Tran-SET

Transportation Consortium of South-Central States

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

Study the Impacts of Freight Consolidation and Truck Sharing on Freight Mobility

---

Project No. 17ITSOKS02

Lead University: Oklahoma State University

Final Report

April 2019

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

Acknowledgements

The authors would like to thank Mr. Prasad Mahajan and Transplace, Inc. for sharing of their freight movement data. The research team would also like to acknowledge direction and guidance of the Project Review Committee.

TECHNICAL DOCUMENTATION PAGE

1. Project No. 17ITSOKS02	**2. Government Accession No.**	**3. Recipient's Catalog No.**

4. Title and Subtitle Study the Impacts of Freight Consolidation and Truck Sharing on Freight Mobility	**5. Report Date** Apr. 2019 **6. Performing Organization Code**
7. Author(s) PI: Tieming Liu https://orcid.org/0000-0001-8104-2701 Co-PI: Chaoyue Zhao https://orcid.org/0000-0003-0442-2991	**8. Performing Organization Report No.**
9. Performing Organization Name and Address Transportation Consortium of South-Central States (Tran-SET) University Transportation Center for Region 6 3319 Patrick F. Taylor Hall, Louisiana State University, Baton Rouge, LA 70803	**10. Work Unit No. (TRAIS)** **11. Contract or Grant No.** 69A3551747106
12. Sponsoring Agency Name and Address United States of America Department of Transportation Research and Innovative Technology Administration	**13. Type of Report and Period Covered** Final Research Report Mar. 2018 – Mar. 2019 **14. Sponsoring Agency Code**

15. Supplementary Notes

Report uploaded and accessible at Tran-SET's website (http://transet.lsu.edu/).

16. Abstract

The trucking industry is an important sector of the U.S. economy. However, it is quite fragmented, hindering the efficiency of cargo transportation and the ability for small carriers to identify demands to fill full truck loads. The focus of this research is to study models and algorithms in order to aid online freight marketplaces to identify efficient consolidation strategies. To accomplish this aim, a new mixed integer programming model for the pickup and delivery problem has been developed. The model is geared towards identifying effective freight consolidation opportunities. A branch-and-cut algorithm to solve the model was also developed. The model was applied to several case studies using Transplace, Inc. (a third party logistics company) route data to identify optimized, consolidated routes. Emission impacts were also estimated for both the existing and consolidated routes using monetary equivalent cost (MEC) values. A linear regression model was developed to predict freight movement between metropolitan statistical areas (MSAs). Results of the case studies were then applied to estimate the operation and environment-related costs associated with freight movement from New Orleans MSA to Oklahoma City MSA for all commodities. Finally, the results of the case studies were applied at the national level and projected for future years, to estimate the potential cost savings in freight consolidation. Results indicate that it may be possible to consolidate cargo with only 67% of the currently used number of trucks, which may reduce the operation cost by 23% and MEC by 17%.

17. Key Words Cargo Consolidation, Pickup and Delivery Routing, Emission Studies	**18. Distribution Statement** No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 23	**22. Price**

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized.**

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS, ABBREVIATIONS, AND SYMBOLS

BB	Branch-and-bound algorithm
CO_2	Carbon dioxide
DOT	Department of Transportation
EPA	Environmental Protection Agency
ESM	Exponential smoothing method
FHWA	Federal Highway Administration
FMM	Freight movement model
HDDV	Heavy duty diesel vehicle class
HFFVRP	Heterogenous fixed fleet vehicle routing problem
LP	Linear programming
LTL	Less-than-truckload
MEC	Monetary emission cost
MIP	Mixed integer programming
MSA	Metropolitan statistical area
NAICS	North American Industry Classification System
NO_x	Oxides of nitrogen
OKC	Oklahoma City
PDP	Pickup and delivery problem
PM	Particulates material
SCTG	Standard Classification of Transported Goods
SEC	Subtour elimination constraints
TMS	Transportation management system
VRP	Vehicle routing problem

EXECUTIVE SUMMARY

The trucking industry is an important sector of the United States (U.S.) economy. However, the trucking industry is quite fragmented. About 97% of the carriers own less than 20 trucks and around 90% owns 6 or fewer trucks *(1)*. This fragmentation hinders the efficiency of cargo transportation, because it is difficult for small carriers to identify demands to fill full truck loads. An estimated 15% to 25% of trucks are travelling empty *(2)*. At the same time, the trucking industry is a major contributor of greenhouse gas emissions. Effective consolidation strategies may help to increase the efficiency of the trucking industry and decrease the amount of emissions. Effective cargo consolidation techniques without the reliance on depots is investigated in this study, with the primary beneficiary being small-level shippers.

The online market places for matching customers and freight equipment are on the rise, and they are in great need for algorithms to identify efficient consolidation strategies. This study investigates the effects of efficient cargo consolidation strategies on freight movement within the U.S. and emission levels. To that extent, a regression model with socio-economic data as input was developed to predict the future freight movement between metropolitan statistical areas (MSAs). An exponential smoothing method (ESM) was used to predict freight movement at a future time horizon and at a national level. Three major pollutants (CO_2, NO_x and particulates matter (PM)) were considered, quantified, and converted into monetary emission cost (MEC).

Models and algorithms to find truck routes with effective freight consolidation are also an objective of this study. A mixed integer programming model which addresses the pickup and delivery problem and a corresponding branch-and-cut algorithm was developed in order to make the model computationally scalable. Transplace, Inc. (a third-party logistics company) provided one month of freight movement data. This data was used as a basis (comparison) for the developed model. The test beds used were 10 medium-sized transportation networks. Transplace, Inc. used routes with 10 trucks in each instance, whereas the model identified routes with a minimum of 5 and a maximum of 8 trucks across all networks. The operation cost and MEC was also proportionally reduced.

The results of the Transplace, Inc. test beds were applied to a case study involving electronics commodity movement from New Orleans to Oklahoma City. Results indicate that it is possible to consolidate and transport electronics cargo with 67% of currently operated trucks, which reduces the operation cost by around 23% and MEC by around 17%. Using ESM and these results, the savings (operation and MEC) that could result from effective consolidation strategies for longer time horizon was forecasted.

1. INTRODUCTION

The trucking industry contributes over 84% of revenue in the United States (U.S.) commercial transportation sector. This industry is the source of many direct and indirect employment opportunities in the country; it is a major industry with significant economic implications for the country. However, the U.S. trucking industry is quite fragmented. Currently, there are over 110,000 carriers and 350,000 independent owner-operators *(3)*. Among them, around 97% of carriers own less than 20 trucks and around 90% own six or fewer trucks *(1)*. This fragmentation hinders the efficiency of cargo transportation. An estimated 15% to 25% of trucks on the roadway are travelling empty *(2)*. This reduced efficiency increases shipping prices, greenhouse gas emissions, and traffic congestion. Further consideration of unused spaces of non-empty trucks is needed. Truck sharing is one such way to attain better efficiency in cargo transportation.

Internet and mobile computing technology have made truck sharing more viable. The number of online marketplaces for freight-matching is on the rise. The concept of freight-matching is similar to Uber, which connects drivers to passenger on request. However, the working principle behind freight-equipment matching may be more complicated than Uber, due to various sizes and types of freight and trucks. It is difficult and time-consuming for carriers to search shippers' demand information online to identify freight consolidation options. It would be helpful if the online freight-matching marketplace could provide consolidation solutions to the carriers. Therefore, online market places are in great need for effective freight consolidation algorithms. Identifying effective consolidation techniques and quantifying the effect of consolidation on transportation cost and greenhouse gas emissions are the main objectives of this study.

To a certain extent, large shipping companies already implement freight consolidation strategies at designated depots and warehouses. However, small shipping companies struggle to identify consolidation strategies, due to limited warehouse accessibility. Small shipping companies often transport commodities for small businesses, in which case neither party (customer or shipper) have access to a warehouse for logistical operations. Also, renting a warehouse might be a costly proposition. Furthermore, when a small shipper is working with multiple small shipping customers, it is difficult to identify a common warehouse which is acceptable for all customers. The primary beneficiary of this study are small-level shippers. Due to fragmentation of the trucking industry, it is difficult for small-shippers to consolidate shipments and find truck routes transporting full truckloads. The ultimate goal of this research is to provide an online interface that can optimize truck routes to small shipping companies, such that customer orders are consolidated, and full truckloads are transported as much as possible.

2. OBJECTIVES

The main objective of this project is to show the impacts of online freight consolidation on freight mobility, congestion, and emission reduction, and thus draw the attention of transportation authorities and logistics companies. The main project tasks are summarized in Table 1.

Table 1. Project tasks and related report sections.

Task	Topic
1	Conducting Literature Review (Section 3)
2	Identifying and Obtaining Truck Sharing Data (Section 4.1)
3	Developing and Validating Freight Demand Models (Section 4.2)
4	Developing Models for Quantifying Impacts of Truck Sharing on Freight Mobility (Sections 4.3 and 5.3)
5	Application of Models to Forecast Freight Movement (Sections 5.1, 5.2, and 5.4)

3. LITERATURE REVIEW

This section details the current literature on various topics, including new trends in logistics companies, types of transported commodities, truck fleet optimization techniques, and the wide-range of impacts caused by freight movement.

3.1. Logistic Trends, Types of Commodities, and Tonnage Transported

The Freight Analysis Framework (FAF) *(4)* is an integrated data bank created through a partnership between the Bureau of Transportation Sciences (BTS) and the Federal Highway Administration (FHWA). Data sources include, but are not limited to, commodity flow survey and international trade data from the Census Bureau. This framework provides data from agriculture, extraction, utility, construction, service, and other sectors. It is a highly reliable data source. The fields of data available from this framework include: domestic, import, and export freight movement classified by FAF zones, transportation modes, commodity type, and distance bands.

Freight Analysis Framework version 4 (FAF4) *(5)* is a convenient data tabulation tool for generating summary tables from the FAF database. Freight movement summary tables are generated based on type of flow (domestic, international), mode (truck, air, etc.), commodity type, and FAF zone. A small subset of freight movement data extracted from 2016 FAF data bank is shown in Table 2. This table shows total truck movement data from five different FAF zones for meat/seafood type commodity within 250- to 499-mile radius of the origin.

Table 2. Subset of freight movement data obtained from FAF data *(5)*.

Origin FAF Zone	Commodity Type	Mode	Distance Band	Ton-mile
Birmingham, AL	Meat/seafood	Truck	250 - 499	14.14
Mobile, AL	Meat/seafood	Truck	250 - 499	2.28
Rest of AL	Meat/seafood	Truck	250 - 499	96.09
Phoenix, AZ	Meat/seafood	Truck	250 - 499	34.52
Tucson, AZ	Meat/seafood	Truck	250 - 499	2.86
Rest of AZ	Meat/seafood	Truck	250 - 499	0.32

FAF has facts and figures from years of freight movement data. Based on their recent estimates, a daily average of about 49.3 million tons of freight valued at more than $52.5 billion was moved in 2015. Tonnage is projected to increase by 1.4% annually between 2015 and 2045 *(6)*. Owing to this ever-increasing freight movement, online services are playing a major role in logistics trends, especially in the form of the Internet of Things (IoT).

The current rising trend in the logistics sector is transportation management systems (TMS) which offer seamless integration of manufacturing, inventory, and transportation modules. For large shipping companies, TMS offers freight consolidation strategies as cost reduction opportunities. The global TMS market was worth $1.23 billion in 2014 and estimated to reach $1.72 billion by the end of 2019, which is a compound growth rate of 6.95% *(7)*. Products like the Blackberry Radar *(8)* are already being extensively used by shippers and online marketplaces. One of the enticing features of mature TMSs is asset tracking. This makes routing, staffing, and warehousing decisions easier. Many other fleet management software like Verizon connect Reveal, Samsara, and GPS Tracking & E-Log Solutions are trending among large to mid-level shippers. However, the cost of implementing a TMS interface can be economically unaffordable for small shippers. In addition, since the current TMSs were designed for large shipping companies, their suggested freight consolidations are conducted at depots, which small shipping companies typically do not have. Therefore, the current TMSs cannot help small carriers in freight consolidations.

3.2. Current Techniques used by Logistics Companies and Truck Fleet Optimization

To study current techniques used by logistics companies and effective freight consolidation techniques, the vehicle routing problem (VRP) with pickup and delivery, which has been studied extensively in the literature, was explored. For general surveys on this problem, the reader is referred to Parragh et al. *(9)*. Hoff et al. *(10)* presented a comprehensive literature review to describe industrial aspects of combined fleet composition and routing. This paper classifies the problems in various categories: namely heterogeneous fleet problems, network design problems, fleet composition, and routing problems. This taxonomy is a highly useful tool to understand and to conduct further literature review on truck sharing. Among many categories of VRP, heterogeneous fixed fleet capacitated vehicle routing problem (HFFVRP) is a widely explored practical problem.

Tarantilis and Kiranoudis *(11)* presented a model for HFFVRP. They solved this problem using a two-phase construction approach. This approach uses a generalized route construction algorithm (GEROCA) which has the flexibility to accommodate additional time windows and backhauls constraints. They also implemented their methodology for two real-world instances, and it significantly reduced the cost and the fleet size for the two companies.

Tavakkoli-Moghaddam et al. *(12)* introduced HFFVRP with split services. This problem considers a fixed number of heterogeneous vehicles in a network setting. Given a network with vehicles, supply and demand nodes, they find optimal vehicle routes with split services. Split service means the inbound material flow to a demand node and is split between different carriers to reduce unused capacities on various trucks. They develop a multi-commodity model and a simulated annealing (SA) approach to solve this problem. The algorithm finds the optimal solution for small instances within a considerable time. However, the optimal solution for larger instances is not found within a reasonable time limit. This paper is relevant to this study because of the introduction of a new class of vehicle routing problem with split services.

An exact formulation for multiple depot heterogeneous fleet vehicle routing problem with time windows (MDHVRPTW) was developed by *(13)*. The formulation presented in this paper is based on the set-covering model. Given a set of depots, customers and heterogeneous fleet of vehicles, the model seeks to find a set of feasible routes covering customers such that the overall cost is minimized subjected to the capacity and time constraints. As there is an exponential number of routes to select from, the problem is solved in a column generation approach. Many routes are generated using greedy techniques and objectively better routes are identified using the reduced cost expression. The capacity and the time-window constraints are checked for correctness and solutions are updated accordingly in a branch-and-bound framework. This paper discusses many integer programming techniques that can be embedded in the solving process to improve the computational scalability of the algorithm.

One-to-one pickup and delivery problem (PDP) is a VRP category with multiple customer orders, each with a single pickup location and single delivery location. Ropke et al. *(14)* presented two formulations and a branch-and-cut-and-price algorithm to solve one-to-one pickup and delivery problem (PDP). The mathematical model used for our project is very close to the first formulation presented by Ropke at al. *(14)*. The approaches presented in this study assumed a single vehicle depot. We modify that model for a multiple depot setting.

3.3. Freight Movement Forecasting Models and Impacts of Freight Movement

Hwang *(17)* used a forecasting model for freight transportation and studied the impact of freight movement in atmospheric pollution. Two types of freight flow modes are considered for this study: inter-regional (e.g., from Los Angeles to Dallas) and intra-regional freight flow (e.g., freight flow between two urban localities in Dallas). For inter-regional flow, this study proposes a four-step freight transportation demand forecasting model. Intra-regional freight flow is handled by considering it as a network optimization problem. The emission levels in urban transportation is mainly impacted by routing decisions of individual trucks. The intra-regional scenario is solved as a large-scale freight delivery problem and truck routing problem. A case study is also done where the proposed model is applied on the America's geographical regions and emission impacts are identified. The inter-regional framework used by Hwang *(17)* to forecast freight movement has four stages: trip generation, trip distribution, modal split, and traffic assignment.

1. Trip generation forecasts the production of freight movement in a zone based on the characteristics of that zone. This is a simple regression model for which the characteristics of the zones are input parameters.
2. Trip distribution is the stage where freight flow between zones is predicted based on the forecasted data from the trip generation step. After that, an algorithm is used to allocate the predicted freight demand on all origin and destination pairs of the cross-country network. This allocation is done proportionally to the existing freight demand distribution.
3. Modal split is used for deciding the mode of transportation for predicted cargo movement between the zones. Truck, rail, air, and water transportations are the four major modes. Mode selection is based on various factors including oil price, freight mode choices, and demand in network. This step will predict the amount of freight carried by trucks.
4. In the traffic assignment stage of the forecasting model, optimal routes for freight transportation is determined. The selection of delivery routes depends upon the carrier requirements (cost reduction, transportation mode preference, etc.).

The above steps were also used for freight movement forecast in a decision support system for infrastructure and supply chain planning within the Oklahoma region by Kamath et al. *(15)*. This study was also conducted based on the data from the FAF framework.

Schulte et al. *(16)* presented a mathematical model to estimate gas emission and cost objective in transportation between urban ports and hinterland. Empty container transportation is a pervasive problem in ports. This paper presents an extensive study for truck routing models in a portside framework. However, this work presents a model for solving the problem on a restricted network structure. Hwang *(17)* presented techniques to relate freight movement with environmental impacts and traffic congestion. The emission and traffic congestion based dynamic routing approach presented in this paper is a valuable application for urban transportation planning. The quantification methods for environmental impacts presented in this paper have been pivotal for the emission analysis in this study.

4. METHODOLOGY

This section presents an overview of the methodology utilized to identify effective consolidation routes and emission quantification. It begins by discussing the datasets used and presents the developed mixed integer programming model (MIP) for cargo pickup and delivery.

4.1. Sample Freight Data

In order to test the later freight consolidation model and examine its impacts on shipping cost and greenhouse gas emission reductions, detailed sample data on freight movement was needed, including: number of trucks (classified by type) used for transporting commodities between MSAs and cargo weight moved by each truck. These data can be used to estimate unused space in each truck. This sample data set is complimentary to Section 4.2, where we detail the methodology and the case study to predict freight movement between MSAs. Using that methodology, total freight movement between MSAs can be predicted. However, the number of trucks and cargo weight in each truck is difficult to estimate. Moreover, the past data for these fields are relatively sparse. Therefore, this study relied on freight movement data from logistics companies. Unlike FHWA freight movement data, logistics companies can provide shipment by cargo weight, which can aid in understanding the impact of freight sharing.

Transplace, Inc. is a third-party logistics company that matches shippers to customers. They also provide logistic solutions to many companies operating within the North American continent. The research team signed a non-disclosure agreement with Transplace, Inc. and acquired one month of their truck route data (May 2017). A small subset of this freight movement data was used as training and validation sets for this study. The routes selected were less-than-truckload (LTL) and strictly within the U.S. (some provided Transplace, Inc. routes extended to Canada).

The research team also contacted Guiyang Truck Alliance Tech Com (GTATC) Ltd. to obtain additional cargo movement data. GTATC is an online freight-equipment matching market place. They provide an online long-haul logistics platform that matches shippers and truckers to each other. The company has grown rapidly over the past few years. However, GTATC decided to retain their data to establish the Freight Transportation Big Data Center in China; their cargo data was not available for this study.

4.2. Freight Movement Prediction

The freight movement model (FMM) is based on a four-stage procedure to model passenger transportation in an urban environment *(17)*. For this study, we do not consider the traffic assignment stage, because it is not essential for predicting freight movement at a high level.

4.2.1. Freight Generation and Distribution (Stage 1)

The freight generation and distribution stages are to determine the tonnage of freight movement from an origin to destination. In this study, we combine the freight generation and distribution into a single stage. The objective of this stage is to use socio-economic data (employment data and number of establishments) and past freight movement data to predict the future freight movement between regions. Regression models are used for prediction in which socio-economic data are independent variables and past freight movement are dependent variables.

The first step under Stage 1 is to identify the freight production (where the freight originates) and consumption (where the freight is consumed) locations of interest along the highway transportation network. The second step under Stage 1 is data collection (socio-economic factors and past freight movement). The freight movement data was extracted from FHWA using FAF4 which has data classified by 114 metropolitan statistical areas (MSAs). Also, the data is further classified by 43 commodity types as dictated by the *Standard Classification of Transported Goods* (SCTG) federal commodity codes. However, data collection of independent variables (socio-economic variables which are input to the model) is comparatively hard. From the literature *(15)*, the three most influential socio-economic factors for freight movement are: the number of employees, total wage payment, and number of establishments in each MSA. These data are available from the Bureau of Labor Statistics (BLS) *(18)*. However, the commodities in BLS are classified according to the *North American Industry Classification System* (NAICS) codes which are different from the SCTG classification. To build a regression model, NAICS commodity data must be recalibrated to the corresponding SCTG data based on relevancy *(15)*.

The final step under Stage 1 is to build regression models classified by each MSA and commodity type, with the number of employees, total wage payment, and number of establishments in the destination point as independent variables, and freight movement (tonnage) as dependent variables. The output from this model is a regression equation relating commodity-specific freight movement between MSAs to the destination MSA's socio-economic variables. Based on such an equation, we can predict the future freight movement between MSAs for which socio-economic forecast values are available. The final result from Stage 1 is the total tonnage freight movement.

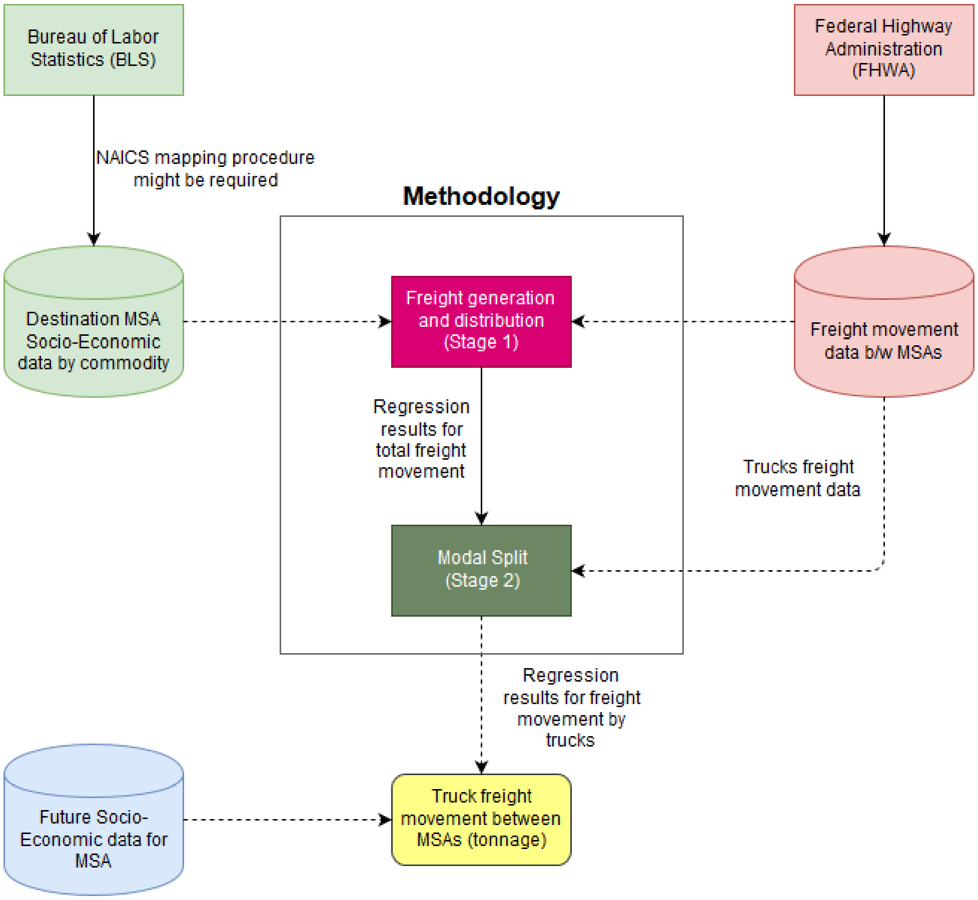


Figure 1. Methodology for freight generation and distribution (Stage 1) and modal split (Stage 2).

4.2.2. Modal Split (Stage 2)

The modal split stage splits the predicted freight movement between MSAs into multiple transportation modes (air, train, and trucks). The total freight movement calculated from the previous stage becomes the input to this step. In the literature, this stage has a simple assumption that for any year, the split percentage is similar to the previous year *(15, 17)*. However, this study implements a different methodology based on linear regression. We find a regression equation with total freight movement as the independent variable and truck freight movement as the dependent variable.

4.2.3. Case Study for Freight Movement from New Orleans to Oklahoma City

For a sample case study, we analyzed the electronics commodity freight movement from New Orleans MSA to Oklahoma City (OKC) MSA. The data extraction, cleaning, and regression analysis were done using MS Excel and SAS 9.4 studio. For the independent variables, we extracted socio-economic data for OKC MSA from 2014 to 2017 from the BLS source *(18)*. The data before 2014 is available, but the NAICS codes for various commodities were altered in 2012, so the cross-mapping between old and new NAICS codes is time consuming. Fortunately, an extended mapping procedure was not necessary for the electronics commodity. The NAICS code for the commodity of interest is NAICS 443.

For the dependent variables, we extracted the electronics freight movement data from New Orleans MSA to OKC MSA from 2014 to 2016 (freight movement data for 2017 is missing from the data source). By cross comparison between FHWA and BTS, we see that the whole data set is available for three years from both data sources (2014 to 2016). We used this data for our regression analysis.

Regression Analysis (Stage 1): The regression equation for electronics commodity freight movement from New Orleans to OKC is:

$$Tonnage = 309.40 + 0.089\ (Establishments) - 0.082\ (Employment) \qquad [1]$$

In the regression analysis, a step-wise variable selection technique (or step selection) was implemented. It is a regression support technique, where the significance of an independent variable is tested by adding and removing it to the model. After such tests, based on significance, variables might be removed from the model. This could be for many reasons (e.g., if two variables are linearly proportional, then it is sufficient to add one of them in the model). Recall that our independent variables are socio-economic factors. One of the variables (total wages of OKC) has been removed from the model by step selection process. The result from these models is the total tonnage freight movement.

Total Freight Movement vs. Truck Freight Movement (Stage 2): For the modal split stage, a regression equation was developed with total freight movement as an independent variable and truck freight movement as a dependent variable.

The regression equation for truck tonnage movement from New Orleans to OKS is:

$$Freight\ Movement\ by\ Trucks = 0.0694\ (Total\ Freight\ Tonnage) + 1.5574 \qquad [2]$$

4.3. Truck Sharing Model and Impacts

This section presents the methodology to identify effective consolidation routes and emission quantification models. It begins with an overview of the developed MIP model for cargo pickup and delivery.

4.3.1 Mixed Integer Programming (MIP) Model

The developed model is designed for a transportation network with multiple vehicles, origin depots, destination depots, and shipment orders. Each shipment order constitutes of a pickup location, delivery location, cargo weight, and pickup and delivery time windows. Given a set of shipment orders, the model identifies shared freight hauling opportunities.

As described in Section 4.2, the model is similar to the three-index pickup and delivery formulation presented by Ropke et al. *(14)*. However, there are two main difference between Ropke's model *(14)* and the developed model in this study:

1. We considered fixed and variable cost for dispatching vehicles, whereas Ropke's *(14)* model considers only variable cost; and
2. We consider multiple origin depots for dispatching vehicles, while Ropke's *(14)* model has a single origin depot.

Formulation for the Cargo Consolidation Problem: Consider a directed graph $G = (N, A)$ with arc set A and node set $N = H \cup P \cup D \cup Z$, where H, P, D, and Z represent the set of origin depots, pickup nodes, delivery nodes, and destination depots, respectively. Let S be the set of shipment orders. Each shipment order $i \in S$ has a pickup node $i \in P$ and a delivery node $n + i \in D$, where n is the number of shipments ($n = |S|$).

Each node $i \in N$ has an associated load value q_i, satisfying $q_i = -q_{n+i}\ \forall i \in P$ and $q_i = 0\ \forall i \in H \cup Z$. Each node $i \in N$ also has an associated time window $[a_i, b_i]$, where a_i and b_i are the earliest and latest times at which service can start at node $i \in N$, respectively. For origin depots and destination depots, a_i and b_i are the earliest and latest times at which vehicles may leave from and arrive at the origin and destination depot, respectively. The latest service time for the dummy sink node represents the truck driver's maximum working hours.

Let K denote a set of homogeneous vehicles with uniform capacity Q. Each vehicle $k \in K$ has an associated fixed operating cost fc_k. Every origin depot $i \in H$ has an associated maximum number of vehicles available denoted by h_i. Also, each arc $(i, j) \in A$ has an associated shortest traveling distance c_{ij} and travel duration t_{ij}. The shippers have to additional restrictions for each vehicle:

- A vehicle cannot pick more than m shipments; and
- If a vehicle picks up more than 1 shipment, then the distance between pickup stops and destination stops must not exceed r miles.

Decision Variables:

1. $x_{ij}^k = 1$ if arc $(i, j) \in A$ is on the route of vehicle $k \in K$; $x_{ij}^k = 0$ otherwise.
2. $y_k = 1$ if vehicle $k \in K$ is used for transportation; $y_k = 0$ otherwise.
3. Q_i^k is the load on vehicle $k \in K$ upon leaving node $i \in N$.
4. B_i^k is the time by which vehicle $k \in K$ begins service at node $i \in N$.

Formulation:

$$\text{Min } \Sigma_{k\in K} \mathrm{fc_k y_k} + \Sigma_{k\in K} \Sigma_{i\in N} \Sigma_{j\in N} \mathrm{c_{ij} x_{ij}^k} \qquad [3]$$

Subject to:

$$\Sigma_{k\in K} \Sigma_{j\in N} x_{ij}^k = 1 \quad \forall i \in P \qquad [4]$$

$$\Sigma_{j\in N} x_{ij}^k - \Sigma_{j\in N} x_{n+i,j}^k = 0 \quad \forall i \in P, k \in K \qquad [5]$$

$$\Sigma_{j\in N} x_{ij}^k \leq h_i \quad \forall i \in H \qquad [6]$$

$$\Sigma_{j\in N} x_{ij}^k - \Sigma_{j\in N} x_{ji}^k = 0 \quad \forall i \in P \cup D, k \in K \qquad [7]$$

$$\Sigma_{i\in D} \Sigma_{j\in Z} x_{ij}^k \geq y_k \quad \forall k \in K \qquad [8]$$

$$\Sigma_{i \in P} \Sigma_{j \in N} x_{ij}^{k} \leq m \quad \forall k \in K \tag{9}$$

$$\Sigma_{i \in P} \Sigma_{j \in P} d_{ij} x_{ij}^{k} \leq r \quad \forall k \in K \tag{10}$$

$$\Sigma_{i \in D} \Sigma_{j \in D} d_{ij} x_{ij}^{k} \leq r \quad \forall k \in K \tag{11}$$

$$n y_k \geq \Sigma_{i \in D} \Sigma_{j \in P} x_{ij}^{k} \quad \forall k \in K \tag{12}$$

$$Q_j^k \geq (Q_i^k + q_j) x_{ij}^k \quad \forall i, j \in N, \forall k \in K \tag{13}$$

$$B_j^k \geq (B_i^k + t_{ij}) x_{ij}^k \quad \forall i, j \in N, \forall k \in K \tag{14}$$

$$B_i^k + t_{i,n+i} \leq B_{n+i}^k \quad \forall i \in P, \forall k \in K \tag{15}$$

$$a_i \leq B_i^k \leq b_i \quad \forall i \in N, \forall k \in K \tag{16}$$

$$\max\{0, q_i\} \leq Q_i^k \leq min\{Q, Q + q_i\} \quad \forall i \in N, \forall k \in K \tag{17}$$

$$y_k \in \{0,1\} \quad \forall k \in K \tag{18}$$

$$x_{ij}^k \in \{0,1\} \quad \forall i, j \in N, \forall k \in K \tag{19}$$

Objective Function and Constraints: The objective function seeks to minimize the total one-time cost for selecting a subset of vehicles and total operation cost.

- Constraints [4] and [5] are to ensure that every shipment is covered by exactly one vehicle;
- Constraint [6] ensures that the number of routes originating from a depot does not exceed the number of vehicles available at that depot;
- Constraint [7] is flow conservation for pickup and delivery nodes;
- Constraint [8] ensures that a vehicle is used, if it picks up at least one shipment;
- Constraint [9] is to restrict each vehicle from picking up more than m shipments on their route;
- Constraints [10] and [11] ensure that the intermediate stops are not mare than r miles apart within pickups and deliveries;
- Constraint [12] is to direct the vehicle to one of the destination depots, if it visits at least one delivery node;
- Constraints [13] and [17] are capacity restrictions for vehicles; and
- Constraints [14,] [15], and [17] are time window restrictions for every node and vehicle.

Model Limitations:

- The model is designed within a one-to-one delivery framework (i.e., a shipment order can have exactly one pickup and one delivery location). The network structure for the model does not permit a shipment order with multiple pickups and delivery.
- The model can only accommodate homogenous fleets (i.e., trucks with same capacity).
- The shipment orders provided as input for the model must be compatible with each other (e.g., biohazard materials cannot be transported with edibles on a same truck). The developed model does not consider this shipment compatibility. The user should be wary of shipment compatibility before providing the input to the model.

Algorithm Structure: The authors solve the MIP model using a branch-and-cut framework. The branch-and-cut technique is one of the most widely used tools in integer programming to solve

NP-hard problems. Each node of the branch and bound (BB) tree represents one of the following solutions:

- A set of routes without any sub-tours, in which case the BB node is pruned by feasibility and the incumbent solution is updated as required.
- A fractional solution, in which case we continue branching.
- An infeasible LP relaxation, in which case it prunes that BB node by infeasibility.
- A set of routes with disjoint sub-tours, in which case it does the following:
    1. For each vehicle, separation problem is solved, and the sub-tours are detected.
    2. The sub-tour elimination constraint (SEC) is added to the current formulation as a lazy constraint and the model is re-solved.
    3. The re-solved model may terminate yielding vehicle routes without sub-tours (in which case the BB node is pruned by feasibility) or a fractional solution (in which case it continues branching) or another set of vehicle routes with sub-tours (in which case steps 1-3 are repeated).

The SECs used in our branch-and-cut algorithm is similar to the negative cycle elimination constraints used by Krishnan *(19)*. In this study, a decomposition branch-and-cut algorithm for solving elementary shortest path problem for networks containing negative cycles was used. Lazy cuts in a branch-and-bound framework was also implemented.

4.3.2. Emission Quantification Model

The aim in the conducted emission study is to quantify and compare the emission rates from Transplace, Inc. routes against the consolidated routes from the model. The emission analysis focused on three major pollutants from trucks, namely: carbon dioxide (CO_2), oxides of nitrogen (NO_x), and particulate matter (PM). Unconsolidated routes refer to the routes used by Transplace, Inc. and consolidated routes refer to the routes optimized by the model.

For measuring emission levels, kg of greenhouse gas emission for unconsolidated routes and the model routes were calculated. For this calculation, emission rates for heavy duty diesel vehicles (HDDV) per ton of cargo were used as presented by Carbonfund *(20)*, Environment Protection Agency (EPA) *(21)*, and Agar et al. *(22)*. The reader is referred to the handbook on FHWA emission rates *(23)* for additional information. The emission rates from the FHWA handbook and our assumptions are quite similar. For example, FHWA refers to 10.15 kg of CO_2 emission for 1 gallon of diesel (from 2013), whereas EPA refers to 10.21 kg of CO_2 emission for 1 gallon of diesel (from 2015). Since there is no large disparity in the emission rates between the two sources, and since EPA has more recent numbers, the authors chose not to do a recalibration according to FHWA data.

Even after using the consolidated routes, it is noteworthy that the ton-mile cargo transportation does not change drastically. For example, if a 1-ton shipment is to be transported from Chicago to Iowa, the total ton-miles is not going to change significantly between unconsolidated and consolidated routes. Therefore, it follows that there will be a minimal difference in cargo weight. However, the model does identify routes with fewer trucks, which may improve emissions. For example, assume an empty truck trailer weights 10,887 kg *(21)*. By removing a single empty truck from the road, this weight is removed from the network, thus providing benefit.

Table 3 shows the assumptions used in the emission comparison (between unconsolidated and consolidated routes). Hwang (*17)* used a monetary equivalent loss value for different types of greenhouse gases. This conversion factor can be used to compute the equivalent loss value for emission levels. The cost conversion factor for different gases are shown in Table 3.

Table 3. Emission rates and equivalent monetary cost for various pollutants.

Emission Rate (kg/tonne-mile)			Monetary Cost Equivalent ($/kg)		
CO_2	NO_x	PM	CO_2	NO_x	PM
0.14645	9.80E-04	4.67E-05	0.28	0.20	0.30

5. ANALYSIS AND FINDINGS

The developed MIP model was applied to a small subset of supplied routes from Transplace, Inc. These case studies are discussed below. The results of the case studies are then applied to estimate the greater impacts of freight movement.

5.1. Application of Model to Transplace, Inc. Routes

This section begins by focusing on a single instance (a set of customer orders) and compares the current routes used by Transplace, Inc. with routes optimized with the developed model.

5.1.1. Results from a Single Instance (Instance 1)

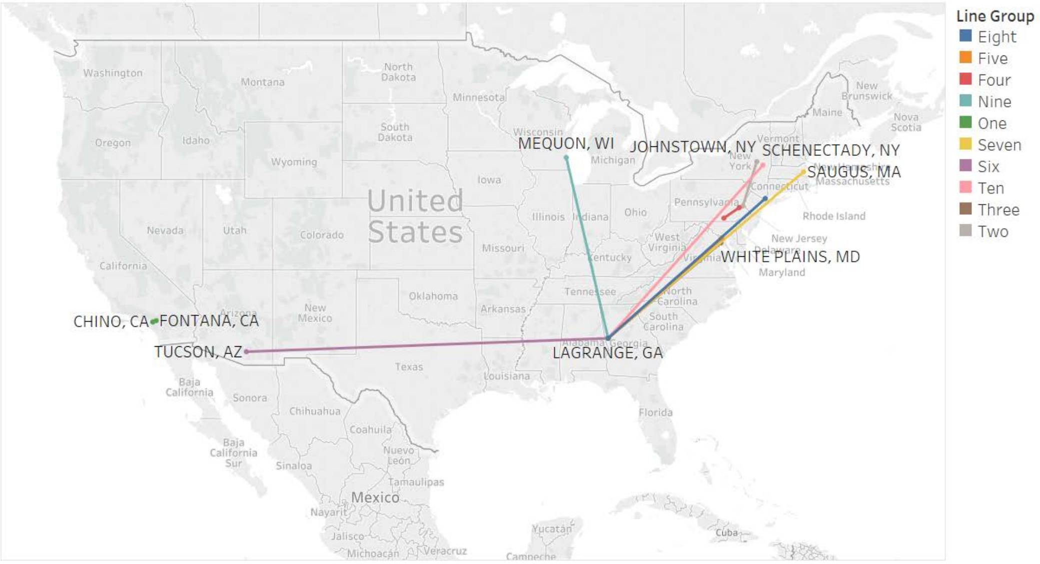
This case study focuses on a single instance of 10 shipment orders (Instance 1) placed by Transplace, Inc., each with a single pickup and a single delivery location. Table 4 shows these LTL routes. All shipments are assumed to be ready for loading at the beginning of a working day (Day1). The delivery time windows are the limits, within which the delivery should reach the destination. The maximum time a driver spends on road was assumed to be 55 hours (excluding stops).

Table 4. Shipment order details for Instance 1.

Shipment	Origin	Destination	Cargo Quantity (lbs)	Delivery Time Window (hrs)
1	Fontana, CA	Chino, CA	709	1
2	Bethlehem, PA	Johnstown, NY	13,016	8
3	Lagrange, GA	White plains, MD	863	22
4	Breinigsville, PA	York, PA	2,675	4
5	Lagrange, GA	District heights, MD	620	22
6	Lagrange, GA	Tucson, AZ	955	50
7	Lagrange, GA	Saugus, MA	210	36
8	Lagrange, GA	White plains, NY	406	30
9	Lagrange, GA	Mequon, WI	765	27
10	Lagrange, GA	Schenectady, NY	2,201	33

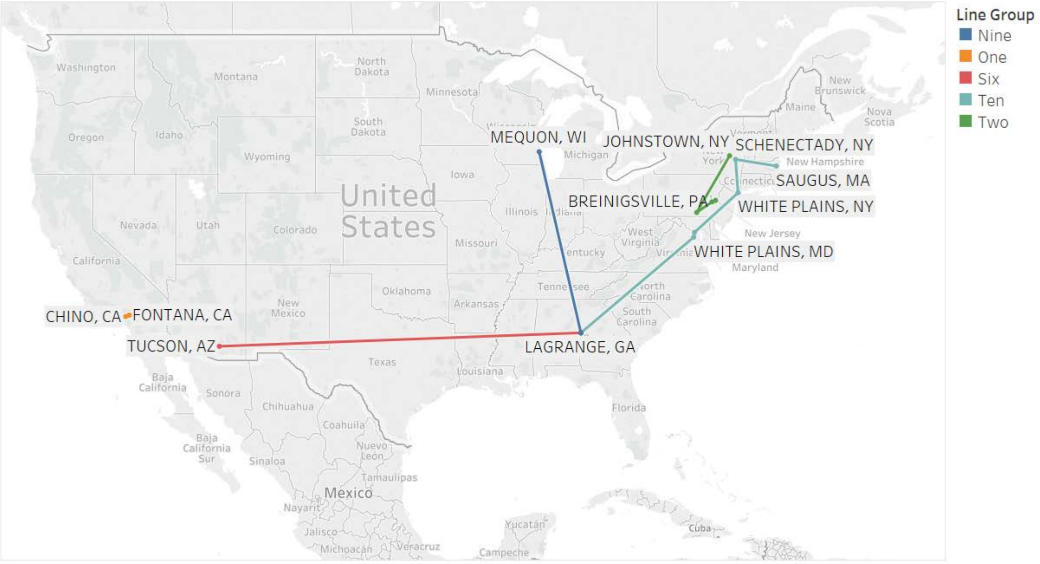
A visual representation of current company routes for Instance 1 is shown in Figure 2. Ten trucks were used covering 7,534 miles, with a total operation cost of $13,117.

The routes from the consolidated model applied to the same instance is shown in Figure 3. Five trucks were used to make the deliveries. The total distance covered by the trucks is 4,356 miles, with a total operation cost of $7,534. Figure 4 shows the enhanced comparison between unconsolidated and consolidated routes along the east coast. From the Figure, the model routes are shown to be more cost effective than the current routes.



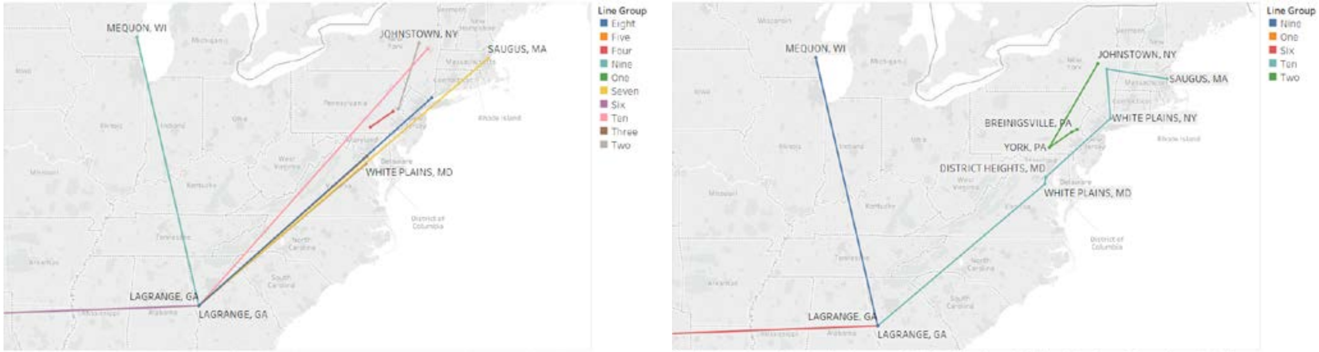
Map based on average of Longitude and average of Latitude. Color shows details about Line Group. The marks are labeled by Station as an attribute. Details are shown for Line Group and Order of Points.

Figure 2. Unconsolidated routes for Instance 1.



Map based on average of Longitude and average of Latitude. Color shows details about Line Group. The marks are labeled by Station as an attribute. Details are shown for Line Group.

Figure 3. Consolidated routes from the optimized model for Instance 1.



Map based on average of Longitude and average of Latitude. Color shows details about Line Group. The marks are labeled by Station as an attribute. Details are shown for Line Group and Order of Points.

Map based on average of Longitude and average of Latitude. Color shows details about Line Group. The marks are labeled by Station as an attribute. Details are shown for Line Group.

Figure 4. Unconsolidated routes (left) and consolidated routes (right) for Instance 1.

5.1.2. Results from Multiple Instances

The consolidated routes from the model are compared with the Transplace, Inc. routes on 10 different instances. Each instance (marked by their respective ID) was satisfied by 10 trucks from a single origin to a single destination. The results are shown in Table 5. The optimized solution from the model still respects customer time window constraints, vehicle capacity constraints, and maximum time on a roadway for a truck driver.

Table 5. Comparison between unconsolidated and consolidated routes for all instances.

Instance	No. of Trucks		Total Cost ($)		Distance (miles)	
	Unconsolid.	Consolid.	Unconsolid.	Consolid.	Unconsolid.	Consolid.
1	10	5	$13,116	$7,369	7,534	4,356
2	10	5	$7,577	$6,018	3,519	3,375
3	10	6	$9,107	$6,618	4,628	3,613
4	10	7	$6,483	$5,627	2,727	2,698
5	10	8	$5,621	$4,669	2,102	1,807
6	10	5	$3,414	$1,918	503	404
7	10	8	$15,466	$13,096	9,236	7,913
8	10	7	$10,617	$9,635	5,723	5,602
9	10	6	$6,021	$4,664	2,392	2,197
10	10	6	$5,669	$3,966	2,137	1,691

From the results, fewer trucks are used in the consolidated routes. For all the 10 instances, the model found consolidated routes that are less expensive than unconsolidated routes. Total costs include the fixed cost for dispatching a truck and traveling cost (which differs based on traveling distance). The fixed cost for dispatching a truck includes trailer rent, licensing, fixed office cost, cargo, collision, bobtail, and life insurance. Using the estimates from *(25)*, the operating cost for trucks was assumed to be $1.38 per mile. Using the estimates from *(26)*, the fixed cost of dispatching a truck was assumed to be $272 per day. The total cost is the objective function that is to be minimized in the MIP model. The distances covered in both cases are also presented in Table 5. As shown, the model identified routes which are shorter in comparison to unconsolidated routes.

5.2. Emission Quantification Results

As discussed in Section 4.3.2, emissions (and associated costs) were compared between the consolidated and unconsolidated routes using cost conversion factors by Hwang *(17)*. This section begins by focusing on a single instance: emission levels from the company routes and from the model results.

5.2.1. Monetary Emission Cost (MEC) of Instance 1

The following formulas were used to measure CO_2 MEC:

$$CO_2\ Emission = Distance * Empty\ Truck\ Container\ Weight * \frac{CO_2\ Emission\ Rate}{1{,}000} \qquad [20]$$

$$CO_2\ MEC = CO_2\ Emission * Cost\ Conversion\ Factor \qquad [21]$$

MECs for NO_x and PM pollutants were calculated using similar formulas as the above.

Table 6 shows the monetary cost calculation for unconsolidated routes for Instance 1. Results show the distance covered by each of the 10 trucks, their corresponding emission levels, and their MEC value. The weight of an empty truck container is assumed to be 10,887 kg. The total MEC for unconsolidated routes in Instance 1 is $3,381.

Table 6. Emission quantification for unconsolidated routes for Instance 1.

Truck	Distance (miles)	Emission Levels (kg)			Monetary Cost Equivalent ($)		
		CO_2	NO_x	PM	CO_2	NO_x	PM
1	20	32.46	0.22	0.01	$9.09	$0.04	$0.00
2	246	392.67	2.63	0.13	$109.95	$0.53	$0.04
3	688	1,096.87	7.34	0.35	$307.12	$1.47	$0.10
4	82	131.16	0.88	0.04	$36.72	$0.18	$0.01
5	713	1,136.35	7.60	0.36	$318.18	$1.52	$0.11
6	1,694	2,700.31	18.07	0.86	$756.09	$3.61	$0.26
7	1,152	1,837.18	12.29	0.59	$514.41	$2.46	$0.18
8	959	1,529.02	10.23	0.49	$428.12	$2.05	$0.15
9	895	1,426.64	9.54	0.45	$399.46	$1.91	$0.14
10	1,085	1,729.18	11.57	0.55	$484.17	$2.31	$0.17
Total	7,534	12,011.82	80.37	3.83	$3,363.31	$16.07	$1.15

Table 7 shows the monetary cost calculation for consolidated routes for Instance 1 (a total of $1,955). As shown, only 5 trucks were used. Therefore, the MEC savings by switching from an unconsolidated strategy to the consolidated strategy is $1,426.

Table 7. Emission quantification for consolidated routes for Instance 1.

Truck	Distance (miles)	Emission Levels (kg)			Monetary Cost Equivalent ($)		
		CO_2	NO_x	PM	CO_2	NO_x	PM
1	20.36	32.46	0.22	0.01	$9.09	$0.04	$0.00
2	430.28	686.04	4.59	0.22	$192.09	$0.92	$0.07
6	1,693.62	2,700.31	18.07	0.86	$756.09	$3.61	$0.26
9	894.78	1,426.64	9.54	0.45	$399.46	$1.91	$0.14
10	1,316.85	2,099.59	14.05	0.67	$587.88	$2.81	$0.20
Total	4,355.89	6,945.04	46.47	2.21	$1,944.61	$9.29	$0.66

5.2.2. MEC Values for Multiple Instances

Using similar calculations, MEC for each instance was calculated (Table 8). A plot comparing emissions between unconsolidated routes and consolidated routes for various instances is shown in Figure 5. As shown, the consolidated model always identified routes with lower MEC.

Table 8. Emission quantification results for all instances.

Instance	Distance (miles)		Monetary Cost Equivalent ($)	
	Unconsolid.	Consolid.	Unconsolid.	Consolid.
1	7,534	4,356	$3,381	$1,955
2	3,519	3,375	$1,579	$1,515
3	4,628	3,613	$2,077	$1,621
4	2,727	2,698	$1,224	$1,211
5	2,102	1,807	$943	$811
6	503	404	$226	$181
7	9,236	7,913	$4,144	$3,551
8	5,723	5,602	$2,568	$2,514
9	2,392	2,197	$1,073	$986
10	2,137	1,691	$959	$759

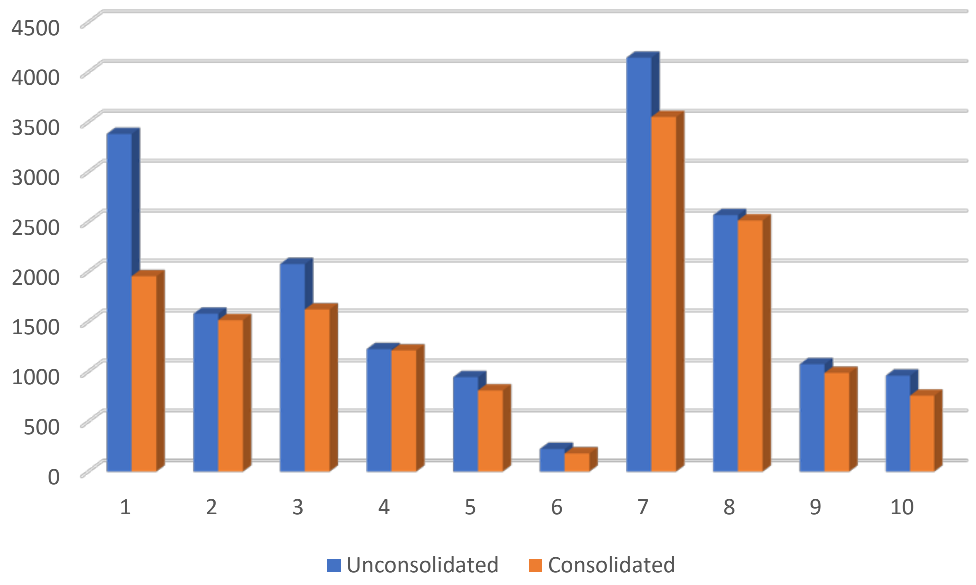


Figure 5. MEC comparison between unconsolidated and consolidated routes for each instance.

5.3. Freight Consolidation Estimates between MSAs

As shown in the case studies using the Transplace, Inc. data (Sections 5.1 and 5.2), the model identified routes in which customer orders can be effectively transported using approximately 67% of the original number of trucks used. This reduction considers customer time windows, vehicle capacity, compatibility between commodities, and maximum on-road time for drivers. For shipping companies, this reduces their baseline operation cost by approximately 23% on average. Considering the cost conversion factors for greenhouse gas emission, the MEC is reduced by approximately 17%.

Table 9 contains the estimates after applying the case study results (i.e., the potential percent reductions) to freight movement from New Orleans MSA to Oklahoma City MSA from 2012 to 2017 for all commodities.

Table 9. Estimates of operation cost and MEC reduction after consolidation.

		2012	2013	2014	2015	2016	2017
Operation Cost ($)	**Unconsolid.**	$ 7,380,303	$ 7,492,900	$ 7,498,800	$ 7,223,500	$ 7,067,300	$ 7,003,100
	Consolid.	$ 5,682,833	$ 5,769,533	$ 5,774,076	$ 5,562,095	$ 5,441,821	$ 5,392,387
MEC ($)	**Unconsolid.**	$ 304,187	$ 308,827	$ 309,071	$ 297,724	$ 291,286	$ 288,640
	Consolid.	$ 252,475	$ 256,327	$ 256,529	$ 247,111	$ 241,767	$ 239,571

5.4. Freight Consolidation Estimates across a Longer Time Horizon

A regression model was built (Section 4.2) to predict future freight movement between MSAs. Inputs for the model are socio-economic data, and the output is tonnage of freight movement. Unfortunately, the research team was unable to apply the regression model to predict future freight movement, since the socio-economic data required in the model is not readily apparent nor available; the research team was unable to find a reliable source to procure socio-economic data for future years. Instead, a simple exponential smoothing method (ESM) was applied using past freight movement data for all commodities within the U.S. to forecast the movement for future years. The research team then applied the case study results (i.e., the potential percent reductions) to estimate transportation and emission cost savings after consolidation.

For the ESM estimates, transportation data (ton-miles) for all commodities within the U.S. from 2012 to 2017 was used as input. The output freight movement forecasts are shown in Table 10.

Table 10. Operation cost and MEC estimates before and after consolidation forecasted to 2021.

Year	Cargo (Tons)	Operation Cost ($) Unconsolid.	Opeation cost ($) Consolid. Cost	MEC ($) Unconsolid.	MEC ($) Consolid.
2012	59,274	$ 1,886,346,611,202	$ 1,433,623,424,514	$ 77,747,680,791	$ 63,753,098,248
2013	67,138	$ 1,948,956,850,300	$ 1,481,207,206,228	$ 80,328,225,032	$ 65,869,144,526
2014	68,460	$ 1,994,007,530,400	$ 1,515,445,723,104	$ 82,185,034,313	$ 67,391,728,137
2015	68,609	$ 1,999,544,882,400	$ 1,519,654,110,624	$ 82,413,261,868	$ 67,578,874,732
2016	68,092	$ 2,010,880,730,800	$ 1,528,269,355,408	$ 82,880,480,309	$ 67,961,993,854
2017	69,756	$ 2,023,456,220,700	$ 1,537,826,727,732	$ 83,398,791,827	$ 68,387,009,298
2018	68,557	$ 2,046,587,575,489	$ 1,555,406,557,372	$ 84,352,173,977	$ 69,168,782,661
2019	72,686	$ 2,068,648,032,251	$ 1,572,172,504,511	$ 85,261,417,984	$ 69,914,362,747
2020	75,004	$ 2,090,708,489,013	$ 1,588,938,451,650	$ 86,170,661,990	$ 70,659,942,832
2021	72,422	$ 2,112,768,945,774	$ 1,605,704,398,788	$ 87,079,905,997	$ 71,405,522,917

Figure 6 shows the comparison between the operation cost before (projected) and after consolidation. Figure 7 shows the comparison between the MEC before (projected) and after consolidation. The benefits resulting from freight consolidation across a longer time horizon is promising for companies (i.e., economical) and the environment.

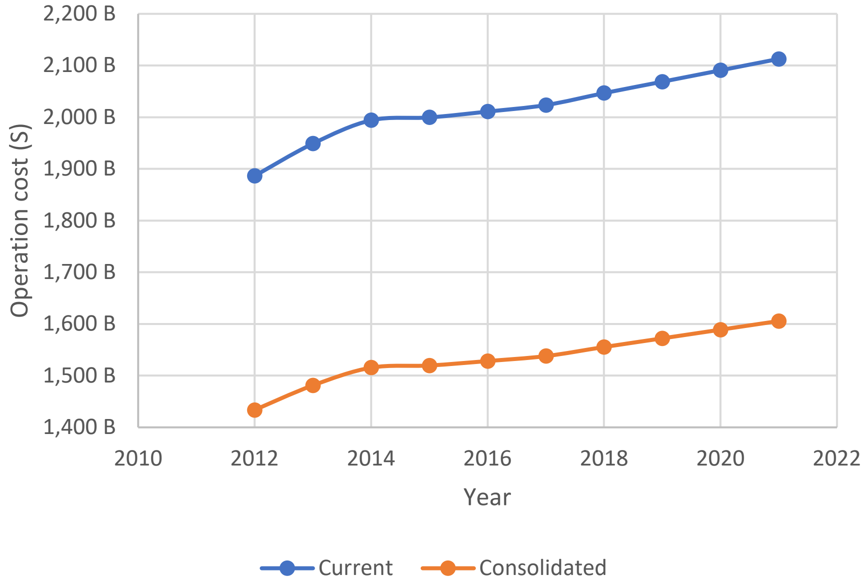


Figure 6. Operation cost comparison before and after consolidation (2012 to 2021).

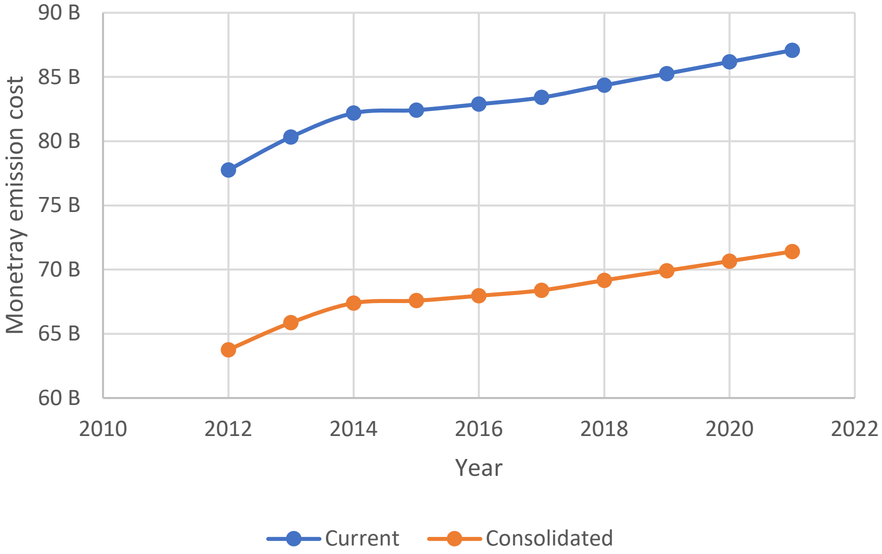


Figure 7. MEC comparison before and after consolidation (2012 to 2021).

6. CONCLUSIONS

Due to the fragmentation of the trucking industry in the U.S., it is hard for small shipping companies to find customers and transport full truckloads of cargo. Most trucks on the roadway do not operate at full capacity. Online market places help shipping companies by matching customers and trucks. However, effective consolidation techniques are needed. The main objectives of this project are to address this need and to quantify the effects of optimized consolidation on the operation cost and the environment. To that extent, this research study:

1. Developed a linear regression technique which can predict the future freight movement between MSAs based on socio-economic data;
2. Formulated a MIP model and algorithm which can identify effective consolidated routes for a given number of trucks and practical constraints (customer preferences, DOT enforcement, and shipping company preferences);
3. Identified a technique to convert greenhouse gas emission levels into monetary equivalent;
4. Tested the consolidation model on Transplace, Inc. customer orders and identified cheaper and eco-friendlier routes;
5. Quantified the benefits of effective freight consolidation, by applying the results of the case study to electronics freight movement from New Orleans MSA to Oklahoma City MSA; and
6. Applied the results of the case study to total freight movement across the U.S. for a longer time horizon (to 2021).

From the Transplace, Inc. case study, consolidated routes were identified that could satisfy customer orders using only 67% of the existing number of trucks. The results from this limited case study were applied to longer time periods to estimate the benefits of truck sharing. From the case study, it was estimated that the current emission levels could be reduced by approximately 17%.

After applying the results of the case study to freight movement at a national level for all commodities, it was estimated that operation cost savings could be in the millions. It follows that emission levels are also significantly reduced. By extrapolating this scenario for a longer time horizon, the appeal of effective freight consolidation techniques only increases. Although there are above mentioned advantages in using the framework, the biggest hurdle for implementation is the exponential runtime growth with the instance size. Future tasks are to address this by implementing the model in a heuristics framework with valid inequalities to reduce the runtime.

The mathematical formulation and computerized calculations validate the developed consolidation technique as a cost-effective and eco-friendly model. Naturally, integrating this framework on a real-world setting is the next step in the process. Running the model on a small real-world network (10 to 50 shipments) is not a costly proposition. This implementation process may involve the following steps:

1. Identify a small number of shipment orders which can be placed in a truck together (e.g., no mixing of edible and hazardous materials).
2. Identify a set of trucks with uniform capacity (homogenous fleet) and drivers.
3. Input the data into the MIP model, and solve using a commercial solver. The necessary data includes time windows for customer delivery, truck capacity, maximum time a driver is willing to spend on the road, fixed cost, and variable cost for truck operation.

4. Dispatch the trucks with drivers as per the solution provided by the model. Calculate the total cost and emission levels incurred by implementing the whole strategy. This step may incur the cost of using emission measuring equipment.
5. Compare the results with computer generated values for unconsolidated dispatching strategy.

REFERENCES

1. American Trucking Association. *Reports, Trends & Statistics*. American Trucking Association, Washington, DC. https://www.trucking.org/News_and_Information_Reports.aspx. Accessed May 22, 2019.

2. Environmental Defense Fund. *Green Freight Facts & Figures*. Environmental Defense Fund, Washington, DC. https://business.edf.org/projects/green-freight-facts-figures. Accessed May 22, 2019.

3. California Department of Transportation. *Trucking*. California Department of Transportation, Sacramento, CA. http://www.dot.ca.gov/hq/tpp/offices/ogm/key_reports_files/National,%20 Technical%20studies/Trucking_industry_overview.pdf. Accessed May 22, 2019.

4. Federal Highway Administration. *Freight Analysis Framework*. U.S. Department of Transportation, Washington, DC. https://ops.fhwa.dot.gov/freight/freight_analysis/faf/. Accessed May 22, 2019.

5. Federal Highway Administration. *Freight Analysis Framework Data Tabulation Tool (FAF4)*. U.S. Department of Transportation, Washington, DC. https://faf.ornl.gov/fafweb/Extraction0. aspx. Accessed May 22, 2019.

6. Bureau of Transportation Sciences. *Freight Facts & Figures 2017 - Chapter 2: Freight Moved in Domestic and International Trade*. U.S. Department of Transportation, Washington, DC. https://www.bts.gov/bts-publications/freight-facts-and-figures/freight-facts-figures-2017-chapter-2-freight-moved. Accessed May 22, 2019.

7. TechTarget Network. T*ransportation Management System (TMS)*. TechTarget Network. https://searcherp.techtarget.com/definition/transportation-management-system-TMS. Accessed May 22, 2019.

8. BlackBerry. *BlackBerry Radar: Asset Monitoring Engineered for Intelligence*. BlackBerry, Waterloo, CAN. https://www.blackberry.com/us/en/products/blackberry-radar/overview#top. Accessed May 22, 2019.

9. Parragh, S.N., K.F. Doerner, and R.F. Hartl. A Survey on Pickup and Delivery Problems. *Journal fur Betriebswirtschaft*, 2008. 21-51.

10. Hoff, A., H. Anderson, M. Christiansen, G. Hasle and A. Løkketangen. Industrial Aspects and Literature Survey: Fleet Composition and Routing. *Computers & Operations Research*, 2010. 37: 9, 2041–2061.

11. Tarantilis, C. and C. Kiranoudis. A Flexible Adaptive Memory-Based Algorithm for Real-Life Transportation Operations: Two Case Studies from Dairy and Construction Sector. *European Journal of Operational Research*, 2007. 179(3): 806-822.

12. Tavakkoli-Moghaddam, R., N. Safaei, M. Kah, and M. Rabbani. *A New Capacitated Vehicle Routing Problem with Split Service for Minimizing Fleet Cost by Simulated Annealing*. Journal of the Franklin Institute, 2007. 334(5): 406-425.

13. Bettinelli, A., A. Ceselli, and G. Righini. A Branch-and-Cut-and-Price Algorithm for the Multi-Depot Heterogeneous Vehicle Routing Problem with Time Windows. *Transportation Research Part C: Emerging Technologies*, 2011. 723-740.

14. Ropke, S. and J.F. Cordeau. Branch and Cut and Price for the Pickup and Delivery Problem with Time Windows. *Transportation Science*, 2009. 267-286.

15. Kamath, M, R. Ingalls, C. Jones, G. Shen and P.S. Pulat. *A Decision Support System for Transportation Infrastructure and Supply Chain System Planning*. OTCREOS7, 1-25-F. Oklahoma Transportation Center, Oklahoma City, OK, 2012.

16. Schulte, F., E. Lalla-Ruiz, R.G. González-Ramírez and S. Voß. Reducing Port-related Empty Truck Emissions: A Mathematical Approach for Truck Appointments with Collaboration. *Transportation Research Part E: Logistics and Transportation Review*, 2017. 105: 195-212.

17. Hwang, T.S. *Freight Demand Modeling and Logistics Planning for Assessment of Freight Systems' Environmental Impacts*. PhD Dissertation. University of Illinois at Urbana-Champaign, Chicago, 2014.

18. Bureau of Labor Statistics. *Quarterly Census of Employment and Wages*. U.S. Department of Labor, Washington DC. https://data.bls.gov/cew/apps/data_views/data_views.htm#tab=Tables. Accessed May 22, 2019.

19. Krishnan, T. *Decomposition Algorithms for the Elementary Shortest Path Problem in Networks Containing Negative Cycles*. PhD Dissertation. Oklahoma State University, 2015.

20. Carbonfund Foundation, Inc. *How We Calculate*. Carbonfund, Foundation, Inc., East Aurora, NY. https://carbonfund.org/how-we-calculate/. Accessed May 22, 2019.

21. Environment Protection Agency. *Emission Factors for Greenhouse Gas Inventories*. U.S. Environmental Protection Agency, Washington, DC. https://www.epa.gov/sites/production/files/2018-03/documents/emission-factors_mar_2018_0.pdf. Accessed May 22, 2019.

22. Agar, B.J., B.W. Baetz, and B.G. Wilson. Fuel Consumption, Emissions Estimation, and Emissions Cost Estimates using Global Positioning Data. J*ournal of the Air & Waste Management Association*, 2007. 57(3): 348-354.

23. Federal Highway Administration. *Handbook for Estimating Transportation Greenhouse Gases for Integration into the Planning Process*. U.S. Department of Transportation, Washington, DC. https://www.fhwa.dot.gov/planning/processes/statewide/practices/ghg_emissions/handbook.cfm. Accessed May 22, 2019.

24. Department of Energy. *Fact #621: May 3, 2010 Gross Vehicle Weight vs. Empty Vehicle Weight*. U.S. Department of Energy, Washington, DC. https://www.energy.gov/eere/vehicles/fact-621-may-3-2010-gross-vehicle-weight-vs-empty-vehicle-weight. Accessed May 22, 2019.

25. The Truckers Report. *The Real Cost of Trucking – Per Mile Operating Cost of a Commercial Truck*. The Truckers Report. https://www.thetruckersreport.com/infographics/cost-of-trucking/. Accessed May 22, 2019.

26. Transportation Business Associates. Fixed Expenses. Transportation Business Associates. http://www.tbabz.com/wp/tractor-trailer-ops/fixed-expenses. Accessed May 222, 2019.