of e-commerce by reducing energy usage by as much as 29% compared with the baseline. Further analysis should be conducted to understand the necessary passenger fleet composition and/or minimum market penetration of BEVs required to reduce the overall energy consumption per tour.

3. Delivery of goods from the parcel lockers to a consumer's final destination by drone can have a profound impact on energy reduction by as much as 72%. This finding is quite different from the Columbus case studies. Of course, a more realistic mix of delivery vehicle and drone usage should be investigated, but the potential is evident under the right conditions.

4. Finally, an important finding is that while delivery vehicle electrification reduced the operating costs for a fleet operator, the net result of parcel lockers and delivery vehicle electrification for a full tour considering consumer pick up was not as momentous. This result is due to the substantial reduction in energy usage for the delivery vehicle (electrified or not) when moving to the parcel locker approach as depicted in Figure 11. Here, the delivery to the parcel locker represents a very small percentage of the overall energy consumed for the entire tour and is dwarfed by the consumer pick-up energy required.

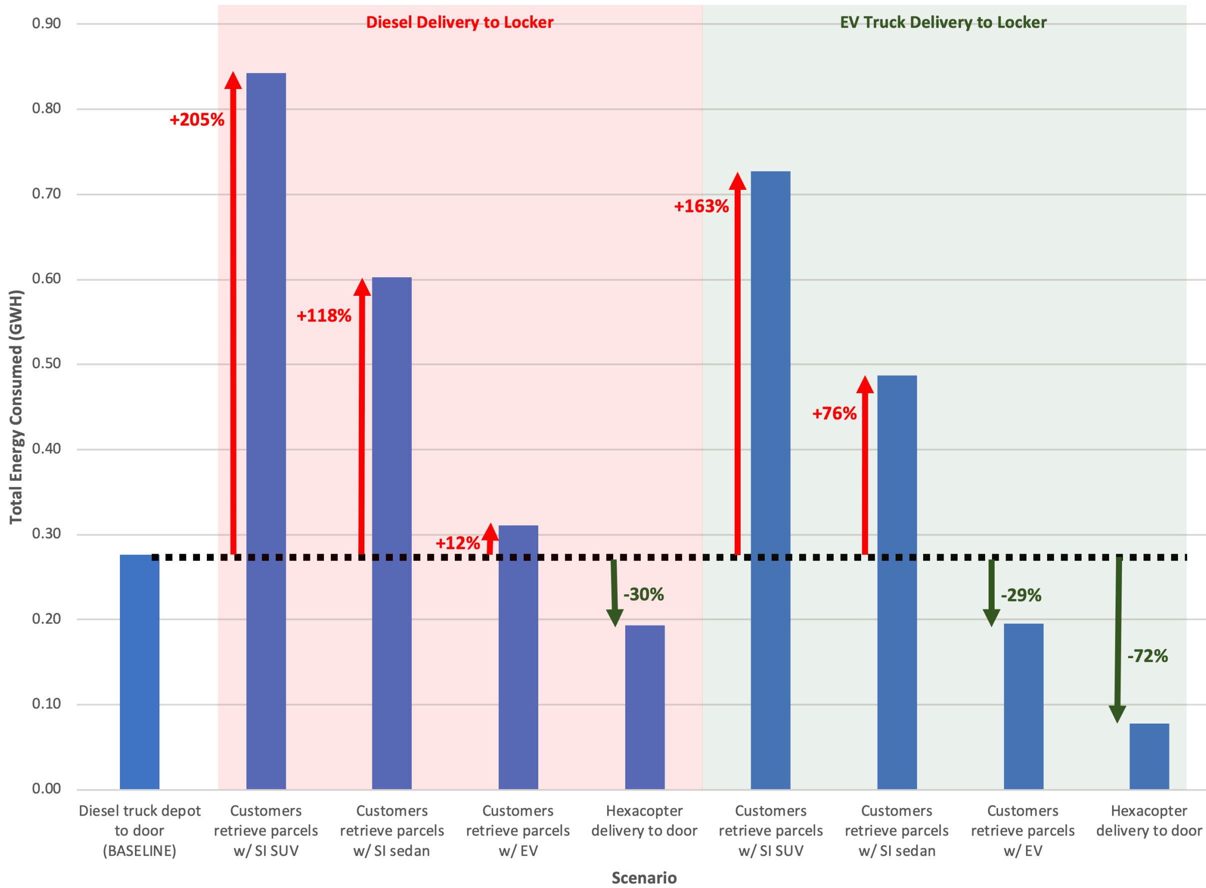


Figure 12. Effect of parcel lockers on total energy usage for Chicago, Illinois.

2.2 Intercity Freight Movement

2.2.1 Introduction

As noted in Section 1.2.1, US transportation of freight by all modes consumed energy equivalent to 4.4 mbpd in 2018 and accounted for 33% of total US transportation energy. The EIA projects this consumption to grow to 4.7 mbpd and 39% by 2050 because of increases in economic productivity and efficiency gains in other LDVs (EIA, 2019).

Per ton-mile, road transportation is the second most energy-intensive mode for freight transportation after aviation, while water and rail are the least, as shown in Figure 13. Total freight energy use can potentially be reduced by applying emerging technologies and optimizing freight movement through mode shifting. However, new technologies and trends also present possible challenges to improving freight efficiency. For example, improved logistical efficiency and associated cost reductions in trucking could shift freight movement away from more efficient modes, resulting in an increase in total energy consumption.

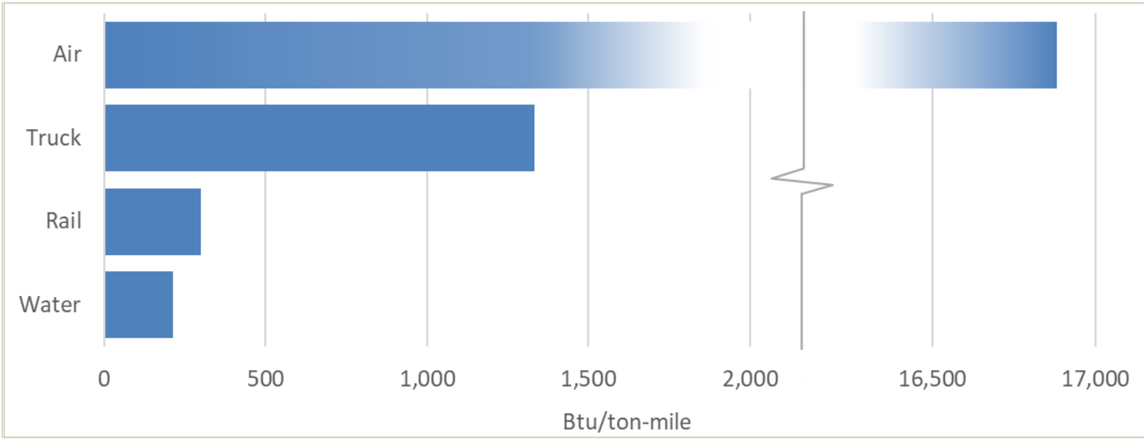


Figure 13. Estimated energy intensity of freight modes. Data sources: Davis & Boundy (2019), US DOT (2018), US Census Bureau (2004).

2.2.2 Objectives

The objectives of the intercity freight analysis were to

- Analyze energy reduction opportunities and challenges provided by new technologies and services in intercity freight movement
- Create tools and methods that can be applied to other research questions and other geographic areas
- Establish repeatable methods for quantifying energy impacts of new technologies to enable efficient goods movement for intercity freight

The emerging technologies and trends in freight analyzed in this study can be categorized into three main groups: emerging vehicle technologies, connectivity and efficient logistics, and e-commerce increases. The MMF pillar researchers addressed the research questions through analysis of freight data from FAF, development of analysis methodologies to estimate freight movement on highway and rail transportation networks, and development and application of models. The intercity freight analyses addressed the upper bound of potential impacts of technologies in stand-alone scenarios as described in Section 2.2.3. The Appendix provides a detailed description of the models used.

The remainder of this section provides background on technologies that were selected for analysis, describes the scenarios and approach used for analysis, and presents a summary of analysis results. The analysis included three specific technologies that impact intercity freight: vehicle electrification, platooning, and load-pooling, the latter two being connectivity and efficient logistics technologies.

2.2.3 Electrification

Freight truck electrification provides opportunities to reduce highway energy consumption and emission of both criteria pollutants and greenhouse gases (GHGs). Full electrification efforts have focused mostly on applications with duty cycles that involve low speed, stop-and-go operation, and low daily range, such as urban delivery and drayage. Heavier and longer-haul market segments are technically more challenging, requiring higher energy per mile and total energy storage. Battery cost is the largest contributor to the relative cost of an electric truck compared with a conventional diesel truck, and the high battery weight required for these long ranges may displace payload capacity. However, recent improvements in the cost and power density of batteries have raised the possibility that battery electric powertrains may become viable and cost-effective for longer-distance heavy-duty freight movement (US DOE, 2019). To accommodate these higher demands, several manufacturers are now developing battery electric Class 8 tractors with 300- and 500-mi range goals, while one manufacturer is developing a hydrogen fuel cell range extender with a 500- to 750-mi range.

Commercial vehicle purchases are highly cost-driven, with the overall price of running and maintaining a fleet the deciding factor in truck choice. Higher unit costs may be offset by a lower total cost of ownership, providing opportunities for more energy-efficient technologies. However, even with the relatively low price claimed by some manufacturers, electric combination trucks are still much more expensive than diesel counterparts in the United States (Burnham, n.d.). Additionally, federal rules limit Class 8 truck gross weight to 40 tons. Considering the weight of the battery pack, researchers estimate that a 600 mi-ready truck could carry only 9 tons of cargo, or two-thirds of the current average payload of 16 tons, and only 40% of the maximum possible payload of around 22 tons (Sripad & Viswanathan, 2017). Lower operating cost and fuel savings may not compensate for this major disadvantage. Alternatively, lighter, lower-capacity batteries may be combined with fast, high-power charging to accommodate electrification of long-haul trucking, but this solution presents additional challenges in infrastructure development, grid integration, power demand, and electricity demand charges.

2.2.3.1 *Scenario definition*

In early analysis in FY 2018, the researchers assumed the electric ranges of future medium-duty (Class 3–6) and heavy-duty (Class 7–8) BEV trucks of 300 and 500 mi as announced by several manufacturers. Using a "top-down" approach, two scenarios were defined assuming technology adoption sufficient to cover all freight movement below each of these daily trip distances. Subsequent analysis expanded the technology suite and refined technology assumptions using vehicle simulations performed for DOE Vehicle Technologies Office (VTO) benefits analysis, which considers the impact of DOE research program goals. Table 4 summarizes the resulting vehicle characteristics, assuming US Environmental Protection Agency (EPA) fuel consumption regulatory drive cycles. This study focused on the energy impact of Class 7–8 electric trucks for long-haul freight movement in the future, and assumed that, because of continued R&D success, there is no reduction in payload capacity due to batteries required for 300- or 500-mi BEV trucks.

Table 4. Assumed electrified powertrain characteristics.

	Diesel		HEV			PHEV					BEV			
	Cost	MPGd	Cost	MPGd	Batt. (kWh)	Cost	CS MPGd	CD MPGe	CD Range (mi.)	Batt. (kWh)	Cost	MPGe	CD Range (mi.)	Batt. (kWh)
Sleeper tractor														
2025	$163,900	7.89	$177,500	9.03	3.7	$306,300	7.60	19.51	265	665	$434,200	17.14	452	1,296
2050	$175,100	8.96	$195,500	11.33	3.8	$211,900	10.29	23.04	274	643	$237,000	20.31	469	1,037
Day cab tractor														
2025	$156,000	7.12	$166,800	8.33	3.5	$226,800	7.19	18.52	136	343	$280,500	17.18	242	661
2050	$163,700	7.96	$185,200	10.21	3.6	$182,900	9.56	21.55	140	276	$185,600	19.96	249	532
Single-unit														
2025	$152,100	7.97	$162,700	9.67	5.8	$209,000	9.27	23.75	151	255	$247,800	22.67	292	490
2050	$151,000	9.27	$166,700	12.57	6.6	$174,200	12.83	29.39	162	219	$173,600	28.22	317	420

HEV = hybrid electric vehicle; PHEV = plug-in hybrid electric vehicle; BEV = battery electric vehicle; CS = charge sustaining; CD = charge depleting; MPGd = miles per gallon of diesel; MPGe = miles per gallon diesel equivalent of electricity

To estimate the upper bound of potential impacts of electrification, the later analysis (FY 2019) applied optimistic assumptions for vehicle adoption as summarized below:

- Fuel prices: $3.14/gal diesel and 10.3¢/kWh electricity in 2025 and 2050
- Daily range and maximum annual mileage limited assuming 24-h operation and average speed calculated from EPA regulatory cycles

- Charge power of 600 kW in 2025 and 800–1,000 kW (plug-in hybrid EV [PHEV] and BEV) in 2050
- 7% annual discount rate for future fuel expenditures and savings
- 100% willingness to adopt a technology if the net present value (NPV) of vehicle incremental cost and fuel cost savings reaches zero within 4 years
- If multiple technologies pay back within 4 years, the one with the smallest lifetime NPV (total cost + fuel cost) is adopted
- Sleeper tractor life: 7 years; day cab tractor and single-unit (SU) truck life: 10 years.

2.2.3.2 *Modeling approach*

The first electrification analysis (FY 2018) applied a top-down approach by estimating the number of trucks required to fully electrify freight within the limits of current product development. Freight movement for 2045 was classified into shipping distance ranges to determine how much could be electrified, based on published goals for vehicle ranges. The analysis estimated the percentage of truck ton-miles that could be electrified based on an average length of haul between 123 domestic FAF zones in the United States. For example, if the average length of haul between given zones is lower than 500 mi, those commodity flows could be moved by a 500-mi Class 7–8 electric truck without on-route charging.

The MMF pillar researchers then estimated the number of Class 7–8 electric trucks needed in 2045 to fulfill the projected freight movement, in ton-miles, assuming trucks with 300- or 500-mi electric ranges. The team extended the projections to 2050 assuming no changes in electric truck stock share from 2045 to 2050. From the number of electric trucks on the road, the team back-calculated the required electric truck sales between 2017 and 2045 using a logit function. The study assumed that an electric truck will have the same survival rate as its diesel counterparts in the future (Zhou, 2018a). The analysis estimated the number of trucks required for two cases defined based on truck payload (cargo tonnage per truck) and an average annual truck usage of 60,000 mi. The "high" scenario, representing a higher estimate of the number of trucks required, assumed an average truck load of 16 tons, whereas the "low" scenario assumed a truck load of 22 tons, with an assumption of higher truck payload resulting in fewer trucks required to move the projected freight demand.

With stock, annual mileage and energy consumption per mile per truck, the team estimated the petroleum consumption and electricity consumption using Argonne National Laboratory's VISION and NEAT models and compared the estimated petroleum and electricity consumption with projections made by the EIA (EIA, 2019).

The second electrification analysis (FY 2019) applied a different set of assumptions and methodology. This analysis applied vehicle performance characteristics arising from VTO R&D targets and estimated potential vehicle adoption rates based on payback period and NPV of purchase and operating costs. To estimate the upper bound of potential impacts of electrification, the following optimistic assumptions were used to calculate technology adoption based on vehicle mileage:

- Maximum daily range and annual mileage were determined assuming 24-h operation and average speed calculated from EPA regulator cycles as well as fast charging
- Charge power of 600 kW in 2025 and 800–1,000 kW (PHEV and BEV) in 2050
- 100% willingness to adopt a technology if break-even is achieved within 4 years, considering only vehicle and fuel costs on a NPV basis with a 7% discount rate
- If multiple technologies pay back within 4 years, the one with the lowest lifetime cost is adopted
- Sleeper tractor life: 7 years; day cab tractor and SU truck life: 10 years.

Using Vehicle Inventory Use Survey (VIUS) 2002 data, the new truck market was segmented by vehicle type (sleeper tractors, day cab tractors, and SU trucks), primary trip distance, and annual mileage (US Census Bureau, 2004).[2] To estimate national impacts, aggregate new fleet powertrain shares and fuel economy were used to project vehicle stock, fuel economy, and fuel use (diesel and electricity) assuming the same survival rates and average annual mileage for all powertrains. The new fleet fuel economy and levelized per-mile costs within trip-distance bins were also used as inputs to the multimodal intercity freight energy model to estimate the impact on intercity freight energy for Chicago.

2.2.3.3 *Results*

As shown in Table 5, the FAF[4] projects that a total of 32% and 48% of freight ton-miles in 2045 will have an average length of haul less than 300 and 500 mi, respectively, and could be electrified with vehicles currently under development. Depending on assumptions for truck average payload, 17–24% of the Class 7–8 truck stock would need to be battery electric to fully electrify all freight movement under 500 mi, whereas 11–15% would be needed to fully electrify only freight movement under 300 mi. These results, summarized in Table 6, are assumed to apply from 2045 through 2050 and used to determine sales shares required to achieve this fraction of the in-use fleet by 2050. The researchers estimated that electric trucks with a 500-mi electric range could potentially reduce Class 7–8 petroleum consumption by 40%, or 1.61 quads, in 2050, while electricity consumption increases by 0.99 quads, relative to the EIA Annual Energy Outlook (AEO) 2017 reference case as shown in Figure 14 and Table 7. Similarly, assuming 300-mi electric range BEVs (case 2) shows that Class 7–8 petroleum consumption would decrease by 28%, or 1.14 quads, in 2050, whereas electricity consumption would increase by 0.69 quads.

Table 5. US truck freight movement by average length of haul in 2045 (domestic).

Length of haul (mile)	Total weight (million tons)	Total ton-miles (millions)	Total value (billion 2012 $)	% of ton-miles
<300	11,752	809,400	9,704	31.7%
300–500	1,131	416,428	2,065	16.3%
500–1,000	902	621,348	2,358	24.4%
1,000–2,000	342	457,339	1,469	17.9%
>2,000	100	244,922	627	9.6%
Total	14,226	2,549,438	16,223	100%

Source: Freight Analysis Framework Version 4. Estimates represent total truck freight moved on all road types.

[2] While VIUS 2002 is unquestionably out of date, it represents the most recent, nationally representative information on US truck operations by vehicle type, particularly VMT and trip distance.

Table 6. FY 2018 analysis: electric Class 7–8 truck stock share needed in 2045.

		Case 1: 300-mi Class 7–8 Truck		Case 2: 500-mi Class 7–8 Truck	
		High	Low	High	Low
Total ton-miles (million)	2,549,438				
% ton-miles could be electrified		31.7%		48%	
Electric trucks needed		843,125	613,182	1,304,405	948,658
Total Class 7–8 truck stock	5,472,842				
% stock share		15.4%	11.2%	23.8%	17.3%

“High” scenario assumed a 16-ton average payload; “low” scenario assumed a 22-ton average payload. Estimated stock shares are assumed to apply from 2045 through 2050.

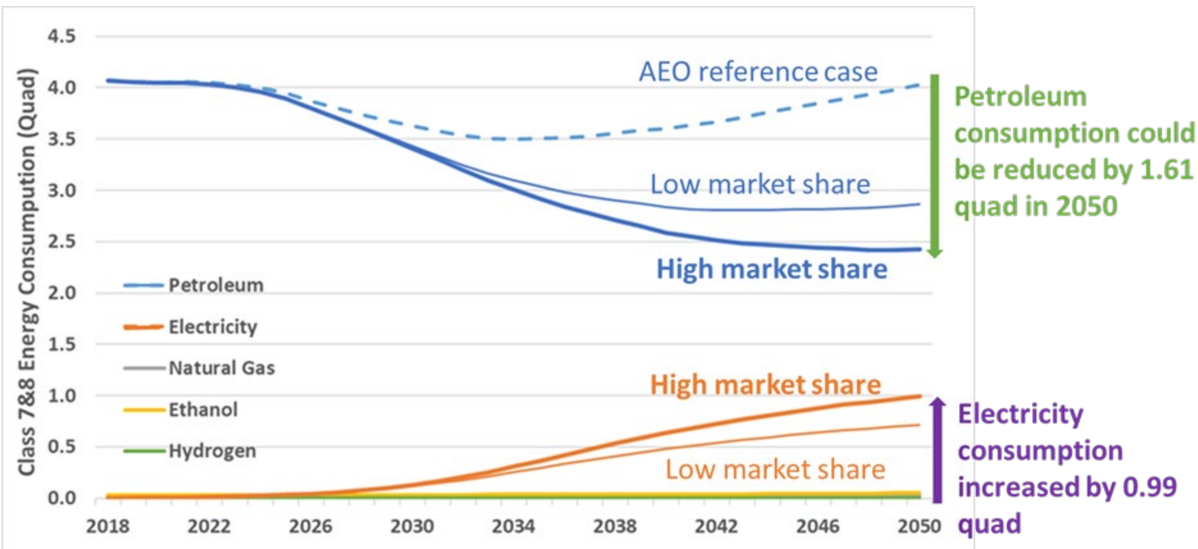


Figure 14. FY 2018 electrification analysis—energy impact of full electrification of Class 7–8 freight under 500 mi.

Table 7. 2050 results for FY 2018 analysis: full electrification scenarios.

Freight electrified	Technology case	Energy reduction (quads)	Petroleum reduction (quads)	Increase in electricity (quads)
Under 300 mi	BEV 300	0.5 (11%)	1.1 (28%)	0.7
Under 500 mi	BEV 500	0.6 (15%)	1.6 (40%)	1.0

BEV = battery electric vehicle. Changes are relative to the AEO 2017 reference case. Percentages are relative to Class 7–8 total. Electricity consumption by Class 7–8 in the AEO reference case was less than 0.005 quads.

The second analysis expanded the technology options to include hybrid and plug-in hybrid powertrains with the characteristics shown in Table 4. This study estimated that tractor market share for electrified Class 7–8 tractors could optimistically reach 82% of tractors and 31% of SU trucks (Figure 15). PHEVs were adopted over full battery electric trucks because of their smaller and cheaper batteries coupled with optimistic assumptions about full charging availability and 24-h operation. This adoption allowed electrification in all freight shipment distance bins, though no segment was fully electrified. Total estimated energy reduction was higher than the first analysis of 0.99 quads in 2050, but petroleum reduction was smaller at 1.4 quads.

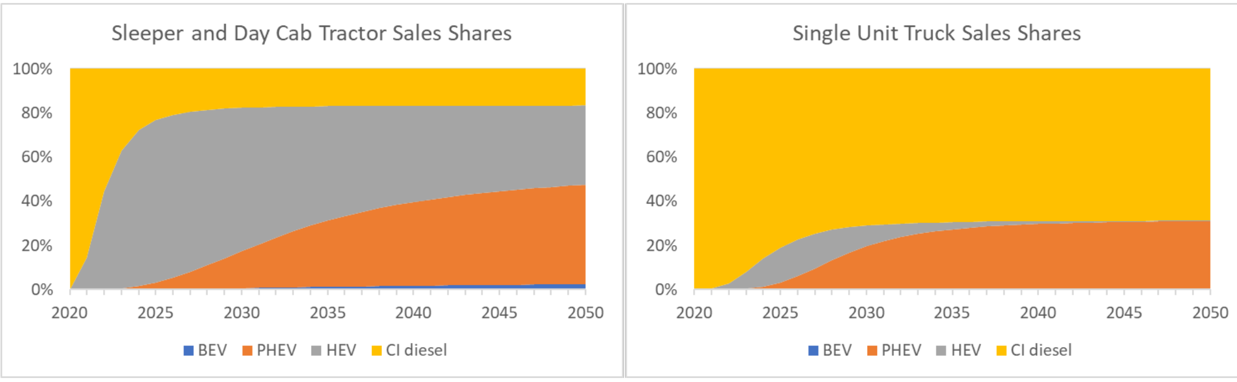


Figure 15. Projected adoption of electrified Class 7–8 trucks.

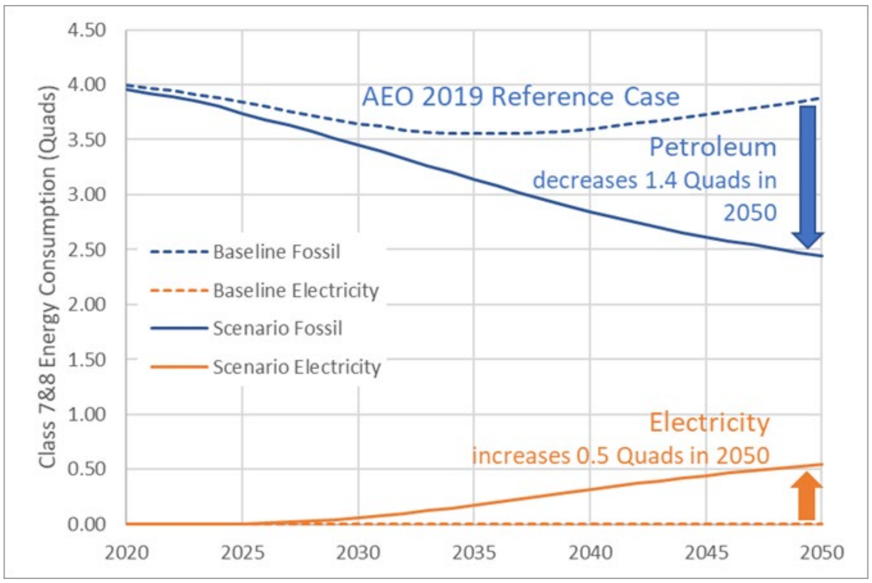


Figure 16. FY 2019 electrification analysis: energy impact of electrification of Class 7–8 trucks including hybrids and adoption potential.

Table 8. Results of FY 2019 electrification analysis including hybrids and adoption potential for 2050.

Freight electrified	Energy reduction (quads)	Petroleum reduction (quads)	Increase in electricity (quads)
Tractors	0.85	1.34	0.50
Single-unit	0.04	0.09	0.04
Total	0.89 (23%)	1.43 (39%)	0.54

Changes are relative to AEO 2019 reference case. Percentages are relative to Class 7–8 total. Electricity consumption by Class 7–8 in the AEO reference case was less than 0.005 quads.

Figure 17 shows the powertrain adoption within primary trip distance bins. Based on payback period and NPV, plug-in hybrid trucks were the primary solution for trips under 200 mi. For SU trucks, BEVs were only adopted in the 200–500 mi trip bin; their 250 mi range limitation prevents adoption for longer trip distance and higher payback periods prevent adoption in shorter distance usage. Meanwhile, tractors in this range also adopted PHEVs, which were assumed to have longer all-electric range than the SU trucks. While HEVs were attractive in 2025, they lost share to plug-in powertrains in 2050 as battery cost reductions decreased the payback time. However, HEVs remained viable in the 500+ mi range since it was assumed that BEVs must be capable of completing a trip without recharging. In general, electrified powertrain adoption was lowest for trucks whose primary trip distance was under 50 mi. Most of these trucks did not have sufficient annual usage for electrified powertrains to pay back within the assumed 4-year requirement.

In summary, using the vehicle characteristics shown in Table 4, PHEVs provided cost-effective fuel cost savings for both tractors and SU trucks in which trip distances were under their all-electric range (~150 mi for SU and 150 or 275 mi for tractors). This finding was predicated on sufficient availability of fast-charging and duty cycles that allowed fleets to maximize all-electric use. BEVs for SU trucks with a 300-mi range and for tractors with 250- and 500-mi ranges were only more cost-effective when the PHEV electric range could no longer outweigh the higher cost of carrying both a diesel engine and battery. Only a few long-haul tractors (trips >500 mi) had a combination of daily range and annual mileage that allowed cost-effective use of PHEVs, whereas no SU trucks did. However, hybridization could provide cost-effective fuel savings in this trip bin.

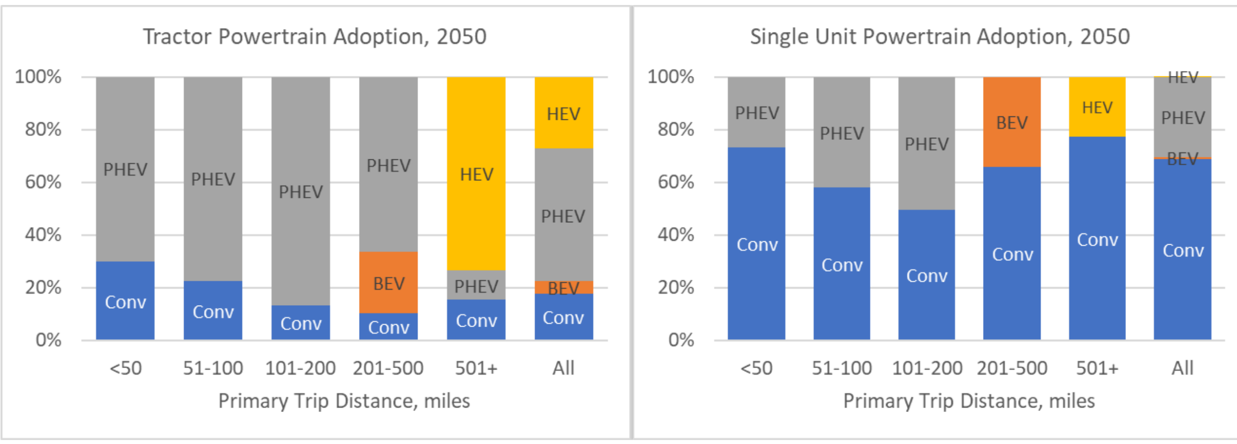


Figure 17. Powertrain adoption by primary trip distance for 2050.

Table 9 summarizes the impact of electrification on the cost of operations for new trucks in 2050, calculated from the NPV of purchase price and fuel costs over the lifetime miles of the trucks. Based on the assumptions used in this study, electrification can reduce the fleet cost of operations across all distance bands and truck types. Cost reductions relative to a 2050 all-diesel fleet ranged from $0.033 to $0.101/mi, with a sales fleet average of $0.062/mi for tractors and $0.059/mi for SU trucks. Although technology adoption was much smaller in SU trucks, their absolute costs were higher because of lower annual usage, resulting in comparable cost reductions.

Table 9. 2050 sales fleet cost of operations ($/mi).

TRIP_PRIMARY	Sleeper and day cab tractors			Single-unit trucks		
	Diesel	Scenario	Reduction	Diesel	Scenario	Reduction
<50 mi	$0.584	$0.488	$0.096	$0.818	$0.768	$0.050
51–100 mi	$0.553	$0.452	$0.101	$0.707	$0.631	$0.076
101–200 mi	$0.519	$0.426	$0.093	$0.635	$0.545	$0.090
201–500 mi	$0.491	$0.417	$0.074	$0.649	$0.585	$0.064
501+ mi	$0.487	$0.454	$0.033	$0.606	$0.576	$0.030
All	$0.508	$0.446	$0.062	$0.772	$0.713	$0.059

Costs are net present value including vehicle purchase and lifetime fuel expenditures.

2.2.4 Platooning

Several emerging connectivity and automation technologies such as platooning have demonstrated the potential to improve trucking freight efficiency. Platooning digitally connects two or more trucks through automatic speed control and a dedicated radio frequency that allows the vehicles to communicate. By safely reducing the distance between trucks, platooning reduces aerodynamic drag for the following trucks, and to a lesser extent, the lead truck. However, the energy-saving potential of platooning is limited by numerous factors, including the availability of platoonable ton-miles (based on sustained speed), availability of trucks with similar schedules and routing, the gap spacing between trucks, the number of trucks in the platoon, the slope of the road, traffic conditions, and more. This project explored the opportunities and limitations of connection and automation technologies such as platooning and documented their overall potential for national-scale energy impacts.

2.2.4.1 *Scenario definition*

The team defined an initial scenario in FY 2017 with the following assumptions based on the literature and results from other SMART Mobility Consortium research:

- Based on early analysis using sustained vehicle speed only, platoonable ton-miles increase from 0% to 65% from around 2015 to 2040 because of vehicle connectivity and automation technology availability and adoption
- Energy intensity (Btu/ton-mile) decreases 4% for leading trucks and 10% for following trucks. On average, one leading truck is followed by three more trucks (a second analysis scenario considers different platoon sizes)
- Sensitivity analysis: the platoonable ton-miles vary from around 50 to 80% in 2040
- Analysis time period: 2016–2040

Subsequent analysis in FY 2019 defined a second scenario by refining these assumptions, considering the spatiotemporal distribution of truck movements. For this second analysis, 2025 served as the base year for implementing truck platooning technology on the national highway network. The team used 2025 vehicle OD demand matrices for four vehicle types—platoonable FAF trucks, non-platoonable FAF trucks, non-FAF trucks, and passenger cars—as input to the platooning algorithm.

For the platoonable FAF trucks, the second scenario assumed that all the trucks were potentially allowed to form a platoon if a road link was eligible for platooning. A road link was considered eligible for platooning if it satisfied the following three conditions:

1. If the road type (i.e., rural/urban [non-]interstate) is allowed for platooning. In the scenario analyzed, platooning was allowed only on rural interstate roads
2. If the road length is not shorter than a predetermined threshold, which was assumed to be 5 mi in the baseline
3. If the time ratio (platoon formation time/time on the link) equals an externally specified threshold of 0.2

This second analysis scenario further assumed the following platoon characteristics based on field experiments conducted by McAuliffe et al. (2018). The impact of these assumptions was further explored through a sensitivity analysis:

- Three trucks per platoon
- An intertruck time gap of 0.4 s, which provides a 9.5% truck-level fuel saving

2.2.4.2 *Modeling approach*

Initial efforts used Argonne National Laboratory's NEAT model to identify potential energy use of intercity freight. The NEAT model estimates energy demand and GHG emissions from non-light-duty freight modes through 2050. NEAT provides estimates of the potential up-stream and end-use energy consumption and GHG emission impacts through 2050 for five domestic freight modes: truck, rail, domestic marine, domestic aviation, and pipeline. In an initial analysis, the team reviewed literature, real-world data, and SMART CAVs pillar analysis to establish limits to the following: (1) truck efficiency from platooning, (2) possible platoonable mileages based on highway speed, and (3) possible future mode shares due to increasing demand for fast shipping. These limits were applied as inputs to the NEAT model to quantify national energy impacts.

Subsequent work refined the platooning analysis to consider the spatial-temporal distribution of truck flow on the network; that is, where and when trucks were moving along the network. The researchers adopted a methodology developed for the FAF[4] to convert truck tonnages to the number of truck trips by commodity and vehicle configuration, including movement of empty trucks, between freight OD pairs specified from 129 FAF zones (Maks, Inc, 2016).

However, FAF zones are defined at a coarser level than needed to distribute truck flows onto the national road network. Additionally, a significant portion of shipments occur within a single FAF zone. Such intra-FAF zone flows are not assigned to the highway network because they start and end using the same centroid connector. Therefore, the FAF commodity and truck flows were spatially disaggregated into finer sub-FAF zones. These truck flows were then assigned to major networks by peak and non-peak hour to reflect their spatial-temporal distribution. To minimize computation costs in traffic assignment, the analysis designed a zoning system between the county and FAF zone level using a new spatially constrained multivariate clustering method. The methodology defined 1,603 zones based on population, employment rate, adjacency, and spatial proximity from the center of each zone to the nearby highway. Resulting network truck flows were analyzed to determine the national potential for platooning and associated energy reduction.

2.2.4.3 *Results*

The first analysis estimated that annual intercity freight sector energy consumption could be reduced by about 4.2% from truck platooning in 2040 as shown in Figure 18. Cumulative energy savings for 2016 through 2040 were estimated to be 5,330 trillion Btu (including upstream energy).

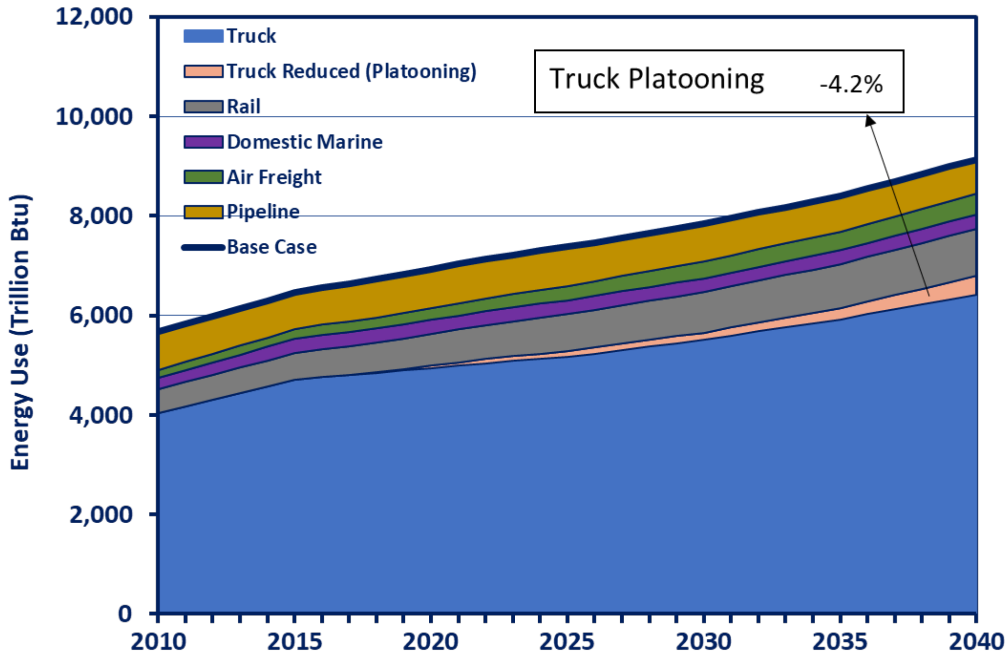


Figure 18. Initial analysis of freight sector energy reduction due to platooning.

Figure 19 and Figure 20 illustrate the process for refining the assumptions for the second analysis considering the spatial and temporal distribution of truck freight, converting tonnage to truck trips, and assigning trucks to the road network.

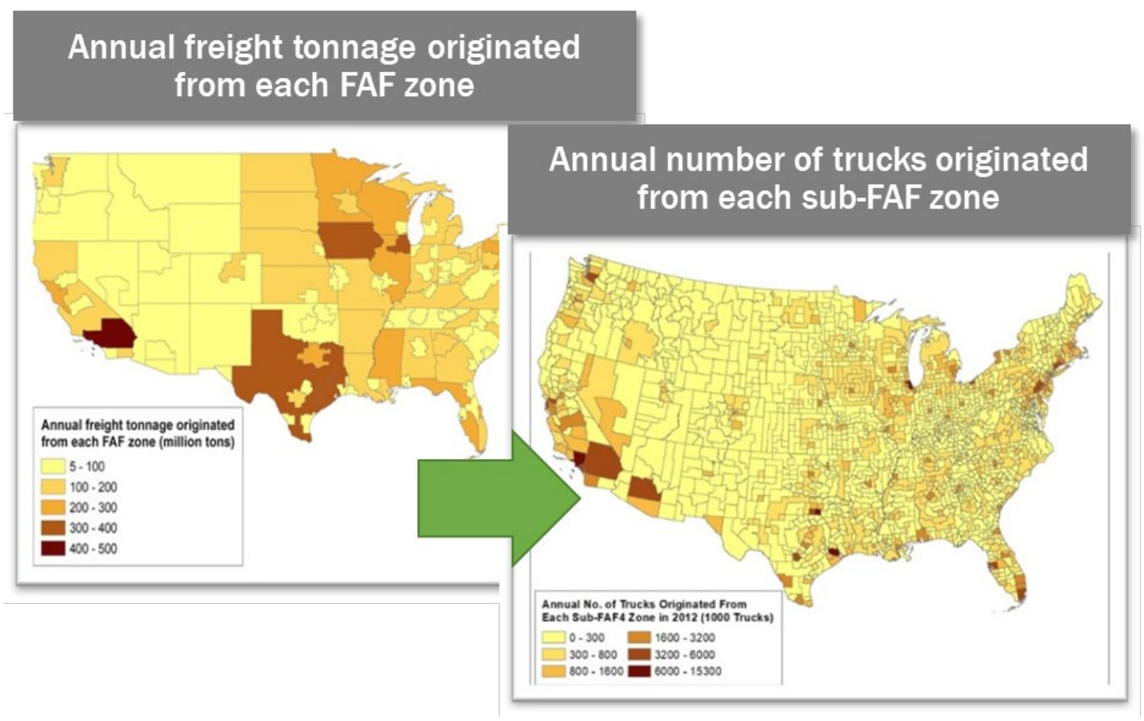


Figure 19. Results of conversion from Freight Analysis Framework (FAF)–level tonnage to sub-FAF-level truck trips.

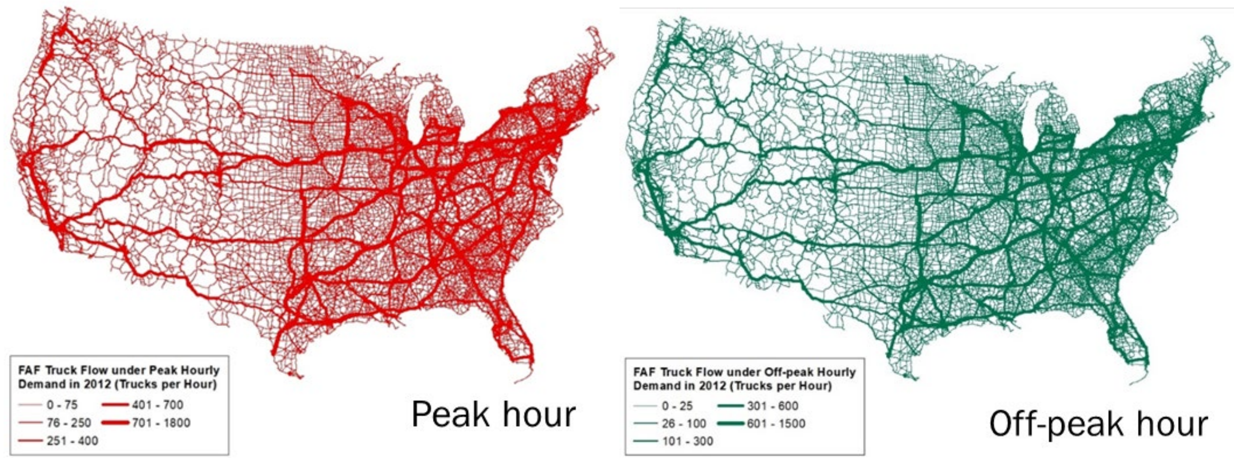


Figure 20. Results of truck network assignment and temporal disaggregation.

Results of the second refined platooning analysis suggest system-level fuel savings of nearly 7.9% for all platoonable FAF trucks across the national highway network, compared with fuel consumption without consideration of platooning (Figure 21). These savings are 1.6% smaller than truck-level fuel savings because platoonable trucks can only form platoons on eligible road links. The spatiotemporal analysis found that 59.5% (or 35,346 mi) of the total length of rural interstate highways are eligible for platooning. This analysis agrees with findings from Muratori et al., (2017) that, based solely on sustained speed in real-world driving data, up to 65% of the total 3.17 million sampled truck miles are eligible for platooning.

Because of truck platooning on some rural interstate highways, the total capacity of rural interstate highways increased by 1.54%. However, no changes occurred in the total VMT of the platoonable trucks or those of other vehicle types because (1) platoonable trucks accounted for only a small portion of the total traffic volume in the network, and (2) the algorithm allowed flexibility in the platoon formation decision. For example, when truck volume is low, platoon formation time costs are high since the likelihood of truck proximity is low and rerouting to a higher-volume route also increases time, VMT, and associated costs. Therefore, the decision is left to the truck operator based on the perception of the generalized travel cost. Because of this flexibility, the results over all the investigated scenarios (except for the scenario with dedicated platooning lanes) indicate that the total VMT of platoonable trucks will not change after implementing platooning. For platoonable trucks that move on eligible routes for platooning, the results indicate a considerable reduction in their fuel costs.

Two parameters characterize a platoon: the platoon size (number of trucks) and the intertruck gap (the time distance between platooning trucks). Figure 21 shows the truck- and system-level fuel cost savings as a result of implementing truck platooning on rural interstate highways, with platoon size ranging from two to five trucks. The system-level fuel savings were obtained by comparing the total fuel consumption of platoonable trucks across the network in a platooning scenario with that in a non-platooning scenario. As expected, fuel savings increased with platoon size. Additionally, the gap between system-level and truck-level fuel savings increased with platoon size. Figure 22 illustrates the impact of platooning on the total effective capacity of rural interstate highways. Again, the impact increased with platoon size. The increase in capacity of the interstate highways would result in a decrease in energy consumption by non-platoonable trucks and other vehicles. However, this study did not quantify these benefits.

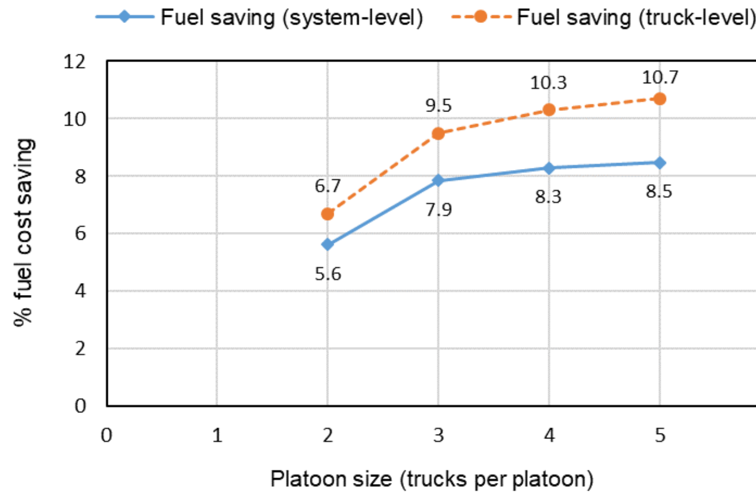


Figure 21. Truck- and system-level fuel cost savings as a function of platoon size.

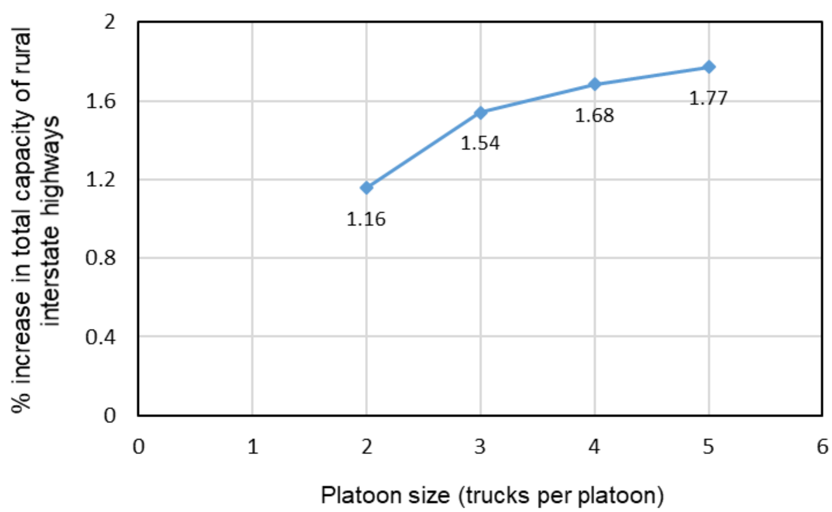


Figure 22. Effect of platooning on capacity of rural interstate highways.

Figure 23 illustrates the impact of the intertruck gap on fuel savings. As expected, a smaller gap between trucks results in larger benefits due to reduced aerodynamic drag, and system-level fuel savings increase nearly 100% as the gap decreases from 2 to 0.2 s. For context, state statutes for "following too closely" often do not specify an actual distance or time gap, but where quantified, they vary from 100 to 500 ft. The most frequent distance specified is 300 ft, which equates to 3.1 s at 65 mph (Scribner, 2019). Meanwhile, the Federal Motor Carrier Administration suggests that a safe following distance for a tractor-trailer is 5 s when traveling over 40 mph (FMCSA, 2015). Yang et al. found that drivers testing prototype platooning technology preferred gaps around 1.2 to 1.5 s over both shorter and longer gaps as a compromise between safety/comfort and deterring cut-ins by other vehicles (Yang, et al., 2018). The authors of that report did not test gaps shorter than 0.6 s.

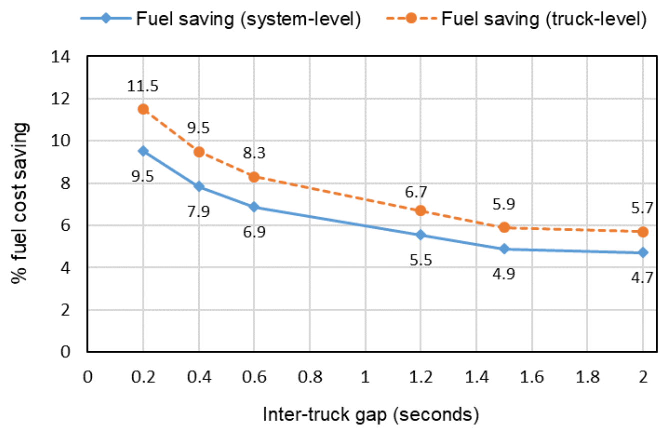


Figure 23. Effect of intertruck gap on system-level fuel savings.

2.2.5 Load-Pooling

The freight industry has a complex business and operational structure, consisting of multiple agents (shippers, receivers, carriers, brokers, and third-party logistics providers) and firms of varying sizes with diverse interests. Coordinating freight movement across these agents incurs resource costs and results in inefficiencies. Additionally, agents have different and sometimes conflicting incentives to minimize costs, shipping times, and/or risks; maximize asset use; and maintain control or at least visibility of freight and assets. Therefore, cargo containers—trailers, trucks, intermodal containers, rail cars, and so on—are not always loaded to capacity by weight or volume. Furthermore, a nearby load for a return trip often does not exist, resulting in the movement of empty assets, especially when the asset is specialized (e.g., refrigerated trailers). New technologies are enabling higher efficiencies for the complex process of matching loads with assets, scheduling deliveries and routes, and improving freight tracking.

Load-pooling is an efficiency approach in which shipments are consolidated by geographical region into a common logistics service line. Under this approach, entities use one another's assets to deliver and distribute products beyond their normal range, which reduces capital and operational costs and the overall stress on the transportation system. Additionally, this arrangement increases asset use by consolidating cargo, decreasing downtime, and/or filling unused cargo space. This concept is not new; it has been widely employed in passenger movement (e.g., carpooling and transportation network companies such as Uber and Lyft) and to some extent in freight (e.g., Uber freight, Convoy). Recent improvements in connectivity and efficient logistics, such as digitalization of logistics and communication networks reduce coordination costs and inefficiencies and are expected to extend applications in freight. For example, an online platform can match shipments that share the same OD pair and enable transportation as a single freight load.

For trucking, load-pooling can yield fewer truck trips with higher volume or weight and fewer empty miles, all with low infrastructure investment. Bouton et al. (2017) estimated that reductions of up to 25% of delivery cost and up to 30% of emissions could be achieved with load-pooling in urban areas. However, no research has been conducted (to the knowledge of the authors) that analyzes system-wide impacts of the technology on intercity freight movement over the multimodal network and that captures modal shifts and corresponding energy consumption.

Because of speed to market and network accessibility, trucking is the dominant mode of freight transportation in the United States. However, it is less energy-efficient and more expensive (per ton-mile) than rail and water. Moving goods over the multimodal transportation network results in efficient, reliable, flexible, and sustainable freight transportation (SteadieSeifi, Dellaert, Nuijten, Van Woensel, & Raoufi, 2014). Load-pooling will lower barriers to shifting from single-mode trucking to multimodal shipping and will reduce costs and energy by minimizing distances traveled by truck. However, other factors such as delivery time, accessibility to non-truck modes, and capacity at terminals might limit multimodal shipping.

2.2.5.1 *Scenario definition*

This project explored the impact of load-pooling on intercity freight energy consumption using a model of the national MMF network. An inverse modeling approach was used to infer model parameters by assuming that observed aggregate line haul or transfer link flows are optimal flows in the freight assignment system optimization. FAF tonnage flows between OD pairs were assumed to represent observed freight movement over the network. The multimodal intercity freight energy model was calibrated with the 2020 FAF estimates and validated with the 2040 FAF estimates. Additionally, load-pooling was assumed to not influence the freight shipped by air or pipeline since the freight movement by these modes has very different characteristics. Thus, the model included truck, rail, water, and intermodal approaches, assuming that FAF freight designated as "multiple modes" is the intermodal.

Load-pooling scenarios were specified based on the observed logistics costs in 2016, and load and empty factors that were used for the development of FAF. Those values were assumed to will remain the same in the base year and 2045 but change according to different scenarios.

For truck load-pooling, the following assumptions were used to specify exploratory scenarios:

- Collaborative logistics caused by truck load-pooling will reduce truck operation costs to 95% of conventional operations
- The market of truck load-pooling will grow from 5 to 30% of base-year truck volume in 5% increments
- The increase in load efficiency will be captured by an increase in payload (truck load factors) and a reduction in the empty truck factor: payload increases by 10 to 40% while the empty truck factor decreases by 10 to 40%.

For multimodal load-pooling, the following assumptions were used to specify exploratory scenarios:

- The intercity freight system at the strategic level will achieve a system optimal. Then, assuming there exists a sufficient number of shippers and carriers who are willing to use the intermodal mode, route and mode choice will be determined by optimizing total cost
- The increase in load-pooling is captured by increasing the capacity at intermodal terminals: capacity is increased by 5 to 30% of the observed baseline in 5% increments.

2.2.5.2 *Modeling approach*

In FY 2018, the team developed a preliminary intercity freight model to demonstrate the energy impacts of modal shifts and new technologies. The model was designed to be suitable for evaluating the benefits of multimodal load-pooling for long-haul freight movement and adopted Dijkstra's shortest path algorithm to find the optimal energy-efficient paths using energy required to ship one ton of cargo between each OD pair. This model might be suitable to provide an optimistic scenario with multimodal load-pooling in which decision-makers select the paths to minimize energy consumption without considering any other constraints such as delivery time, cost, or relationship between commodity and transportation mode. Thus, the preliminary model needed structural improvements to

- Incorporate emerging freight technologies that enable load-pooling
- Generate acceptable estimates of freight flow for answering research questions
- Include cost, energy, and time in the formulation
- Provide a reasonable bounding analysis of the impact of technologies.

In FY 2019, the team developed a new modeling approach that aims to optimize intercity freight movements in the context of system optimal freight assignment on the multimodal network including truck, rail, water, and intermodal mode. The objective function consisted of total transportation and transfer time costs independent of energy, reflecting that shippers and carriers will consider logistics costs and travel time rather than energy use, with the value of energy only partially captured by its financial cost. To quantify the energy consumption for intercity freight movement and the benefits of emerging technology, energy consumption was calculated after obtaining mode-route flows.

The modeling framework evaluated different scenarios and yielded a bi-level optimization problem as shown in Figure 24. The model considered mode-route selection simultaneously and was specified based on Zhang et al. (Zhang, Janic, & Tavasszy, 2015). The model parameters at the lower level were inferred using an inverse modeling approach proposed by Chow et al. (Chow, Ritchie, & Jeong, 2014). The model was calibrated and validated using FAF flows. The model was then applied to evaluate selected load-pooling scenarios with energy consumption for optimized intercity freight movement. This modeling approach was designed to be applied to analyzing other technologies such as electrification and platooning explored in this study. However, this model is limited in the sense that it can only deal with aggregate input parameters influenced by emerging technologies.

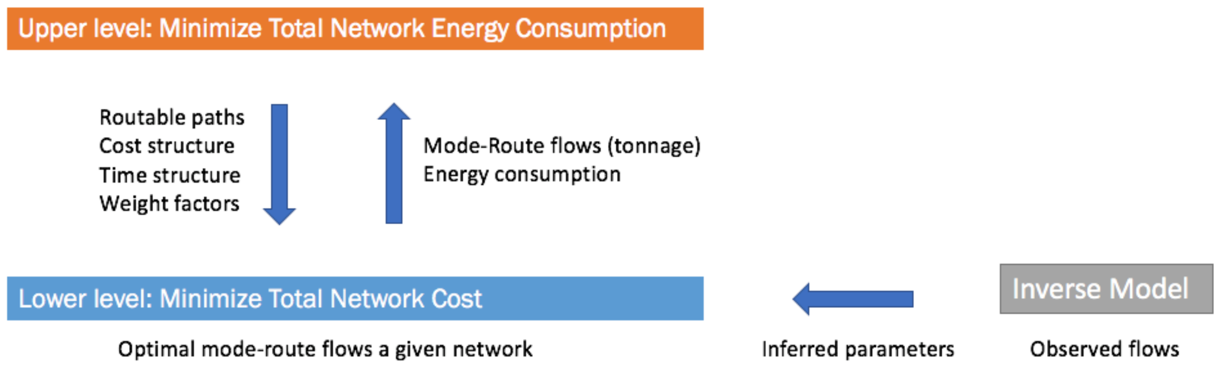


Figure 24. Multimodal freight energy model framework.

2.2.5.3 *Results*

To examine the energy impact of multimodal load-pooling scenarios without considering any constraints, a preliminary model was implemented for the Columbus, Ohio region and for the entire United States using 2012 Commodity Flow Survey data. With the optimistic assumption that there is no restriction on freight mode shifting, the initial results showed that load-pooling has the potential to save approximately 58% of energy use for shipments originating from Columbus and 60% nationally, when compared with the baseline scenario for observed tonnage flows. To minimize the energy consumption, the model shifted all truck freight to rail (54%) and water to rail (41%) as shown in Figure 25. While these results present an ultimate upper bound for energy savings, they are not realistic because of mode-route limitations and shipper objectives other than energy usage minimization.

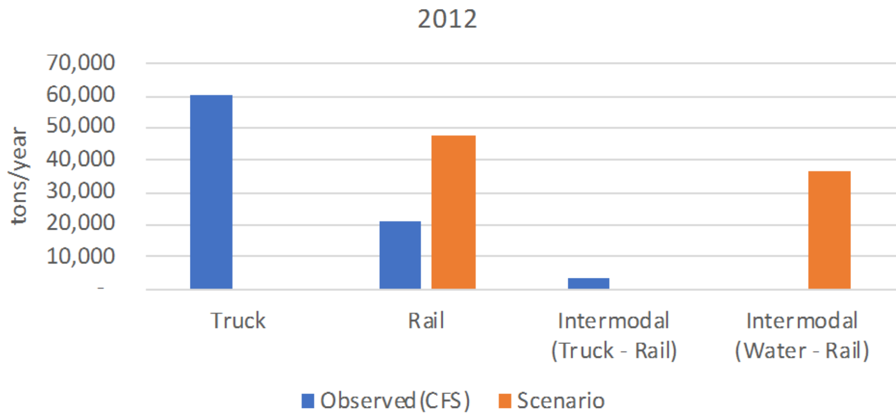
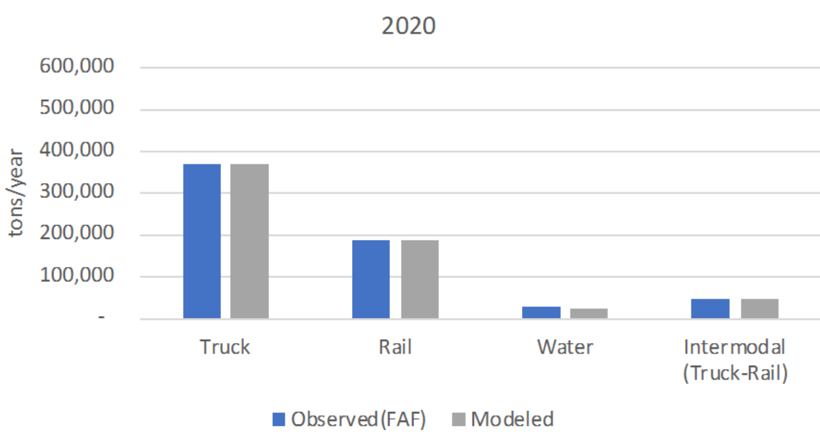
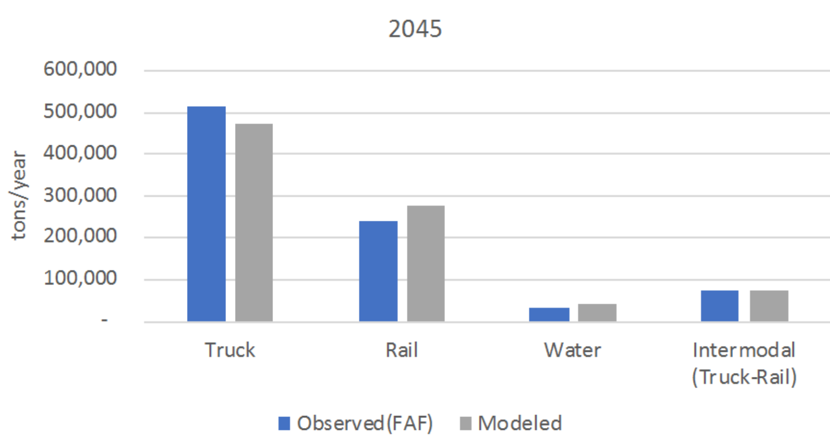


Figure 25. Freight volumes for Columbus, Ohio under load shift for energy optimization from the preliminary model.

The multimodal intercity freight energy model was applied to all freight shipments originating from or destined to the Chicago region. Figure 26 represents comparisons of observed (FAF) and modeled annual tonnage flows by mode. Outputs from the model were deemed to be acceptable, though future work could improve the model calibration.



(a) 2020 (calibration)



(b) 2045 (validation)

Figure 26. Multimodal freight energy model (a) calibration and (b) validation.

2.2.5.3.1 Truck load-pooling

To explore the impact of load-pooling within just trucking, six scenarios were defined by varying participation in a collaborative, load-pooling market from 5 to 30% of the base year truck volume. These scenarios were intended for exploration only, and future work should address both the potential for participation and the expected range of impact on logistical costs, truck load factors, and empty truck movements. Without any improvement in other modes, the load-pooling scenarios provide benefits to truck operations by reducing logistical costs by an assumed 5%. Additionally, load-pooling increases truck payloads (trucks are more fully loaded on average) and reduces movement of empty trucks. Figure 27 shows freight flow changes by mode relative to the 2045 baseline, and shows a shift from other modes to truck as a result of cost reductions.

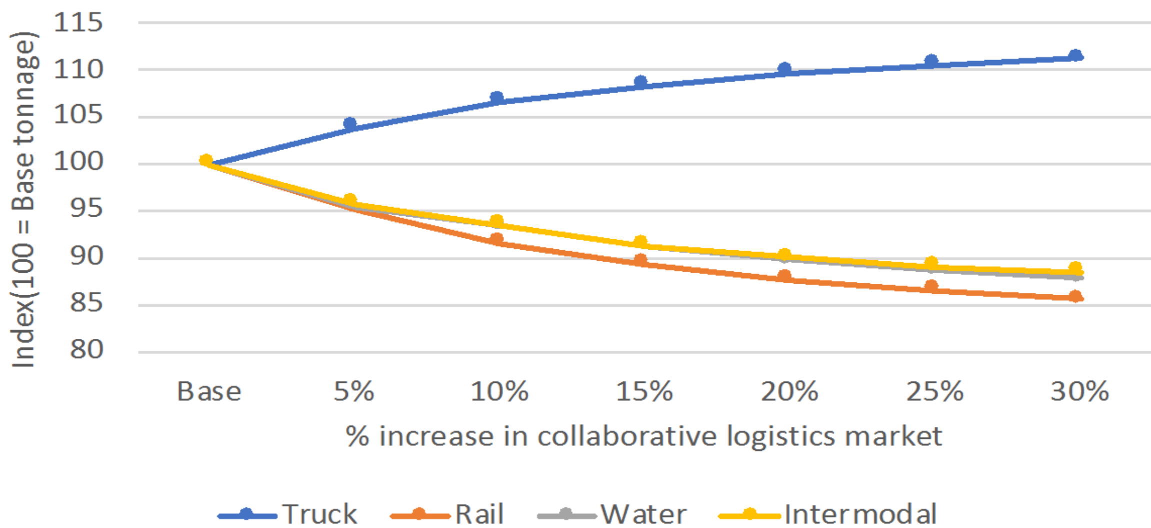


Figure 27. Change in freight flows according to truck-pooling scenarios in 2045.

Since trucks are more energy-intensive than rail or water, total energy consumption increases. Figure 28 shows the change in total energy, assuming for illustration that truck payloads (by tonnage) increase 10% on average and empty truck movements decrease 10%. This finding implies that truck load-pooling without improvements in energy use of trucks could result in increased energy consumption, depending on the impact on truck use. This effect was further explored by varying the payload and empty truck impacts over seven scenarios defined in Table 10. Scenarios exploring the impact of change in truck payload and the empty truck factor., assuming 30% market participation. As shown in Figure 29, truck energy consumption decreased as truck use improved. However, the impact was marginal in the context of the overall energy consumption increase due to the modal shift, and energy consumption in the most aggressive scenario (S7) was still higher than the baseline. Interestingly, energy consumption appears to be more sensitive to payload increase than the empty truck factor.

These results indicate that more energy-efficient powertrain technologies may be required to offset the energy increase that would occur from modal shifts from rail and/or water that would arise from truck load-pooling. Such mode shifts could also increase highway congestion, and such feedbacks were not analyzed in this study. The truck load-pooling exploration scenarios highlight the need to consider changes to a freight mode’s efficiency within a multimodal framework if total energy consumption or modal shares are of interest.

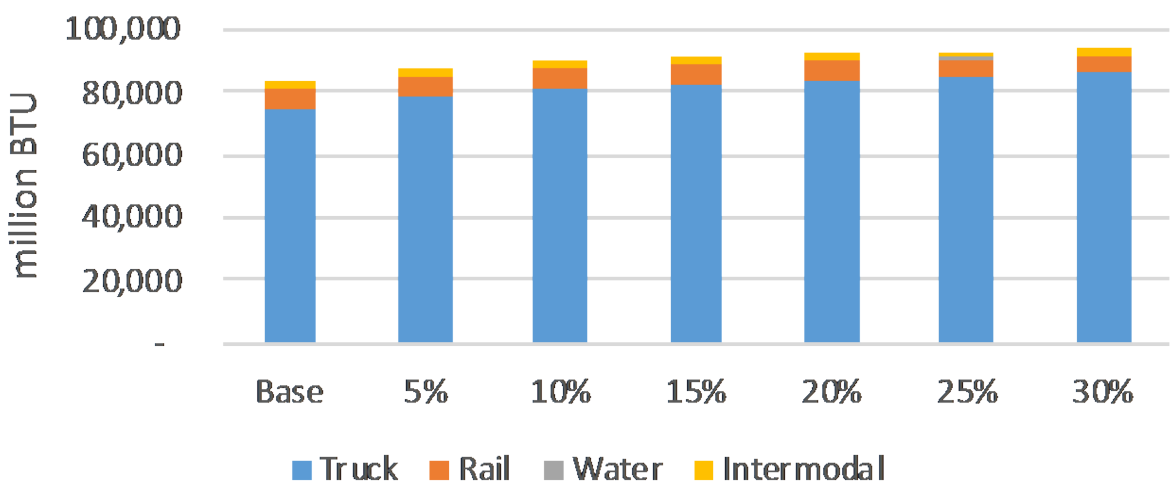


Figure 28. Total energy consumption for Chicago truck-pooling scenarios in 2045.

Table 10. Scenarios exploring the impact of change in truck payload and the empty truck factor.

	Scenario						
	S1	S2	S3	S4	S5	S6	S7
Payload change	10%	10%	10%	10%	20%	30%	40%
Empty truck factor change	−10%	−20%	−30%	−40%	−10%	−10%	−10%

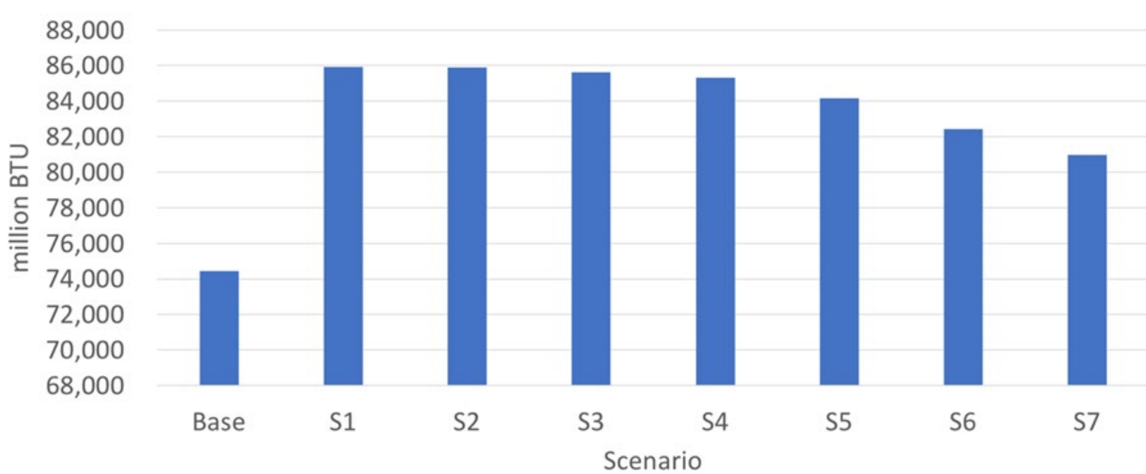


Figure 29. Chicago truck freight energy consumption for payload and empty truck factor scenarios.

2.2.5.3.2 Multimodal load-pooling

To explore the impact of multimodal load-pooling, six scenarios were defined by increasing the capacity on intermodal transfer links by 5 to 30% of the observed baseline system. Since the intermodal approach (truck-rail in this study) provided cost savings compared with trucking, intermodal capacity expansion resulted in a shift from single-mode truck. Meanwhile, changes in water and rail tonnage flows were marginal as shown in Figure 30. These results are more reasonable than those obtained using the preliminary model. Though freight flows moved by intermodal flow increase, Figure 31 shows that multimodal load-pooling can reduce system wide energy consumption. From an energy perspective, the findings from these scenarios suggest that multimodal load-pooling could be a better intercity freight movement alternative than truck load-pooling.

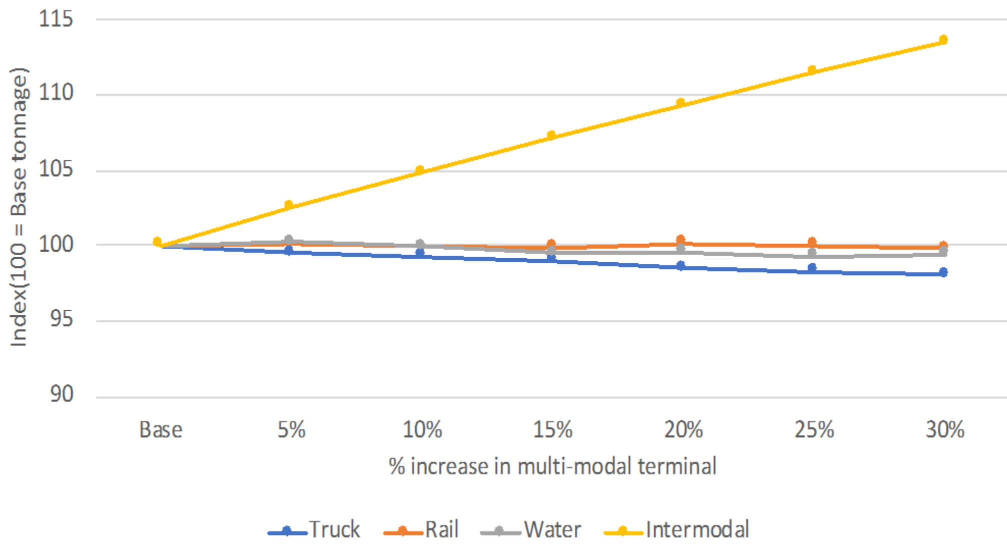


Figure 30. Change in freight flows for multimodal load-pooling scenarios in 2045.

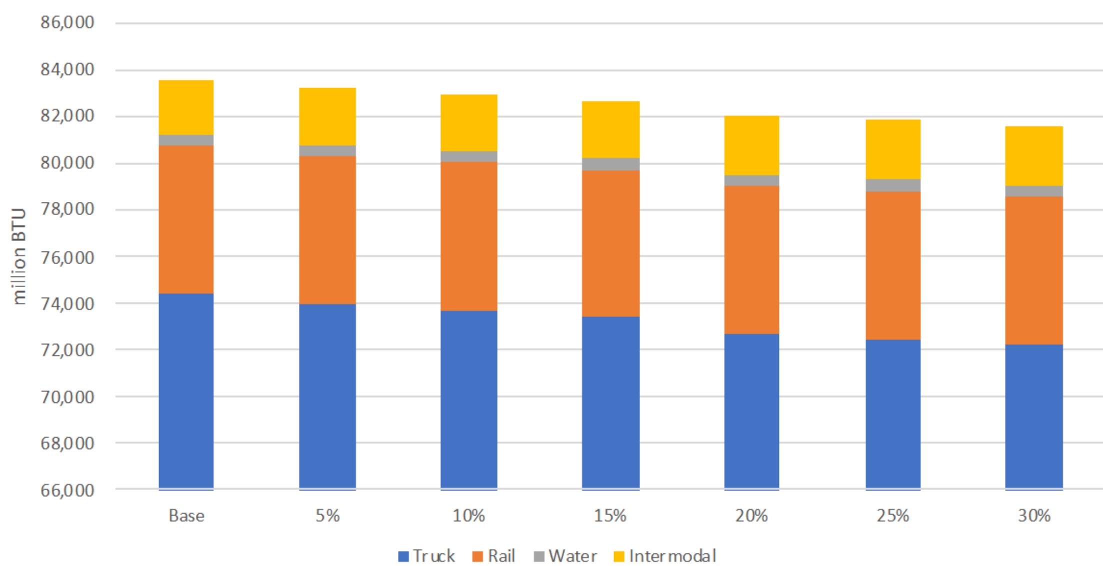


Figure 31. Energy consumption for multimodal load-pooling scenarios in 2045.

2.3 Regional Transportation System Impacts of Freight

2.3.1 Introduction

As described in Section 1, freight transportation has significant impacts on energy consumption, mobility, and emissions. In the United States, medium-duty trucks (MDTs) and heavy-duty trucks (HDTs) constitute about 10% of traffic, yet consume roughly 30% of transportation energy. Because freight has such major impacts, it is important to consider how freight transportation could change in the advent of new vehicle technologies, shifts in consumer or business behavior, and other factors. Analytical tools that can evaluate both freight transportation and passenger transportation can deliver this type of assessment.

In this task, the researchers developed a powerful, agent-based freight forecasting model. The model uses a behavioral framework, treating business establishments and truck drivers as agents that make decisions. The framework is fully integrated in the Argonne National Laboratory agent-based transportation system modeling platform, POLARIS.

The model was applied to study the impacts of freight transportation on regional mobility, which were measured using VMT, and energy use across three types of scenarios:

- The first type examines the energy and mobility impacts of commodity flow growth that is projected to occur in the future
- The second evaluates the energy impacts of potential future adoption rates of advanced technologies such as electrified powertrains
- The third examines the impacts of e-commerce, using "what-if" cases to quantify the potential net effects on mobility and energy as households receive an increasing number of deliveries

2.3.2 Objectives

The objective of this project was to estimate the energy and mobility impacts of freight by modeling commercial activity, the movement of goods at the intraregional and intercity levels, and interdependencies between commercial and household activity. The project includes both model development and model application to various case studies. The goal of the model development was to produce freight forecasting models that can analyze the impacts of various scenarios on freight transportation and energy consumption within a computational environment. The goal of model application was to evaluate select scenarios of interest. In this study, the model was applied to estimate the baseline impacts of freight on transportation mobility and energy consumption. After the baseline was established and calibrated, the impacts of commodity flow growth, increased use of powertrain technologies, and varying e-commerce demand rates were evaluated.

2.3.3 Approach

The project used two stages to accomplish its objectives. A different freight model was developed in each stage. Both models used freight establishments and truck drivers as agents, but differed in the approach used for generating and allocating shipments to establishments. The initial version of the model was called the "top-down" model because its freight movements were based on a combination of truck trips from the regional model and high-level commodity flows, which have been disaggregated to individual agents in the model. In contrast, in the "fully agent-based" model, freight movements were generated directly by the agents themselves. Both versions of the models used individual establishments and trucks as agents, and both models perform a regional freight traffic simulation that was fully integrated with passenger vehicles.

Another difference between the two approaches was the method for modeling long-haul trips. In the top-down model, intercity truck trips were included in the traffic assignment, but their terminus outside of the region was not modeled in detail (although the information was available to the model through the FAF). The agent-based model had unbounded geographic coverage: business establishments, supply chains, and shipment trades were modeled at the global, national, and regional levels. In both versions of the model, the dynamic traffic assignment (DTA) and subsequent energy and mobility analysis focused on the portions of trips that are in the Chicago MSA, covering about 10,000 mi^2.

Since the top-down model could be developed more quickly than the agent-based model, it was used to evaluate the SMART Mobility workflow scenarios. The latter was intended for longer-term use because it is more versatile and powerful than the initial model. Each model is discussed in turn in the following sections, along with features that are common to both models.

2.3.3.1 *Top-down model development*

The top-down model generated shipments between establishments by apportioning truck trips from the regional CMAP model and interregional commodity flows from the FAF[3] to individual pairs of establishments in the Chicago region. Establishments were paired to form links in the supply chain based on trip estimates and

[3] https://faf.ornl.gov/fafweb/

land use data from the CMAP (CMAP, 2019) and data on buildings from the city of Chicago (Chicago Data Portal, 2018). An algorithm was developed to transform the inputs into a truck trip table. In this initial model version, all intercity freight trucks were assumed to be HDTs, which covers Class 7 and Class 8 trucks. Intercity trucks enter or leave the region and have one trip end within the region. Intraregional trucks include both HDTs and MDTs (Class 3 to 6 trucks).

The overall approach to developing the top-down agent-based freight model is illustrated in Figure 32. As an example of establishment pairing, a truck may carry goods from a factory to a store (Figure 32).

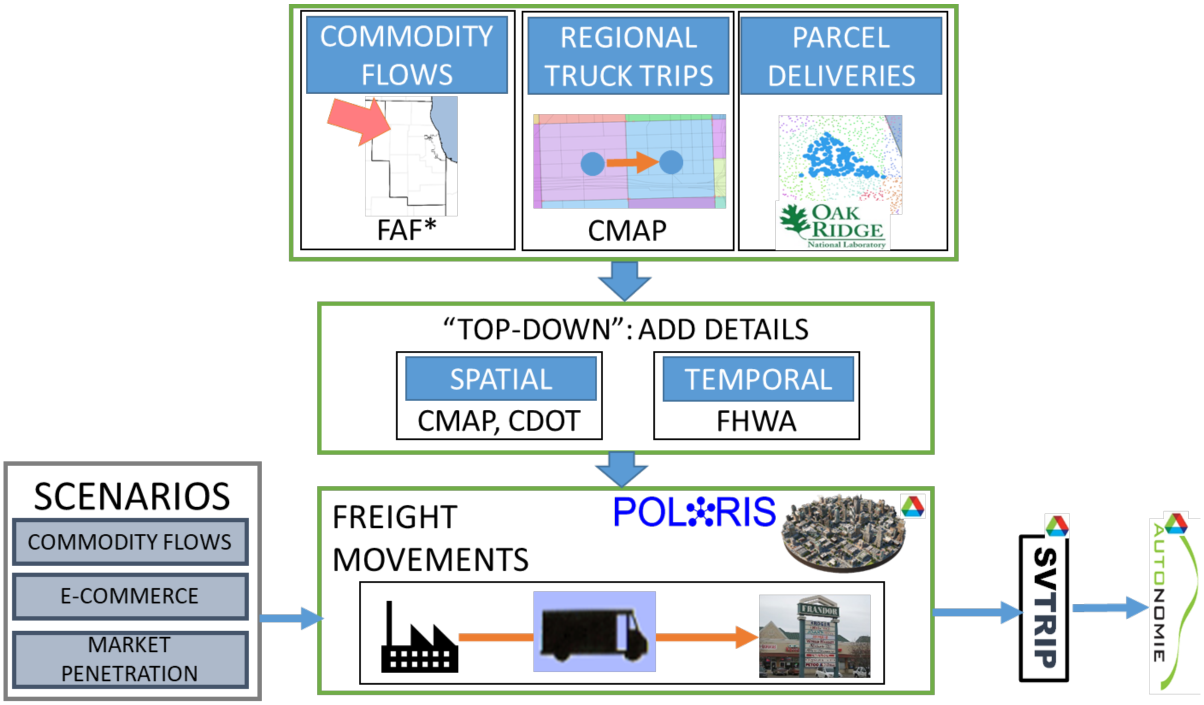


Figure 32. Approach to developing the top-down agent-based freight model.

Intracity freight flows were developed as follows. First, MDTs from the CMAP[4] trip tables, which use the CMAP TAZ system, were disaggregated from the TAZ to the establishment level. TAZ-level trips from the CMAP HDT trip tables were likewise disaggregated and were used in conjunction with growth rates from the FAF data to develop HDT OD flows for each scenario.

Figure 33 illustrates the process of allocating high-level flows to individual agents for the base and future years.

[4] https://www.cmap.illinois.gov/data

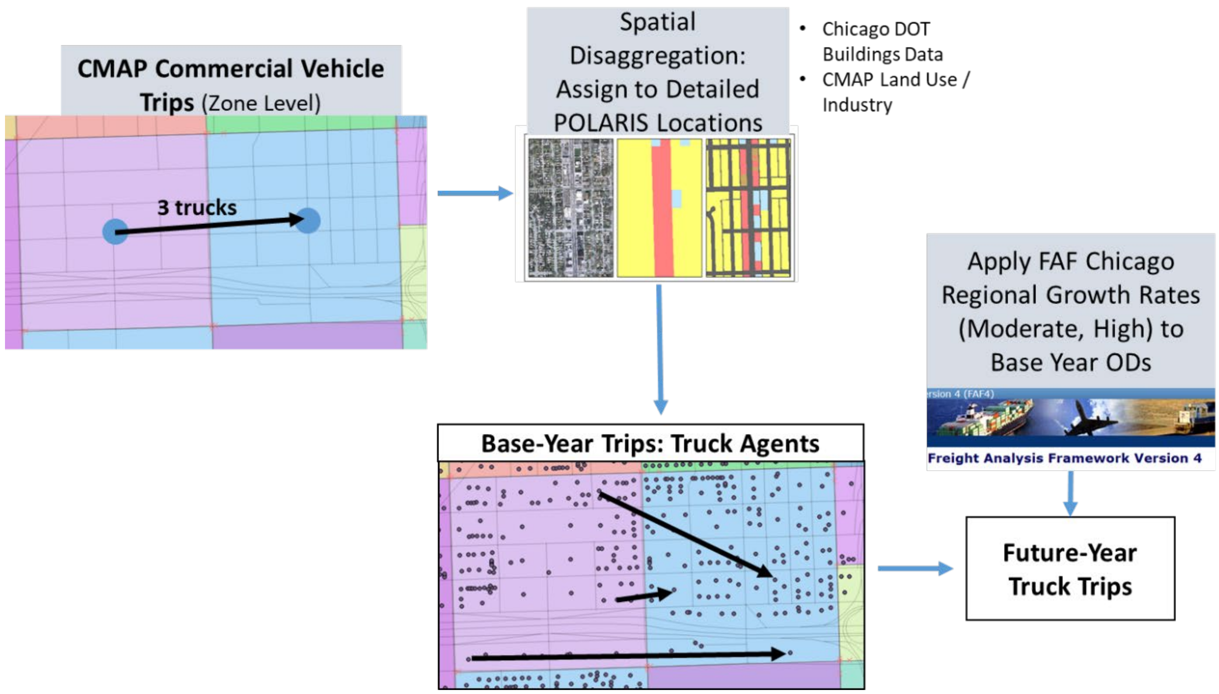


Figure 33. Disaggregation of high-level freight flows to individual agents.

2.3.3.2 *Agent-based model development*

The agent-based model was adapted from work developed by Urban et al., and began by synthesizing a population of business establishments around the world (Urban, Kuppam, Beagan, Fischer, & Lemp, 2013). The model agents made sourcing decisions to form trade partnerships with each other, set trade volumes, select shipment sizes and frequencies, and choose mode- and logistics-related options. Logistics options included whether to use a transload or distribution facility. The model was multimodal and included truck, rail, and air shipping options.

Figure 34 shows the results of the population synthesis globally. This illustration shows 0.1% of modeled agents using dot density mapping (a random location within the region is portrayed for each establishment). Internationally, a few representative agents are pictured to demonstrate the geographic scope of the model. Figure 35 zooms in to show the land use associated with each synthesized establishment in the Chicago MSA. The US Census County Business Patterns (CBP) data set was the primary source of industry, establishment size, and location data for US establishments outside of the region. The CBP data were combined with CMAP and POLARIS data inside the region to synthesize the regional establishment population. The international establishments were representative, but are expected to be updated with data sources in potential future work.

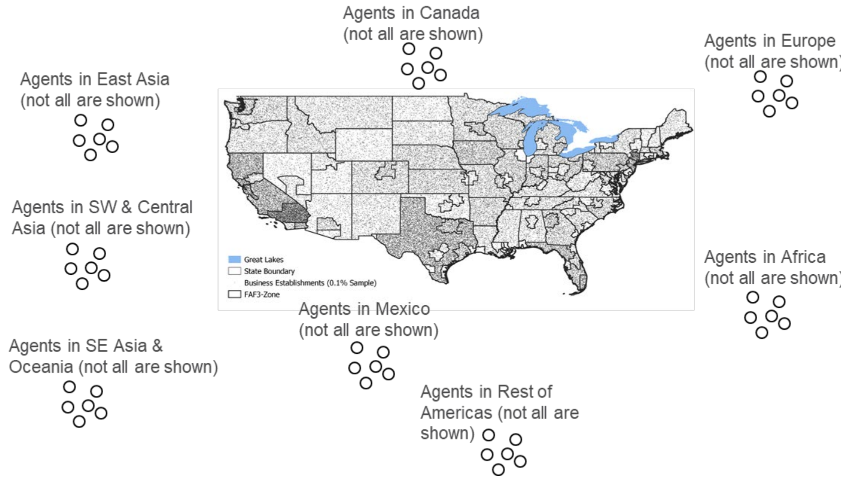


Figure 34. Sample of synthetic establishment population in the agent-based model.

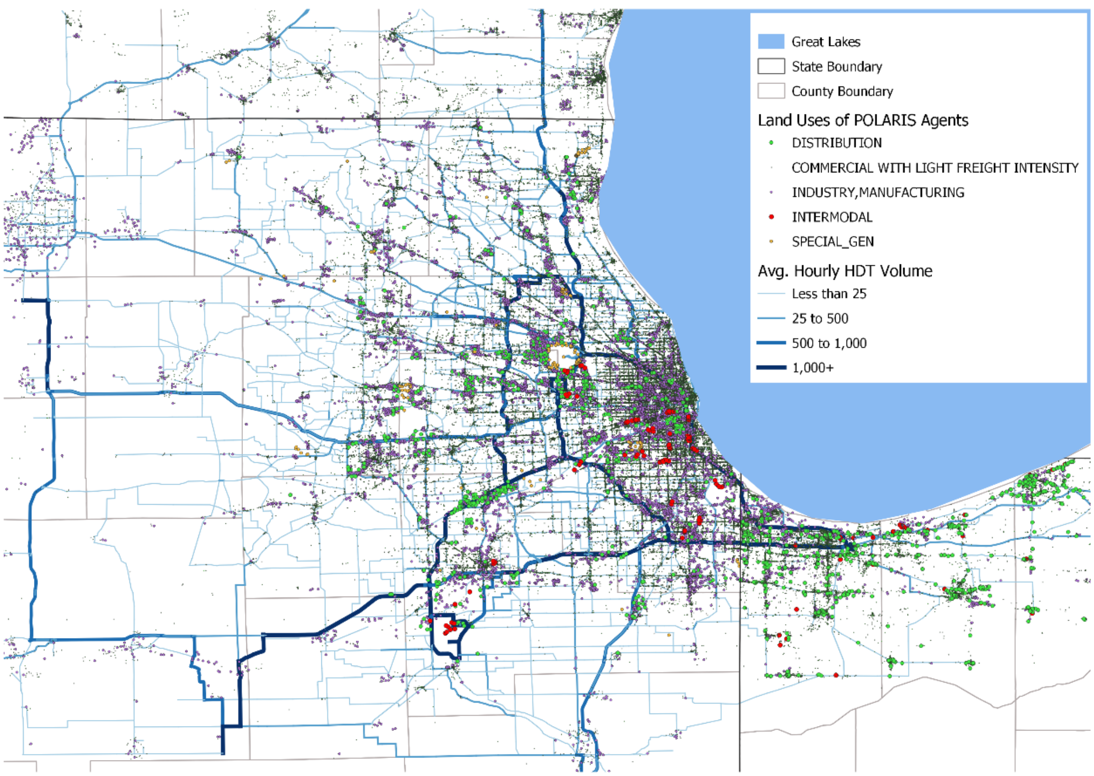


Figure 35. Closeup of synthetic establishments in the Chicago, Illinois metropolitan statistical area.

Following population synthesis, the model estimated the annual volume of goods that are produced or consumed by each establishment. This estimation was made for each commodity type that the establishment buys or sells. The input data for this process included the FAF data, the CBP data, and the US Bureau of Economic Analysis Make and Use Tables.

Next, for each commodity type, each buyer establishment selected a supplier establishment from which to purchase the required commodity and volume (Figure 36). Trading partnerships for the entire model population were formed in this way.

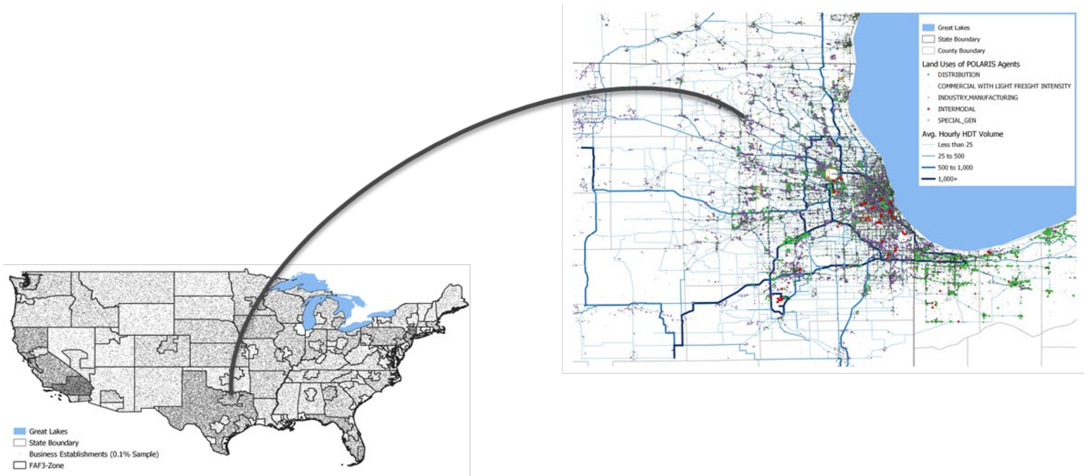


Figure 36. Establishments selected trading partners based primarily on industry type, but also on size and distance.

At this point, the model generated trade partnerships along with annual trade volumes for each partnership. However, annual trade volumes were not sufficiently detailed for analyzing energy impacts, which can highly depend on congestion. The annual volumes had to be broken down into individual shipments for more detailed analysis to take place.

The framework applied a joint shipment size mode selection model that estimated the shipment size (or frequency) along with the choice of mode (Stinson, et al., 2017). This initial version of the model included rail, truck, and air modes as shown in Figure 37. Influential path characteristics in the model included travel time and distance, as well as time for transloading shipments at intermodal or distribution facilities.

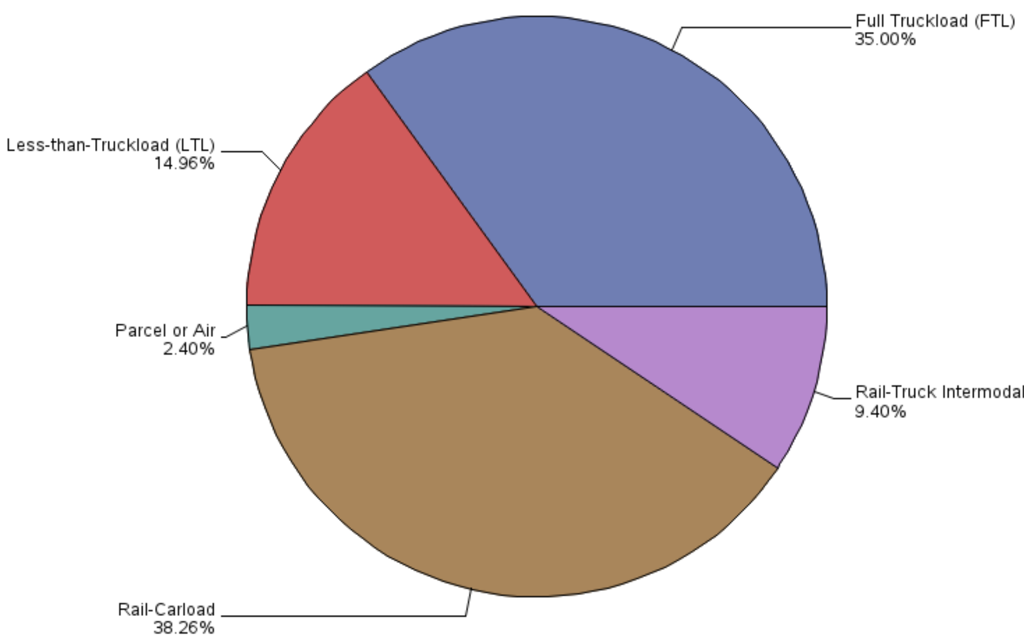


Figure 37. Example results for modes selected by model agents to transport goods produced by establishments in the agriculture, forestry, fishing, and hunting sectors.

Goods movement relies heavily on network nodes where storage and/or transloading (transferring goods from one vehicle to another) occur. The model network included these logistics nodes, which were located throughout the network; furthermore, it modeled the flow of shipments through these nodes. Modeled shipments that entered or left the region stopped at a transload or distribution point. The model generated truck trips between the logistics nodes and the trip origin (or destination). Less-than-truckload, rail carload, rail intermodal, air, and parcel shipments used this process in the model. Figure 38 illustrates the truck traffic that resulted from this model process based on air shipments that entered or left the region through O'Hare International Airport (trucks going to or from other locations were also included in the volume shown on the map).

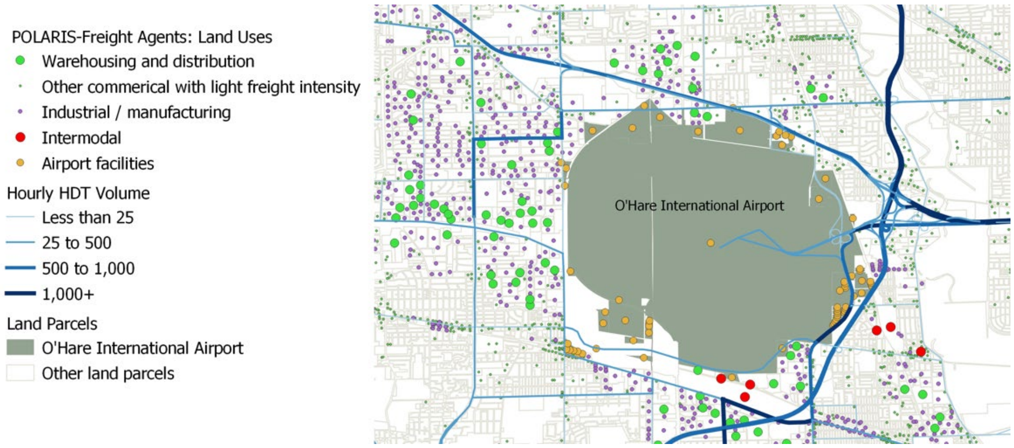


Figure 38. POLARIS-freight agents and modeled truck volumes around O'Hare International Airport.

Figure 39 illustrates the average hourly HDT volumes that the agent-based freight model generated throughout the Chicago MSA.

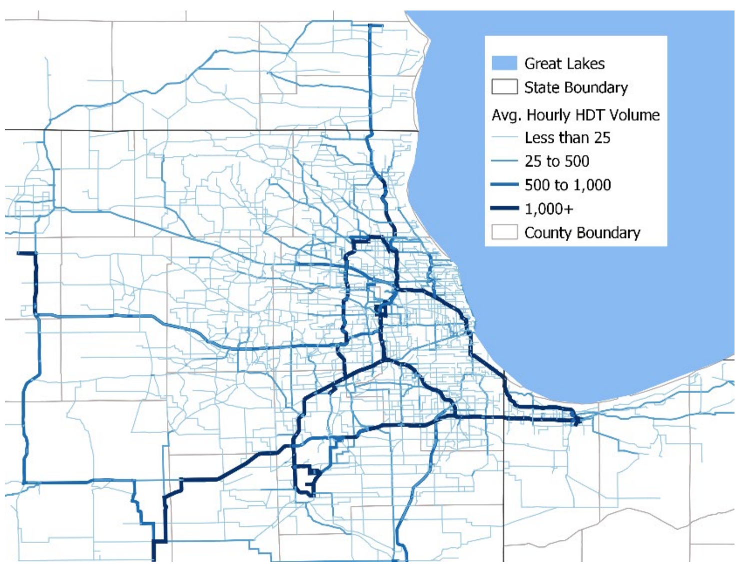


Figure 39. Truck volumes generated by the agent-based POLARIS-freight model in the Chicago, Illinois metropolitan statistical area.

2.3.3.3 *Common model elements*

Both the top-down and fully agent-based processes result in a table of truck trip data For both inter- and intracity trips, another important process was developing an algorithm to assign daily flows to specific start times throughout the day. Figure 40 shows the probability functions used in this process. A probability mass function from the Federal Highway Administration (FHWA) Traffic Data Computation Method: Pocket Guide was used for most trucks. Start times of individual trip segments on parcel truck tours were assumed to be uniformly distributed between 9 a.m. and 5 p.m. (i.e., parcel trucks were assumed to leave the depot in the morning and make deliveries around the region throughout the day).

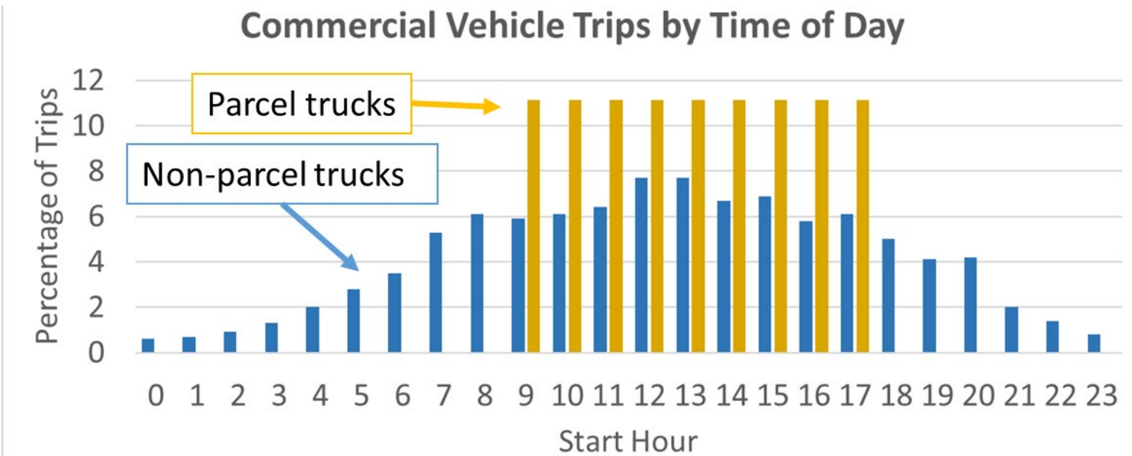


Figure 40. Probability functions for trip start time assignment.

Finally, the top-down model was calibrated and validated using data from the FHWA Highway Performance Monitoring System (HPMS) and national benchmarks[5]. Table 11 shows the validation results, comparing VMT and share of fuel consumed by MDTs and HDTs. The modeled VMT and fuel share of trucks compared well with the national benchmarks. The modeled VMT was slightly lower and the fuel share was slightly higher than the observed values, likely because the current assessment focused on quantifying regional impacts (where, compared with national averages, trips are shorter and congestion is more severe, which likely guided these differences). Volumes on major interstates and arterials using the HPMS also compared well between the modeled and observed cases. Model volumes in the agent-based model prototype showed expected patterns in comparison with HPMS data. In the future, this model will be calibrated in more detail.

Table 11. Validation results.

Medium- and heavy-duty truck share	Model	Benchmark (national average)
Vehicle miles traveled	8%	10%
Fuel	36%	30%

2.3.3.4 *Development of inputs for workflow scenarios analysis*

E-commerce-related inputs for the top-down model were developed as follows. First, Argonne National Laboratory staff developed a household-level model of e-commerce demand using data from the SMART Mobility Decision Science WholeTraveler survey. This model was implemented in POLARIS to predict demand for e-commerce goods for each household in the Chicago region. Second, Oak Ridge National Laboratory estimated parcel delivery tours (Section 3.1) for major parcel carriers to be commensurate with the household-level demand estimates. These supply and demand elements were integrated in POLARIS and used to estimate the net effect of e-commerce on mobility and energy.

Future commodity flows were estimated as follows. A moderate 1% compound annual growth rate commodity flow growth from FAF was used to adjust the baseline CMAP freight truck trip tables. Changes in interregional (long-haul) and intraregional flows were developed and applied in this way. For each scenario,

[5] US DOT Beyond Traffic 2045 report incl. special tabulation prepared by the Bureau of Transportation Statistics; 2017 HPMS-Highway Performance Monitoring System)

the resulting truck trips were simulated using the network DTA. The scenarios were bundled together, along with numerous other passenger scenario parameters. More information on the entire workflow analysis can be found in the SMART Mobility Workflow Capstone Report.

2.3.4 Results/Findings

The top-down version of the agent-based model was used to evaluate regional freight impacts in accordance with the workflow scenarios. Travel markets that are relevant to this analysis are

- HDTs, which include both long-haul and regional, or inter- and intracity, travel markets
- MDTs, which include all types of MDTs, including parcel delivery MDTs
- Passenger LDV shopping trips; the model includes these trips to fully account for the energy and mobility impacts of e-commerce

Figure 41 puts into perspective the relative size of each of these markets. It shows the total daily VMT by HDTs, MDTs, parcel delivery MDTs, and passenger trips (including shopping) in the Chicago MSA for the base year (2015).

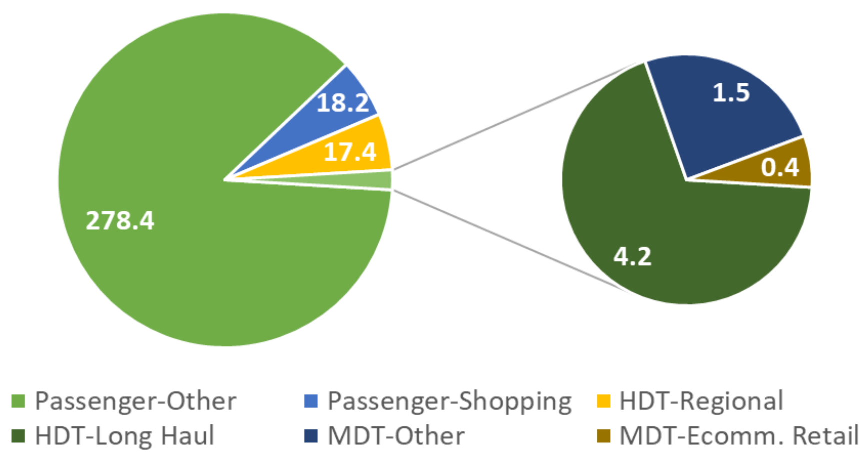


Figure 41. Modeled vehicle miles traveled by various vehicle types and trip purposes in the Chicago metropolitan statistical area in the base year.

The rest of this section presents the results of the workflow scenario analysis along with supplementary analysis related to mobility by time of day. More details on the scenarios can be found in the Appendix. A brief summary of scenario details as they relate to the freight and e-commerce analysis is shown in Table 12. The baseline scenario (Base0) established a reference point based on transportation mobility and energy use in the base year. The baseline short-term scenarios and A scenarios (A2/A3) examined what-if scenarios for the short term. The baseline long-term scenarios and the B and C scenarios (B5/B6 and C5/C6) evaluated potential VMT and energy impacts of scenarios in the long term. The most important scenario assumptions for the freight analysis were

- Vehicle component technology has three different levels across the scenarios: baseline (current-day) technology, business-as-usual (BAU) technology, and VTO target technology, which involves the most electrification across all vehicle classes
- Vehicle class market penetration changes in accordance with the baseline/BAU/VTO categories as documented in the Appendix
- Commodity flows grow at a 1% compound rate annually in the future

- E-commerce deliveries grow from about one delivery per household per week to three (A2/A3) to five (B and C scenarios); the base rate of one per week is used for all baseline model runs
- Ride-hailing is relatively high in A and B scenarios and relatively low in C scenarios
- Privately owned autonomous vehicles are widespread in C5/C6
- Vehicle automation is widespread in B and C scenarios, leading to decreased travel times

The vehicle component and vehicle class market penetration assumptions majorly impacted the energy results, which are described in this section. The commodity flow and e-commerce assumptions were important in evaluating the freight-related transportation system impacts mentioned above. The last three assumptions were important in understanding the magnitude and direction of VMT and energy associated with shopping trips.

Table 12. POLARIS freight scenarios summary.

<table>
<tr><th>Scenario group</th><th>Scenario</th><th>Component technology</th><th>Long haul commodity flow—CAGR (%)</th><th>E-commerce deliveries per household</th><th>Passenger vehicle retirement rate (%)</th><th>Passenger VOTT factor</th></tr>
<tr><td>Baseline</td><td>Base0</td><td>Baseline</td><td>N/A</td><td rowspan="7">0.16/day (about 1/week)</td><td rowspan="7">0</td><td rowspan="7">1</td></tr>
<tr><td rowspan="3">Baseline short-term</td><td>Base1</td><td>Baseline</td><td rowspan="12">1</td></tr>
<tr><td>Base2</td><td>Short-term BAU</td></tr>
<tr><td>Base3</td><td>Short-term VTO targets</td></tr>
<tr><td rowspan="3">Baseline long-term</td><td>Base4</td><td>Baseline</td></tr>
<tr><td>Base5</td><td>Long-term BAU</td></tr>
<tr><td>Base6</td><td>Long-term VTO targets</td></tr>
<tr><td rowspan="2">A</td><td>A2</td><td>Short-term BAU</td><td rowspan="2">0.4/day (about 3/week)</td><td>45</td><td rowspan="2">High</td></tr>
<tr><td>A3</td><td>Short-term VTO targets</td><td>45</td></tr>
<tr><td rowspan="2">B</td><td>B5</td><td>Long-term BAU</td><td rowspan="4">0.7/day (about 5/week)</td><td>68</td><td rowspan="2">Low</td></tr>
<tr><td>B6</td><td>Long-term VTO targets</td><td>75</td></tr>
<tr><td rowspan="2">C</td><td>C5</td><td>Long-term BAU</td><td>15</td><td rowspan="2">Low</td></tr>
<tr><td>C6</td><td>Long-term VTO targets</td><td>20</td></tr>
</table>

CAGR: Compound annual growth rate; BAU: business-as-usual

Table 13 shows the main POLARIS results by scenario for the various market segments included in the analysis. The first section in each table includes results for all MDTs and HDTs, and the second section only includes parcel-delivery MDTs and passenger shopping results. Percentage changes are all computed as described in the footnotes of the table. The table uses shades of green to denote lower levels of VMT, vehicle hours traveled (VHT), and energy, whereas red shades denote higher levels. Truck electrification in Base0 does not exist, so the magnitude of change is shown when comparing scenarios B and C with Base0. Electricity results represent electricity from the grid only. Other types of electricity, such as from hybrid powertrains, are not included.

Table 13. POLARIS freight impact results summary.

Market	Metric	Unit	Reference baselines: Base0	Reference baselines: Base 1/2/3[1]	Reference baselines: Base 4/5/6[1]	%Δ from Base0[2]: A2	A3	B5	B6	C5	C6	%Δ from short-term[3]: A2	A3	%Δ from long-term[3]: B5	B6	C5	C6
All MDT, HDT Trips	**Vehicle miles traveled (VMT)**	**M miles**	**23**	**23**	**29**	**3%**	**1%**	**31%**	**32%**	**32%**	**34%**	**1%**	**-1%**	**2%**	**3%**	**3%**	**4%**
	VMT, HDT	M miles	20	20	26	-0.2%	-2%	28%	30%	30%	31%	-1%	-3%	-1%	0%	0%	1%
	VMT, MDT	M miles	2.6	2.9	3.2	24%	23%	50%	51%	51%	55%	12%	13%	25%	25%	26%	29%
	Vehicle hours traveled (VHT)	**M hours**	**0.6**	**0.7**	**0.8**	**-1%**	**-4%**	**25%**	**31%**	**58%**	**77%**	**-5%**	**-9%**	**-6%**	**-1%**	**18%**	**33%**
	VHT, HDT	M hours	0.53	0.56	0.70	-3%	-6%	24%	31%	56%	71%	-7%	-10%	-9%	-3%	15%	27%
	VHT, MDT	M hours	0.09	0.10	0.11	13%	11%	35%	36%	68%	113%	5%	0%	11%	12%	38%	76%
	Fuel	**M gallons**	**4.5**	**4.6 3.6 3.2**	**5.6 4.3 3.5**	**-20%**	**-31%**	**-6%**	**-23%**	**-0.5%**	**-16%**	**-1%**	**-3%**	**-2%**	**-1%**	**4%**	**8%**
	Fuel, HDT	M gallons	4.2	4.3 3.4 3	5.3 4.1 3.3	-21%	-31%	-6%	-22%	-0.7%	-16%	-2%	-4%	-3%	-2%	3%	7%
	Fuel, MDT	M gallons	0.28	0.32 0.25 0.21	0.34 0.22 0.16	-1%	-17%	-4%	-28%	1.8%	-18%	12%	11%	24%	25%	31%	41%
	Fuel	**GWh**	**151**	**155 122 108**	**188 145 118**	**-20%**	**-31%**	**-6%**	**-22%**	**-0.2%**	**-15%**	**-1%**	**-3%**	**-2%**	**-1%**	**4%**	**8%**
	Electricity	**GWh**	**0**	**0 0 0**	**0 0.4 0.7**			**0.5**	**0.9**	**0.5**	**0.9**			**15%**	**25%**	**19%**	**31%**
	Total Energy	**GWh**	**151**	**156 122 109**	**189 145 118**	**-20%**	**-31%**	**-6%**	**-22%**	**0%**	**-15%**	**-1%**	**-3%**	**-2%**	**-1%**	**4%**	**8%**
E-commerce & Retail Shopping Only	**VMT: Total**	**M miles**	**20**	**22**	**23**	**-31%**	**-32%**	**-50%**	**-47%**	**-42%**	**-36%**	**-34%**	**-35%**	**-56%**	**-53%**	**-49%**	**-44%**
	VMT, MDT Delivery	M miles	0.2	0.2	0.2	244%	243%	474%	484%	473%	491%	198%	200%	433%	444%	432%	450%
	VMT, LDV Shopping	M miles	20	21	23	-34%	-34%	-55%	-51%	-46%	-41%	-36%	-37%	-60%	-57%	-53%	-48%
	Total Energy	**GWh**	**23**	**24 21 18**	**26 17 14**	**-39%**	**-49%**	**-63%**	**-72%**	**-54%**	**-57%**	**-33%**	**-33%**	**-50%**	**-54%**	**-38%**	**-29%**
	Energy, MDT Delivery	GWh	0.7	0.8 0.6 0.5	0.7 0.5 0.4	175%	129%	294%	221%	320%	260%	195%	196%	408%	420%	441%	483%
	Energy, LDV Shopping	GWh	22	24 20 17	25 17 14	-45%	-55%	-74%	-81%	-65%	-66%	-40%	-40%	-65%	-68%	-53%	-45%

1. Each of the 'Short' and 'Long' baselines has two sub-cases shown as business as usual / VTO program success

2. Change in electricity is shown as magnitude (MD/HD has zero electricification in Base0, so % change cannot be obtained)

3. Scenario A2 vs. Base2, A3 vs. Base3, B5 & C5 vs. Base5, B6 & C6 vs. Base6

HDT = heavy-duty truck; MDT = medium-duty truck; LDV = light-duty vehicle

In the baseline scenario (Base0), freight transportation generated about 10% of regional VMT but consumed about 30% of fuel (Figure 42) because of a lower fuel economy than that of passenger cars. This comparison is consistent with other studies, which indicate that freight traffic has a disproportionately high impact on energy consumption (US DOT, 2017). As a result, potential improvements in MD/HD vehicle energy efficiency could have dramatic impacts on transportation energy consumption. Some of the energy consumption impacts of trucking are due to traffic congestion, which is caused by both passenger and freight vehicles (see the Workflow Capstone Report for a full description of passenger and systemwide congestion results). For example, comparing the percentage changes in truck VMT vs. VHT for C5/C6 with Base0 shows that for each additional mile traveled, truck VHT increases at a higher rate (Table 13). In other words, increased travel comes at the cost of slower travel speeds in this instance.

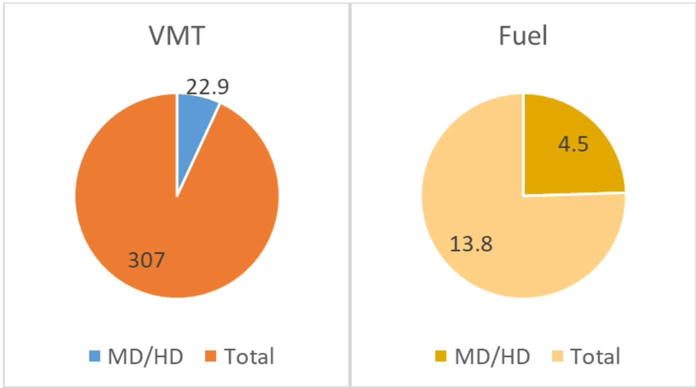


Figure 42. Base1 medium-duty/heavy-duty (MD/HD) shares of vehicle miles traveled (VMT; million miles) and fuel (million gallons) from POLARIS workflow.

As with the above tables, the electricity quantities shown in the rest of these results was based on electricity from the grid only (e.g., by plugging EVs into the grid). A complete discussion of energy results by vehicle class can be found in the Workflow Capstone Report section "Vehicle Technology Impact and Vehicle Class Contribution to Energy Consumption."

At a moderate rate of commodity flow growth (1% compound annual growth rate), total freight VMT in the Chicago region is predicted to grow about 27% in the long term (Base 4/5/6 vs. Base0) with detrimental impacts on energy consumption (as shown in Base4) unless energy-efficient technologies are adopted more widely (represented by moderate and aggressive technology improvements in Base5 and Base6, respectively). As Figure 43 shows, with the same technology as today, there would be a 25% increase in truck fuel use in the long term (Base4 over Base0). More efficient technologies, however, could enable a 4 to 22% energy reduction in the low-technology Base5 and high-technology Base6 long-term baseline scenarios, respectively (relative to Base0). Full electrification plays a small role in improving energy efficiency in Base5 and Base6. Similar conclusions apply for the short term; however, the impact is smaller because of less time for technology advancement. VMT increases slightly from the baseline (Base0) to the short-term (Base1 to Base3) scenarios, with energy consumption increasing commensurately by 5 GWh with no technology improvements (Base0 to Base1) and decreasing significantly by 29 and 42 GWh, respectively, with technology improvements (Base2 and Base3 compared with Base0).

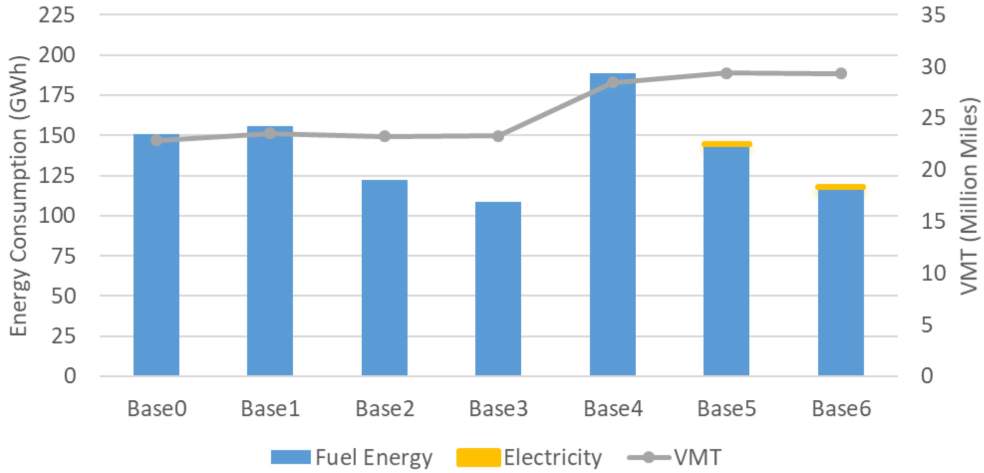


Figure 43. Impacts of commodity flow growth and vehicle technology changes on freight vehicle miles traveled (VMT) and energy consumption from POLARIS workflow.

Under the electrification assumptions used in this study, full powertrain electrification played only a small role in improving energy efficiency in Base5 and Base6, whereas increased efficiency of internal combustion engines played a major role in dampening the overall energy impact of increased truck VMT. At most, fully electrified powertrains were assumed to have a 15% MDT/HDT market penetration (in the long-term B and C scenarios). Therefore, increased electrification and/or increased market penetration of energy efficient technologies among MDTs/HDTs remains a major opportunity space for improving transportation-related energy consumption. Again, a full discussion of this market penetration is available in the Workflow Capstone Report.

Although e-commerce is expected to generate a large increase in last-mile delivery, overall net reductions in VMT (34–56%) and energy use (30–55%) were estimated to occur after considering shopping trip reductions, delivery trip increases, and vehicle technology changes. Table 13 shows how these estimates were derived by comparing the A/B/C scenarios with Base2/3 and Base5/6, and Figure 44 illustrates the VMT and energy results attributed to retail purchasing with shopping and delivery impacts for the scenarios in comparison with Base0. Results for the e-commerce analysis are distinguished by MDT delivery vehicles and passenger shopping vehicles, which are all LDVs. By assumption, the e-commerce delivery rate increased from one delivery per household per week (Base0) to three times per week (A2, A3) to five times per week (B5, B6, C5, C6). Since the average shopping trip is about 7 to 8 mi long and since regular shopping constituted about 7% of all VMT in Base0 (POLARIS; Figure 45), the potential VMT and energy reduction associated with shopping trip reduction was substantial. In comparison with the base year (Base0), if household e-commerce orders were to triple in the short term, net reductions of about 31% in retail-based VMT and about 39–49% in retail-based energy consumption could occur. In the long term, if household e-commerce rates were to grow to 5 days per week, retail-based declines of 36–50% in VMT and 54–72% in energy could occur compared with Base0.

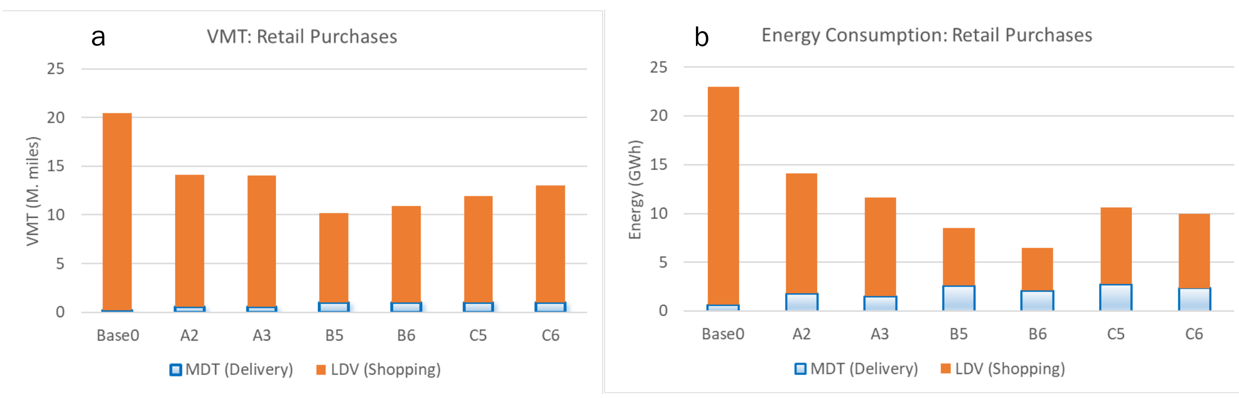


Figure 44. (a) Vehicle miles traveled (VMT) and (b) energy consumption associated with retail purchasing from POLARIS workflow.

Figure 45. Passenger shopping generates 7% of regional vehicle miles traveled (VMT).

The VMT savings were even greater when comparing the future scenarios (A/B/C) with Base1/2/3 and Base4/5/6, which projected that retail VMT will grow by about 5% in the short term and 14% in the long term when household delivery rates remain at today's levels. Finally, total retail activity in A2/A3 used about 33% less energy than in Base2/Base3 (Table 13), demonstrating that increased e-commerce leads to reductions in energy use beyond the energy savings that are due to vehicle technology. Findings for the long term were similar, with energy savings of 29–54% in the B/C scenarios in comparison with Base5/Base6.

The B scenarios had lower VMT and energy use than the C scenarios because of differences in household behavior, namely the differences in trip length when passengers use shared TNC (especially in B) vs. privately owned AV (especially in C). Passenger trips, including shopping trips, that use private AV were forecast to be longer on average than those that use shared TNC. So, although the number of passenger shopping trips was the same in all B and C scenarios (with negligible differences due to the nature of the simulation), shopping trips generated more VMT and energy use in C5 and C6 than in B5 and B6. VMT and energy use by MDT delivery trucks was also higher in C even though the number of deliveries was the same in the two scenarios. The differences for MDTs were caused by the additional congestion in C relative to B, which was due to the changes in passenger travel, thereby causing slower speeds and more circuitous routing.

The e-commerce analysis may be refined in the future to account for repurposing of trips, merchandise returns, or other indirect effects of e-commerce.

The VMT generated by e-commerce delivery has been projected to grow at a much faster rate than VMT generated by commodity types other than e-commerce-based retail goods (per assumption and based on FAF forecasts). However, e-commerce delivery trucks in this study constituted a maximum of only 3% of MD/HD VMT, which underscores the importance of analyzing the other types of freight traffic that make up 97% of VMT. The small percentage attributable to e-commerce was due mainly to the nature of last-mile delivery, in which each delivery trip—in an efficient delivery system, which (based on parcel carrier data) generates about 120 stops per delivery tour—added only a small amount of mileage. Other MDT/HDT trips tended to be much longer; for example, the in-region portion of HDT trips averaged 35 mi in this model. As shown in Figure 46, total truck VMT was highest in the B and C scenarios, which were associated with growth in commodity flows over the long term as well as the highest e-commerce rates. Improved vehicle technology helped mitigate energy consumption in the A/B/C scenarios, with greater energy savings consistently achieved in the high-tech scenarios (A3, B6, C6) compared with the low-tech scenarios (A2, B5, C5). Again, this figure highlights the opportunity space for full electrification of freight vehicles and the major impact that it could have on total freight-related energy consumption (see the Workflow Capstone Report for a full discussion of LDV, MDT, and HDT energy impacts).

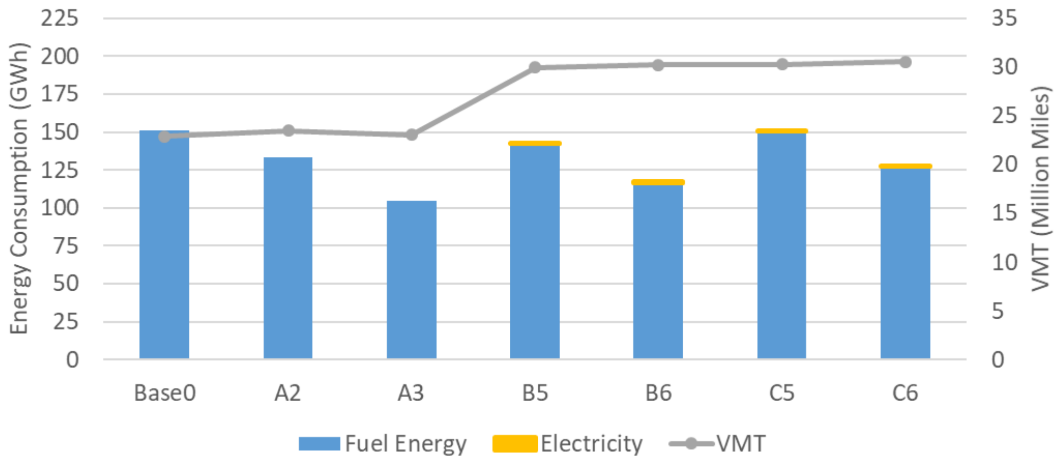


Figure 46. Medium-/heavy-duty truck impacts on vehicle miles traveled (VMT) and energy use across scenarios from POLARIS workflow.

Finally, the timing of freight trips, which were concentrated most intensely during daytime hours, coincided with the time period (daytime) when system demand from passenger vehicles was also at its highest (see Figure 47 for POLARIS output for the Chicago region). The timing of freight trips in the model was not surprising since it was based on the inputs described previously. The competition for system capacity was interesting for passenger vehicles, which, as shown in the figure, had a similar demand pattern to freight, but passenger vehicles constituted the majority of traffic (90% of VMT). This contributes to the challenges that MDTs and HDTs face in delivering goods reliably and in an economically efficient way. Energy efficiency for all travel worsens with congestion, which is most severe during the daytime. A joint study by Rensselaer Polytechnic Institute, Argonne National Laboratory, and George Mason University examines off-hours delivery and other options to improve freight efficiency.

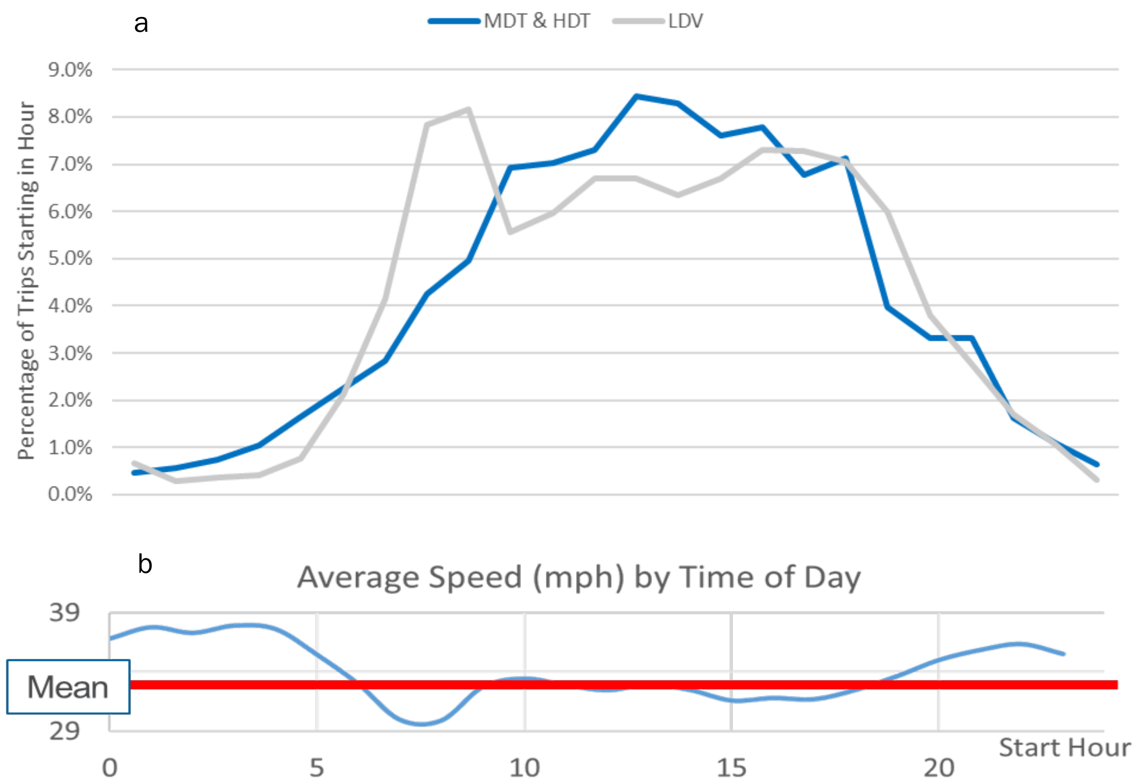


Figure 47. (a) Medium-/heavy-duty truck (MDT, HDT) and light-duty vehicle (LDV) trips and (b) system average speed by time of day.

In summary, two freight models were developed in this study to evaluate the impacts of freight transportation on VMT and energy consumption. The first (top-down) model generated freight flows between individual establishments by using commodity flows. The second (agent-based) model generated flows by first synthesizing a population of agents and their characteristics, and then modeling their trading partnerships and subsequent shipment decisions. Both models then conducted vehicle routing in a DTA environment, using route information to estimate VMT and energy use of freight trips, accounting for the complete congestion impacts of both passenger and freight vehicles. The agent-based model will be applied for future analysis.

The top-down model was applied to evaluate freight transportation impacts across 13 SMART workflow scenarios. The results established the baseline energy and VMT impacts of freight, demonstrating that freight vehicles had a disproportionately high energy impact (30% of fuel) relative to their VMT (10% of VMT). With projected increases of 27% in truck traffic in the long term due to growth in commodity flows, improved powertrain efficiency is needed to mitigate energy consumption. Increased market penetration of efficient powertrain technologies can have sizeable impacts on freight energy consumption, reducing long-term energy use by up to 22% compared with the base year, despite increased freight demand.

Increased e-commerce creates additional truck VMT. However, under certain scenarios, e-commerce reduced overall retail VMT by up to 56% because each delivery adds just a small amount of distance to an efficient delivery tour, creating net savings by replacing relatively long-distance shopping trips. E-commerce can reduce net retail energy use by up to 55%, extending the benefits of improved vehicle technologies.

2.4 Freight Mobility Energy Productivity

As discussed Section 2.3.4, understanding the impact of emerging technologies and trends on the freight movement system's productivity is important. Measuring system impacts with a productivity metric will help public and private stakeholders make informed decisions, depending on their objectives, regarding technology development and deployment, freight establishment location, transport mode selection, infrastructure planning and investment, and regional development.

2.4.1 Introduction

Developing a holistic metric of freight system performance is challenging because of the complex nature of the freight and logistics system and a lack of data and transparency. However, the literature contains many potential indicators spanning a range of quality and performance measures as summarized in Table 14. Many metrics could fall into multiple categories but are listed only once in this table. Frequent data sources include the FAF, the Commodity Flow Survey, the HPMS, the National Performance Management Research Data Set, truck probe and GPS data, and maritime, pipeline, railroad, aviation, and border crossing data sets.

The MMF pillar researchers developed a new freight system performance metric, consistent with DOE goals, to quantify freight system energy productivity in a holistic way. The F-MEP metric can be used as a local planning tool and a scenario evaluation tool to assessing the relative impact of future changes in the freight system. From the freight perspective, mobility was defined as the ability to transport goods to their destination (i.e., business establishments or private consumers). Productivity measured output for a unit of input and, in the context of this work, reflected the efficiency of the transportation system to produce useful work (Hou, Garikapati, Nag, Young, & Grushka, 2019). F-MEP can be thought of as an indicator, for a given location or area, of the quality of the freight transportation system and its ability to move a maximum amount of freight for a minimum expenditure of time, economic cost, and energy.

Table 14. Example freight system performance metrics.

Category	Examples
Freight moved	Number of trucks, rail cars, 10-ft equivalent units Tons, value Ton-miles, value-miles Flights per day (air)
System capacity, accessibility	Road, port, rail, or channel capacity Miles of peak period congestion per day Number of truck rest areas and capacity Percentage of shippers with access to triple trailer network, rail, others Number or capacity of intermodal facilities Shippers within 50 mi of facilities (intermodal, port) Intermodal facility, warehouse capacity Number of docks, cargo-handling acreage

Table 14. Example freight system performance metrics (continued).

Category	Examples
Mobility, reliability	Travel time for select commodities, modes, and markets Peak period travel time Percentage of system with reliable travel time Hours of delay, annual or average daily Travel time index (peak/free-flow)
System condition	Percentage of system in good condition, remaining service life Percentage of rail track-miles with speed >25 mph Number of at-grade rail crossings Number or percentage of bridges with restricted weight or clearance
Safety	Crash rate Number of truck-related fatalities Number of derailments Cost of freight loss and damage per mile, ton, or total value Insurance cost per ton of cargo

Metrics can be classified in multiple categories but are listed only once for brevity.
Sources: (FHWA, 2017) (MnDOT, 2008)

2.4.2 Objectives

The key objective of this project was to develop a geographically based, generalizable framework for quantifying F-MEP, test the framework using initial implementations and available data, and demonstrate the usefulness for future analysis. The goals for the framework were that it be

- Built on a generalized framework that can interact with existing freight modeling tools and publicly available data sources
- Able to be fine-tuned to a region or commodity
- Able to measure performance offered by various modes (and a combination of such modes), both existing and future
- Able to evaluate the impacts of emerging freight trends and technologies such as connectivity and automation, electrification, new delivery solutions, e-commerce, and so on

2.4.3 Approach

This project introduced the F-MEP metric as a concise, scalable measure of system quality. It was a scalable, open-source metric that quantified the energy-productivity of the freight transportation system, capturing both existing and emerging options for freight movement. The F-MEP metric was nationally generalizable, geographically based, and applicable across a range of geographic scales, thereby enabling interregional comparisons. When applied to model outputs, the F-MEP metric also enabled comparison of alternative future scenarios. Separate methodologies, both based on the accessibility theory, were developed for inter- and intracity freight movement to account for differences in scale, scope, data availability, and system architecture.

Accessibility was defined as the ease with which activities could be reached from a given place, using a given mode of transport (Morris, Dumble, & Wigan, 1978). The accessibility theory and its application to passenger travel behavior has been an active area of research in social and geographical sciences, dating back to pioneering research by Ravenstein (1885). Accessibility can be summarized to be (1) the spatial distribution of opportunities; (2) mobility provided by the road infrastructure and transportation system; (3) temporal constraints of individuals and activities; and (4) individual characteristics of people. Distance-based, isochrone-based, and potential accessibility/gravity-based accessibility measures have been widely used by researchers and practitioners (Hou, Garikapati, Nag, Young, & Grushka, 2019).

Very few researchers have adopted the accessibility theory in the context of freight transportation, and no research has combined the accessibility theory with energy, cost, and ease of freight movement to develop a unified performance metric capable of capturing mobility and energy impacts of existing and emerging freight technologies.

The F-MEP metric development adopted a location-based accessibility theory. It was formulated as freight mobility benefits divided by total cost, which consists of different dimensions as shown in Figure 48. Although freight movement is a multiagent problem involving shippers, carriers, receivers, and logistics firms, a shipper perspective was chosen for the development of the F-MEP metric. A shipper perspective can likely provide insights on efficiency of freight transportation systems to decision-makers in the public and private sectors.

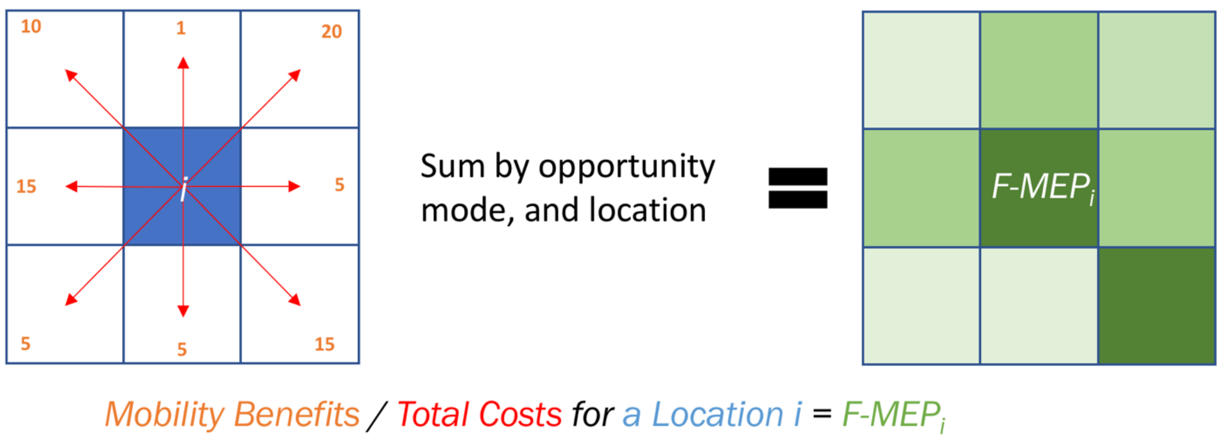


Figure 48. Conceptual freight mobility energy productivity (F-MEP) formulation.

2.4.4 Results/Findings

2.4.4.1 *Intracity*

The intracity F-MEP metric was adapted from the passenger MEP and was a function of the total delivery opportunities, o_{ikt}, that can be reached by mode, k, from the i^{th} cell block (location) within a given travel time, t (the isochrone), and a mode-specific utility function, U_{ikt}, that depends on energy, travel time, and cost, as shown in Eq. 3:

$$F{-}MEP_i = \sum_k \sum_t \left(o_{ikt} - o_{ik(t-\Delta t)}\right) \cdot e^{U_{ikt}} \quad (3)$$

The total opportunity metric for each location, mode, and isochrone was a weighted sum of the individual delivery opportunities by type, o_{ijkt}. The weighting factors were based on the total number of benchmark opportunities calculated from data for multiple cities, N^*, the total number of opportunities of type j within the subject region N_j, and the typical frequency of deliveries for opportunity type j, f_j, as shown in Eq. 4:

$$O_{ikt} = \sum_j o_{ijkt} \cdot \frac{N^*}{N_j} \cdot \frac{f_j}{\sum_j f_j} \quad (4)$$

The team implemented the intracity F-MEP formulation for calculating energy productivity of freight mobility for Columbus, Ohio to demonstrate the metric's capability. The researchers defined a study area that was divided into 1 km by 1 km square pixels. Ten preliminary opportunity types associated with freight activities and corresponding locations were identified based on land use data provided by CoStar. Figure 49 represents the locations of opportunities by their type in Columbus, Ohio, excluding the location of the population.

Information on delivery frequency was difficult to infer from existing freight data. For the purposes of demonstrating the formulation, one visit to business establishments and six visits to residential locations per day were assumed in this implementation. For the opportunity benchmark factor, the total number of post office opportunities (i.e., 67) was used. For the travel time calculation, average travel times between two locations were obtained from the network. For this illustrative implementation, Class 6 and 8 trucks were applied with 8 mi/gal and 5.8 mi/gal of energy intensity, respectively.

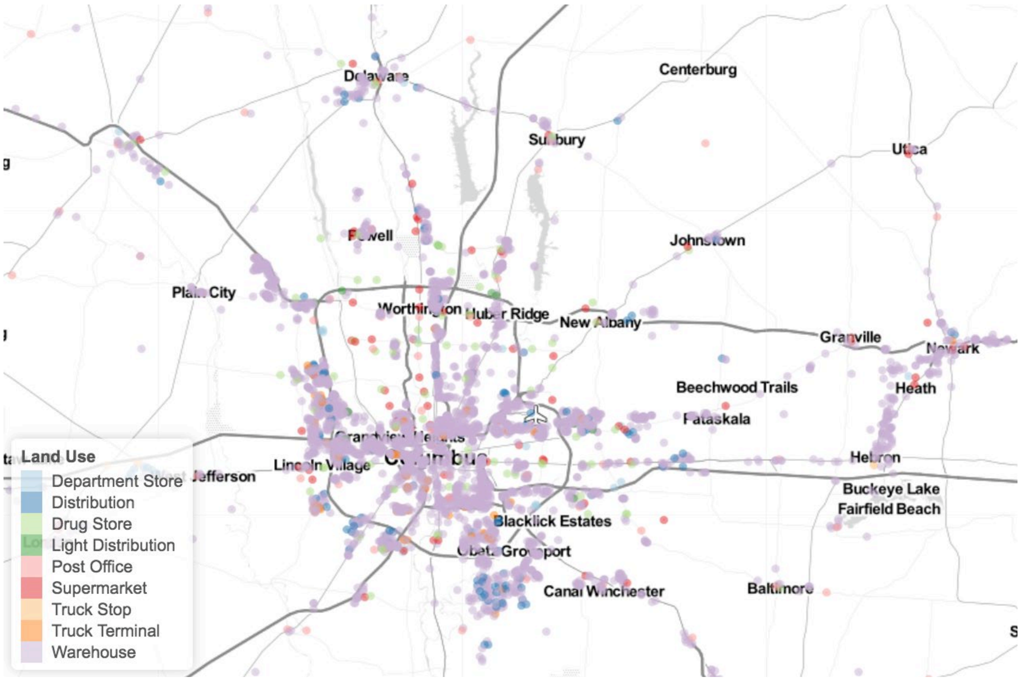


Figure 49. Identified opportunity map (Columbus, Ohio).

Figure 50 represents overall F-MEP scores aggregated over two truck modes for all pixels in the study area. The map is color-coded using a red to green gradient scale in which dark red depicts a score of 0, indicating low MEP, and dark green depicts a score of 100, indicating a healthy location in terms of freight movement. The F-MEP metric scores were scaled from 0 to 100 for relatability. The map also includes the identified opportunities from Figure 49. Locations along the highway and close to the center of the city had high MEP values, which implies that shippers in those locations can easily find their potential customers and send their shipments to other locations. Additionally, the findings seem intuitive in that delivery locations tended to be concentrated in the city center, in populated areas, and along the transportation network.

Scenario analysis could be carried out with varying inputs such as new delivery modes and new policies because the F-MEP metric was designed to respond to input from various freight models. Future work will address limitations in extending the framework to scenario analysis through methodology refinements.

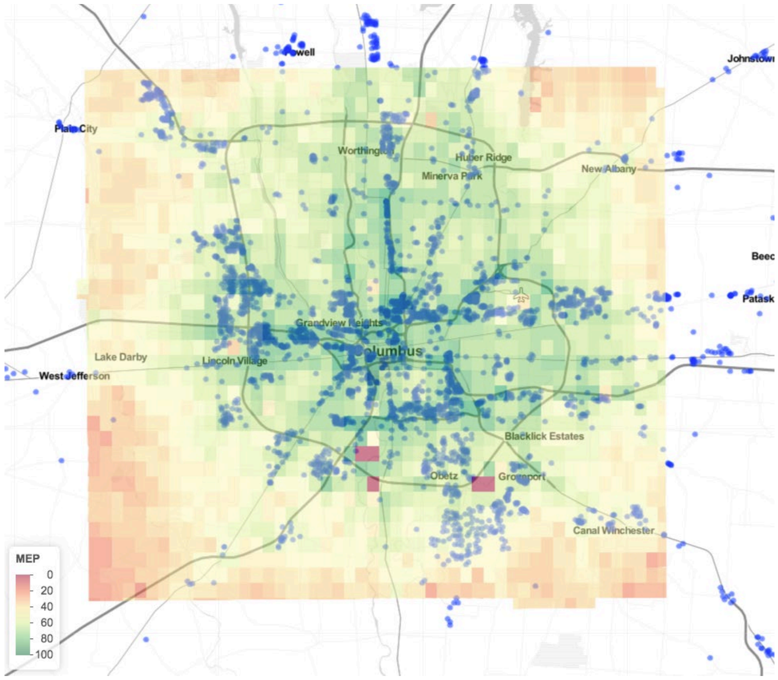


Figure 50. Baseline freight mobility energy productivity (MEP) (Columbus, Ohio).

2.4.4.2 *Intercity*

The intercity $F\text{-}MEP_i$ for location, *I*, was the product of two factors: mobility benefit and impedance. Mobility benefit, B_{cj}, of commodity or business type *c* delivered to location *j,* was a function of freight delivery opportunities, *X*. Impedance, $f_{c,ij}$, was specified for each mode, *k*, and was a function various cost variables, *Y*, as shown in Eq. 5:

$$F{-}MEP_i \;= \sum_k \sum_c \sum_{j \neq i} B_{cj}(X) \cdot f^{k}_{c,ij}(Y) \tag{5}$$

An exponential formulation was selected for the impedance function , including mode-specific measures of energy intensity, E_k, unit logistics costs, p_k, shipping time, and ease of shipping from location *i*, s_{ik}. The exponential form captured an increasing response as costs increased and allowed for mode- and commodity-specific parameters in this decay function. Given the correlation within each mode between distance and time, impedance caused by time was captured through the fraction, *r*, of commodity, *c*, moved by mode, *k*, within a range, *l*, containing the distance between *i* and *j*, as shown in Eq. 6:

$$f^{k}_{c,ij} = \exp(\alpha E_k + \beta p_k) \cdot r_{ck}^{l_{ij}} \cdot s_{ik} \tag{6}$$

To demonstrate the capability and scalability of the proposed formulation, the methodology was implemented for the mainland United States using the FAF data and zonal structure. For zone *i*, the benefit, B_{cj}, of shipping commodity *c* to zone *j* was assumed to be captured by the total commodity tonnage shipped from *i* to *j*. The impedance function parameter values should reflect the user's (e.g., shipper or planner) perceptions of the relative importance of cost and energy, but to provide an initial illustration, the coefficients for both energy and cost were set to −0.5. The FAF was used to determine commodity fraction, *r*. Ease of shipping was set to 1 for trucks and calculated as the ratio of the number of modal facilities in zone *i* divided by the maximum number of facilities in any zone. Energy intensity and logistics cost by mode were estimated from the literature.

Figure 51 presents overall F-MEP scores aggregated over truck, rail, water, and air modes for all FAF zones. The map is color-coded using a red gradient scale in which dark red indicates high scores representing high F-MEP from that zone, whereas light red indicates low scores with low F-MEP from that zone. The F-MEP metric scores were scaled by a factor of 5,000 for relatability. The Chicago FAF zone had the highest F-MEP score (283), whereas the Salt Lake City FAF zone had the lowest F-MEP score of 21. Overall, zones in the Midwest and Mid-Atlantic had better F-MEP scores, indicating attractiveness of shipping from those zones. The findings seem intuitive based on the following reasons: (1) many FAF zones with high F-MEP values were located in the Central United States, with relatively short distances to all other zones; (2) the FAF zones with high F-MEP scores had good accessibility to all transportation modes, including ports; (3) the FAF zones with high F-MEP scores were close to the big freight demand markets in the Northeast; and (4) many FAF zones with high F-MEP were located near manufacturing centers.

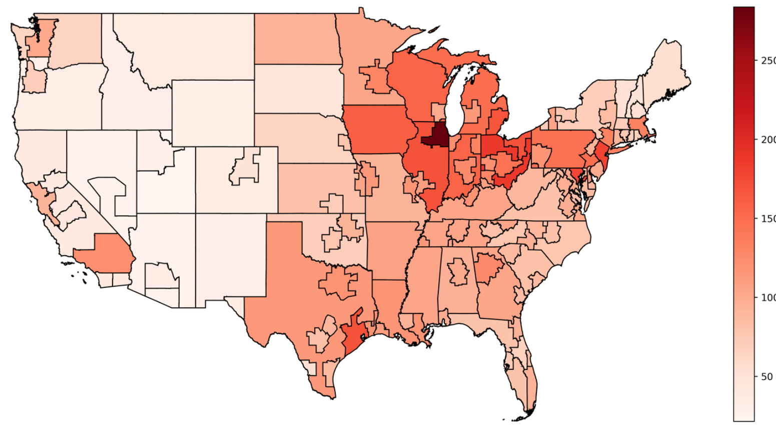


Figure 51. Freight mobility energy productivity map (national scale—Freight Analysis Framework zonal structure).

As mentioned previously, freight movement across commodity types and modes is nonhomogeneous in nature. The F-MEP framework captured this heterogeneity and generated efficiency scores by commodity and/or mode as shown in Figure 52 and Figure 53. The left column of Figure 52 depicts F-MEP maps by commodity type, whereas the right column shows F-MEP maps by mode. Compared with overall F-MEP scores (Figure 51), the F-MEP maps by commodity and mode uncovered some interesting patterns. Although the specific parameterization used here was intended only to demonstrate the framework and was not intended as a definitive ranking of FAF zones, decomposing the metric and comparing these patterns illustrates the power and complexity of the F-MEP approach. For example, the F-MEP map for electronics and mixed freight (Figure 52c and d) show relatively high scores in California and Washington, perhaps because these commodities could be moved easily by rail, air, or water modes from these locations (which is captured in the F-MEP computation through the ease of shipping parameter). The F-MEP scores for truck mode seem to be influenced more by the distance term (since ease of shipping for trucks was assigned a value of 1 across all zones), showing a gradual decay in F-MEP scores for FAF zones from center to east and west. However, local richness of infrastructure played a key role in freight performance for rail, water, and air modes, which is shown by high F-MEP scores for these modes in zones with high densities of ports and terminals (Figure 52 e–h). The current F-MEP framework was not designed to consider demand at international zones, which resulted in relatively low F-MEP scores for the water mode in the Los Angeles FAF zone even though that zone included the largest port in the United States, which plays a significant role in international trade via water.

Figure 53 presents F-MEP maps for different commodities further classified by modes to examine how commodity type affects the freight performance metric (reflected by F-MEP score) for different modes. For example, since logs are not moved by air, no score was assigned for F-MEP for that mode-commodity combination (Figure 44 b-2). In contrast, mixed freight could be easily moved by various modes, including rail and water, depicted by relatively high F-MEP scores for those modes (Figure 44 d). The mode-commodity disaggregation is an extremely useful feature of the F-MEP metric that enables users to conduct customized analyses to understand the impact of different technologies on freight performance improvements for specific mode-commodity combinations.

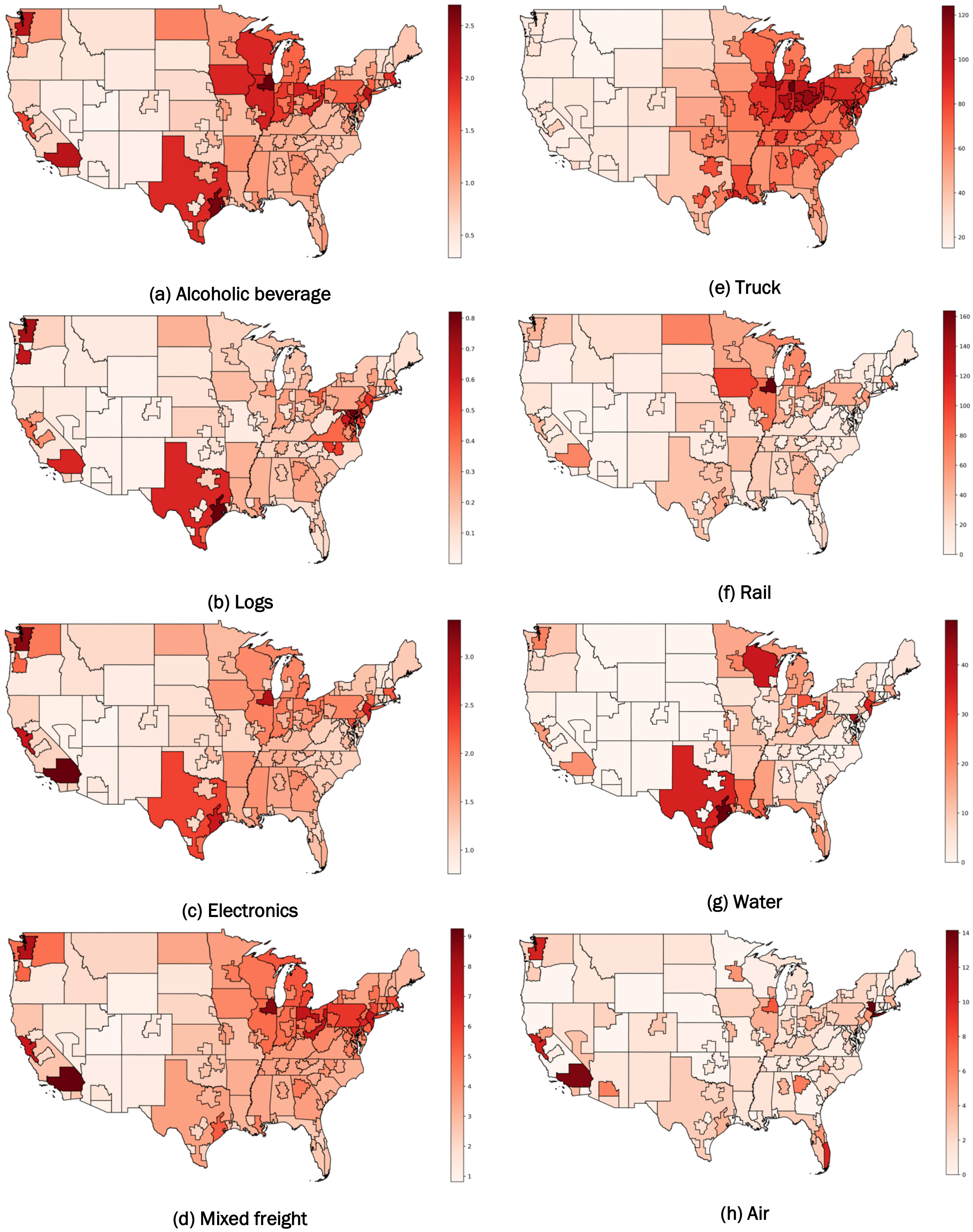


Figure 52. (a–d) Commodity-specific overall freight mobility energy productivity map and (e–h) mode-specific freight mobility energy productivity.

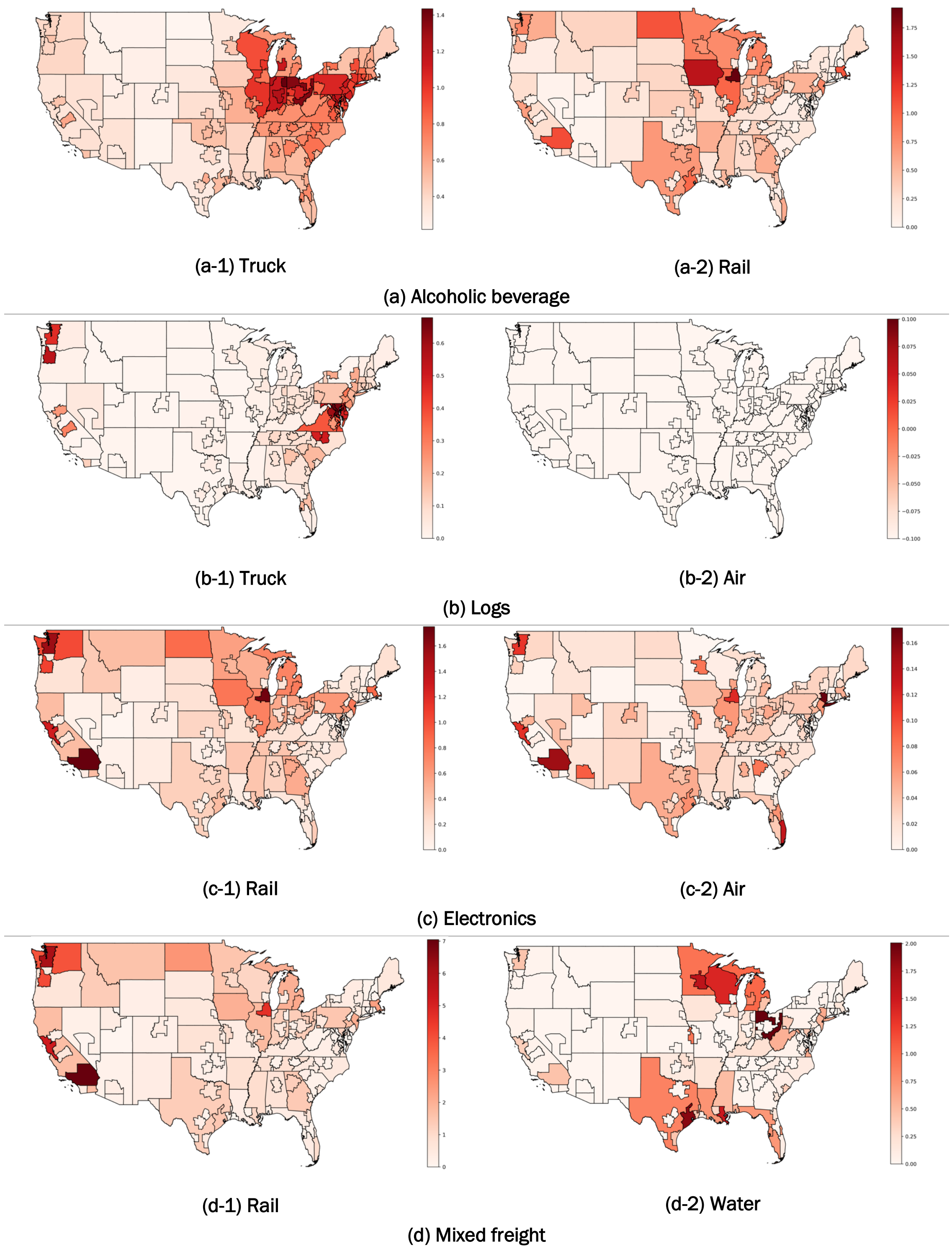


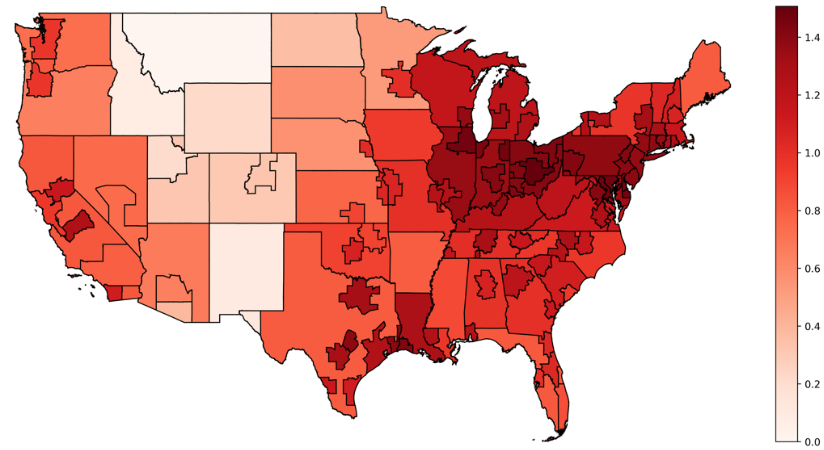
Figure 53. Freight mobility energy productivity map by commodity and mode.

One of the most important facets of F-MEP metric is that it can be used to evaluate the impacts of emerging freight technologies and trends on freight performance at the system level. This evaluation is ideally conducted by obtaining outputs of scenario analyses from freight demand forecasting models and providing them as input to the F-MEP calculation procedure. Such an integrated metric will be an invaluable tool in assessing the relative benefits across multiple freight scenarios. For example, if a city plans to approve building a new freight distribution warehouse, mixed freight shipping is expected to increase. The change in freight productivity (for that city/zone as well as adjacent zones) from such a scenario can be easily captured using the F-MEP framework. Similarly, the increase in freight efficiency with the introduction of new modes for freight delivery with lower energy or cost footprints (such as high-speed rail or autonomous electric delivery shuttles) can also be quantified using the F-MEP metric. To demonstrate the responsiveness of the F-MEP metric to freight technologies, two hypothetical scenario analyses pertaining to long-haul truck electrification are presented here:

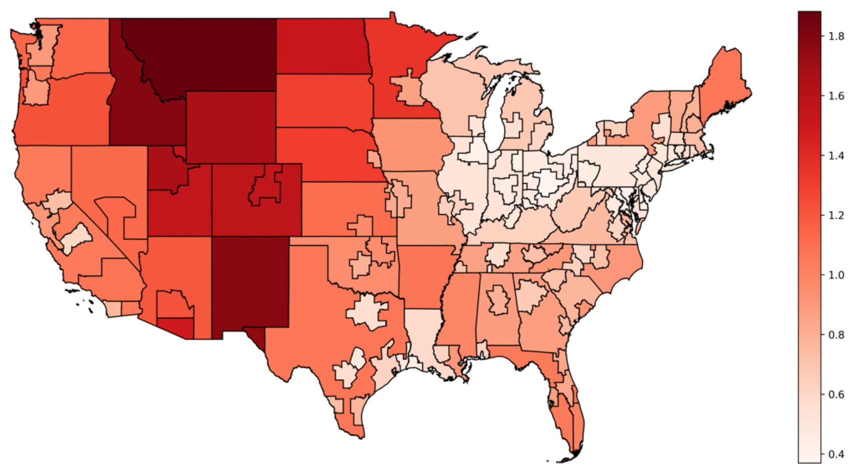
- S1—Electrification of the powertrains with range constraints:
  - $/ton-mile for
  - $/ton-mile for
- S2—Electrification of the powertrains without range constraints:
  - $/ton-mile for all.

In both scenarios, electric trucks were assumed to require one-third of the energy used by conventional trucks. In the first scenario (S1), electric trucks were constrained to travel 500 mi or less, owing to charging infrastructure constraints (reflecting a near term future). Under this scenario, all road freight delivery within a range of 500 mi or less were envisioned to be handled by electric trucks. For deliveries within a range greater than 500 mi, conventional trucks were used. In the second scenario (S2), the charging constraints were expected to be mitigated, and all conventional trucks were anticipated to be replaced with electric trucks. The intent of this scenario analysis was to test the formulation of the metric and to demonstrate the capability of F-MEP metric for scenario analysis. The assumptions used here were intended for illustration only. The team acknowledges that the assumptions were highly aggregated/simplified, were aggressive, and did not account for secondary impacts of market penetration of electric trucks. Such impacts can be captured using freight forecasting models, outputs of which serve as ideal inputs for the F-MEP scenarios. Future efforts will focus in integrating the F-MEP calculation with sophisticated freight forecasting models.

Results of the scenario analysis shown in Figure 54 depict the relative improvements in F-MEP metric from the baseline to S1, and from S1 to S2. For scenario 1, F-MEP for zones that had high freight demand zones within 500 mi (e.g., FAF zones in the Northeast or South) benefited from the vehicle electrification. Once the range constraints were removed, F-MEP gains (or increases in freight efficiency) became significant for zones that were farther away from freight hubs.



S1 compared with baseline



S2 compared with S1

Figure 54. Relative truck freight mobility energy productivity gain (%).

3 Summary and Conclusions

3.1 Concise Review of Major Impacts of This Study

As freight grows to an expected 24% of energy use for the transportation sector by 2050, the relative importance of the science of freight mobility will continue to grow. This capstone report summarized performance characteristics for various classes of MD/HD vehicles in freight operations and classified range estimations for cargo by mass in various segments. The impact of this work feeds into the ability to plan technology specifications for future vehicles and highlights the need for connected vehicle support systems, whether that be infrastructure or deliver support networks to large cargo vehicles.

Major findings from each of the three focus areas of the SMART Mobility MMF pillar are shown in the following sections.

3.1.1 Intracity Last-Mile Delivery

- Retaining the conventional fleet of diesel delivery trucks and moving to a more aggregated delivery system, such as parcel lockers, results in substantial truck fleet energy reductions, up to 86% in the Chicago case study. This reduction is comparable to delivery fleet electrification, in which fleet energy usage can be reduced by up to 77%.

- However, conventional choices of personal transportation (gasoline sedans and SUVs) to pick up parcels at locker locations may significantly raise the total energy usage per tour by as much as 67–150%.
- An increase in market penetration of passenger car BEVs in combination with parcel lockers will have a positive effect on delivered goods because of e-commerce by reducing energy usage by as much as 32% compared with the baseline.
- Delivery of goods from the parcel lockers to a consumer's final destination by drone can have a profound impact on energy reduction by as much as 86%. Of course, a more realistic mix of delivery vehicle and drone usage should be investigated, but the potential is evident under the right conditions.
- While delivery vehicle electrification reduces the operating costs for a fleet operator, the net energy savings of parcel lockers and delivery vehicle electrification for a full tour considering consumer pick up is not as significant as the operational cost savings.

3.1.2 Intercity Freight Movement

3.1.2.1 *Load-pooling*

- From the load-pooling scenario analyses, multimodal load-pooling is expected to outperform truck load-pooling in terms of total energy savings for moving intercity freight.
- This performance results from the inherently higher freight efficiency in rail than in truck freight.

3.1.2.2 *Platooning*

- Platooning could lead to system-level fuel savings of nearly 7.9% for all platoonable trucks across the national highway network, compared with fuel consumption in the scenario without consideration of platooning.
- These savings are 1.6% smaller than all truck-level fuel savings because platoonable trucks can only form platoons on eligible road links. 59.5% (or 35,346 mi) of the total length of rural interstate highways were found to be eligible for platooning in the baseline scenario.
- A sensitivity analysis showed that system-level fuel savings of all platoonable FAF trucks increased from 5.6 to 8.5% when platoon size increased from 2 trucks to 5 trucks.

3.1.2.3 *Electrification*

- Based on projections used in this study, by the year 2050, 32% of freight ton-miles will have an average haul length of less than 300 mi, and 48% of freight ton-miles will have an average haul length of less than 500 mi. This portion of freight movement could be fully electrified with BEVs currently under development.
    - Only 17–24% of the Class 7–8 truck fleet would need to be BEVs with a 500-mi range to fully electrify this sector of freight. This change would reduce Class 7–8 fleet petroleum consumption by 1.61 quads, or 40%, in 2050 and would increase electricity consumption by 0.99 quads, or 23%, for a total Class 7–8 energy savings of 0.62 quads, or 15%, relative to the EIA AEO 2017 reference case.
    - Only 11–15% of the Class 7–8 truck fleet would need to be BEVs with a 300-mi range to fully electrify all freight moved under 300 mi. This change would reduce Class 7–8 petroleum consumption by 1.14 quads, or 28%, in 2050 and increase electricity consumption by 0.69 quads for total Class 7–8 energy savings of 0.45 quads, or 11%, relative to the EIA AEO 2017 reference case.

- Based on a payback analysis of VTO cost and performance projections, adoption of an electrified Class 7–8 truck portfolio, including HEVs, PHEVs, and BEVs, could optimistically reach 82% of tractors and 31% of SU trucks in the next few decades.
  - In this scenario, PHEVs provided lower lifetime costs (purchase price and fuel costs) compared with full battery electric trucks if charging is sufficient for them to maximize all electric driving.
  - This scenario provided higher total energy savings compared with the all-BEV scenarios of 0.99 quads, or 23%, of Class 7–8 consumption in 2050 relative to the EIA AEO 2019 reference case.
  - Adoption of electrified powertrains could reduce the lifetime cost of operations (capital costs and fuel) relative to a 2050 all-diesel fleet for all freight shipment distance bins.
  - For the estimated 2050 adoption levels, sales fleet average cost reductions could be about $0.06/mi. Although these reductions seem modest, for tractors driving 95,000 mi/year, this reduction equates to about $40,000 in cost savings (in NPV terms) over 7 years.

3.1.3 Regional Transportation System Impacts of Freight

- MD/HD trucks generate approximately 8–10% of regional VMT but consume a disproportionately high share of fuel (about 36% in the Chicago MSA).
- Technology improvements help to mitigate fuel consumption of trucks even if their VMT grows substantially. In a Chicago regional case in which truck VMT nearly double, truck fuel consumption increases range from 0 to 20%.
- Passenger LDV shopping trips generate about 6% of VMT in the Chicago region but consume a large amount of fuel (581,000 gal in the base case). An efficient delivery system presents a major opportunity to save on both VMT and fuel consumption. In a case in which household e-commerce demand grows from about one delivery per week on average to about three to four, this could reduce VMT by approximately 2–3 million mi and fuel use by 300,000–400,000 gal.
- Freight transportation impacts are concentrated most intensely during daytime hours, when the transportation system is most used.

3.1.4 Freight Mobility Energy Productivity Metric

- The F-MEP metric captured and illustrated changes in freight system performance due to emerging freight technologies, with geographic specificity (inter- or intracity). The metric can be used as a scenario evaluation tool to assess impacts of various emerging transportation trends on the performance of the freight systems.
  - In the intracity case, locations along the highway and close to the center of city had high F-MEP scores, reflecting the accessibility of the road network and/or freight receivers.
  - For intercity F-MEP, FAF zones with high F-MEP scores had one or more of the following attributes:
    - Located in the Central United States with relatively short distances to all other zones
    - Good accessibility to all transportation modes, including ports
    - Close to large freight demand markets in the Northeast United States
    - Located near manufacturing centers.

3.2 Recommendations for Future Work

Additional research remains to fully evaluate and understand the impact of emerging freight technologies and services. Based on the findings contained within this report, the following items summarize future work that could address research gaps in the multi-modal freight sector.

- Reliance on inadequate and outdated data hinders the ability to conduct systems-level freight research. Identifying more reliable and consistent sources of data (such as fleet delivery duty cycles, updated vehicle in-use data, and more detailed commodity flow data) and new data collection methods could enable more accurate analysis and support new research opportunities.

- A deeper understanding of freight impacts requires increased interaction and engagement among industry, government, and municipal stakeholders (e.g., the National Clean Fleets Partnership, 21st Century Truck Partnership – Freight Operational Efficiency Tech Team, American Association of State Highway and Transportation Officials, and original equipment manufacturers). Detailed definitions for electrification and disruptive delivery modes and vehicle mission environments would allow these industry partners to focus on proper technology advancement.

- To fully quantify the impacts of freight delivery on transportation, more detailed and complete integration of the components/technologies within the freight ecosystem is needed. Topics including urban freight pathways, powertrain technologies, total cost of ownership, infrastructure, disruptive technology impacts, original equipment manufacturer vs. fleet perspectives, and operator training may be included. This integration advances the current approach of "transportation as a set of pieces" to a truly integrated "transportation as a system" level of research.

- Representative scenarios for current and future freight delivery system should be developed and used for systems-level modeling, simulation, and analysis to estimate the impacts of new technologies and services. Validation is a critical part of modeling and simulation, and should leverage hardware-in-the-loop testing and pilot deployments.

- The analysis of freight impacts on the transportation system, and research of vehicle- and system-level freight technologies, should consider diverse geographic and climatic locations, and understand the opportunities and challenges associated with each of them.

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