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QUANTIFYING AND VISUALIZING CITY TRUCK ROUTE NETWORK EFFICIENCY USING A VIRTUAL TESTBED

Models for an Urban Freight and Parcel Delivery Virtual Testbed in NYC

May 2023

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Quantifying and Visualizing City Truck Route Network Efficiency Using a Virtual Testbed: Models for an Urban Freight and Parcel Deliverty Virtual Testbed in NYC		5. Report Date May 2023
		6. Performing Organization Code:
7. Author(s) Joseph Chow, Kaan Ozbay, Haggai Davis III, Hai Yang, Farnoosh Namdarpour, Hector Landes, Jack Gazard		8. Performing Organization Report No.
9. Performing Organization Name and Address Connected Cities for Smart Mobility towards Accessible and Resilient Transportation Center (C2SMART), 6 Metrotech Center, 4th Floor, NYU Tandon School of Engineering, Brooklyn, NY, 11201, United States		10. Work Unit No.
		11. Contract or Grant No. 69A3551747119
12. Sponsoring Agency Name and Address Office of Research, Development, and Technology Federal Highway Administration 6300 Georgetown Pike McLean, VA 22101-2296		13. Type of Report and Period Final report, 3/1/21-5/31/23
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

This project explored routing app designs that can be of use to NYC DOT in informing truck drivers in NYC. This involved developing a prototype app and engaging in a hackathon in Fall 2022 to refine the visualization of the routing data. Second, we leveraged public data to construct a synthetic population of trucks that can be incorporated into a multiagent simulation that allows for dynamic passenger and commercial vehicle interactions. The synthetic truck population, which includes schedules of trip chains for each individual truck, will be incorporated into MATSim-NYC (He et al., 2021). Third, we proposed a new model for predicting zonal residential parcel delivery volumes and VMT that is applicable to large-scale scenarios and validate such a model using data from New York City (NYC).

17. Key Words	18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161. http://www.ntis.gov		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 108	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page author

Quantifying and Visualizing City Truck Route Network Efficiency Using a Virtual Testbed

C2SMART Center is a USDOT Tier 1 University Transportation Center taking on some of today's most pressing urban mobility challenges. Using cities as living laboratories, the center examines transportation problems and field tests novel solutions that draw on unprecedented recent advances in communication and smart technologies. Its research activities are focused on three key areas: Urban Mobility and Connected Citizens; Urban Analytics for Smart Cities; and Resilient, Secure and Smart Transportation Infrastructure.

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Led by the New York University Tandon School of Engineering, C2SMART is a consortium of five leading research universities, including Rutgers University, University of Washington, the University of Texas at El Paso, and The City College of New York.

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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

In addition to the funding support from C2SMART, some of the researchers were supported by NYU's Summer Undergraduate Research Programs. Data shared by NYC DOT and NYMTC are gratefully acknowledged. Comments from Professor José Holguín-Veras were provided to the team regarding the model, which helped improve the design. A hackathon was organized for the truck routing app, which involved volunteers for a judging panel, which is much appreciated.

Executive Summary

The need for tools to evaluate urban freight policies is greater than ever before, as communities face a combination of a pandemic fallout on supply chains (Schofer et al., 2022); e-commerce surge (U.S. Department of Commerce, 2022); technological advances in urban deliveries (Davis and Figliozzi, 2013; Ulmer and Thomas, 2018; Giampoldaki et al., 2021); and innovations in urban policies (Campbell et al., 2018; Holguín-Veras et al., 2011a); all in an increasingly congested urban space with competing users. Conventional modeling tools for urban truck flows range from truck trip models to behavioral tour and agent simulation models (e.g. Chow et al., 2010; Hunt and Stefan, 2007; Wisetjindawat et al. 2006; Gatta and Marcucci, 2014; You et al., 2016). On their own, they can evaluate many policies related to urban goods movement. However, policies that relate to time-of-day traffic dynamics and interactions between commercial vehicle movements and passenger travel require models that are sensitive to these variables. Multiagent simulations of truck movements alone are not enough; multiagent simulations that capture the shifting of departure times of travelers and trucks in highly congested locations and time periods are needed. There are several multiagent simulation platforms in the literature that include both passenger and freight simulation. Unfortunately, they simulate individual establishment and carrier decisions like supplier selection and shipment size selection and require such disaggregate data. In general, such data are not available to public policymakers.

As a result of these motivations, we collaborated with the New York City Department of Transportation (NYC DOT) to address the problems in several ways. First, we explored routing app designs that can be of use to NYC DOT in informing truck drivers in NYC. This involved developing a prototype app and engaging in a hackathon in Fall 2022 to refine the visualization of the routing data. Second, we leveraged public data to construct a synthetic population of trucks that can be incorporated into a multiagent simulation that allows for dynamic passenger and commercial vehicle interactions. The synthetic truck population, which includes schedules of trip chains for each individual truck, will be incorporated into MATSim-NYC (He et al., 2021). Third, we proposed a new model for predicting zonal residential parcel delivery volumes and VMT that is applicable to large-scale scenarios and validate such a model using data from New York City (NYC).

To generate the synthetic freight population, we used a method that combines the freight trip generation, distribution via truck tour set generation and entropy maximizing flow synthesis, after which individual truck itineraries can be sampled similarly to a passenger synthetic population. Freight trips are estimated in three steps. First, freight trips produced and attracted at the establishments level are quantified. Then, inbound/outbound freight trip flows to/from the area of study via gateways are included to have a broader understanding of possible OD movements. Finally, relationships between industries are appended based on supply/production ties to the origin or destination of freight trips.

Unfortunately, we do not have Freight Trip Attraction (FTA) or Freight Trip Production (FTP) data by industry at the establishment level to estimate forecast models with. However, we can estimate it based upon the methodology and parameters specified in National Cooperative Freight Research Program Report 25 (NCFRP 25) (Holguín-Veras et al., 2017). To achieve the level of granularity needed, employment is imputed to an establishment level in the study area and assigned characteristics based upon building use or areal information as necessary which was sourced from the NYC PLUTO dataset and the American Census Survey. Employment data was aggregated to the borough level for validation. It was acceptably close for each as well as at the citywide level where it predicted 4.63M employees which is a 7.5% overestimate of the number reported by the Census.

To account for the role of external regions on the study area, we need to consider the incoming/outgoing flow of trucks with origins and destinations such as other parts of the United States or the world. The Freight Analysis Framework 5 (FAF5) (FHWA, 2022; U.S. BTS, 2017) was used to understand regional level flows, and then 2020 Census data was used to subtract out the surrounding areas from NYC. To address long-haul trips, heavy trucks (FHWA class 8+) at gateways were assumed to be destined directly for a warehouse while medium trucks (FHWA class 5-7) were assumed to be making tour-based deliveries.

Freight Trips Generated (FTG) were then calculated and aggregated at the borough level, added to the gateway FTG, and compared against NCFRP25 for validation. Our total of 667k truck trips was roughly 7% lower than their estimation which again is seen to largely agree. FTP and FTA did not naturally equal each other, but for the purposes of the distribution algorithm, they must be. In general FTP was scaled to be equal to FTA. This process resulted in 725k daily truck trips generated in NYC, which is 7% more and agrees with the NCFRP25 estimate to within 1%.

The tour sets were generated first by calculating an Industry specific length, then assigning an origin, then assigning destinations which promoted clustering. 10,000 tours were generated for each of the 47 industries (resulting in 470,000 tours). Flow is then assigned onto the tours using entropy maximization. The flows are constrained to the freight demands of each custom transportation analysis zone (TAZ), the average length for each tour, functional constraints for the model, and realism constraints such as positive, whole numbers of trucks. Due to factors such as the model's nonlinearity and the size of the constraint matrices, traditional solvers like Gurobi or Scipy could not be used. An iterative balancing algorithm which proportionally reassigns FTP then FTA until the change drops below a threshold was designed and applied. It performed significantly faster than previous methods. A representative industry took 6 iterations to converge below the threshold.

After the tour flow assignment process, validation begins. Routing for the trucks was done on a cutout of NYC from OpenStreetMap with NYC DOT providing truck specific data and Uber Movement dataset (2022) providing link-level travel times by time of day. Two validation frameworks were used, one specified in an NYC DOT report, and another specified by this project. The first factor calibrated was the weighting factor in the origin destination generation process. 0.75 produced the best results across both validation frameworks. Using both frameworks together show an overestimation of trips between Manhattan and Brooklyn as well as Manhattan to Queens, but all other borough boundaries are well estimated. The Manhattan/ Brooklyn is the least accurate boundary overpredicting two-way daily truck trips by 21,464, or +145% of observed total flows of 14,777. The Queens/Bronx boundary is the most accurate at 1566 truck trips overestimated or +5%. Note that these are preliminary assignments; more detailed and accurate assignments will be made through MATSim in a subsequent study which will account for congestion effects on individual bridges more properly. The goal at this stage is to make sure the total volumes across the city on average are reasonable.

Calibrated tour flows were then converted to the synthetic freight population. To do this, tour flows were assigned characteristics such as starting times, service times, and vehicle weight which were derived from real world data. Link-level and tour level quantities were tabulated such as travel times and emissions. Analysis of the synthetic population shows that the total estimated daily VHT in New York City is 2.49M veh-hours with 0.65M veh-hours of that being service time. The total estimated daily emission of CO_2 is 5640 metric tons of carbon equivalent (MTCE). A case study was then considered where the vehicle capacity was shrunk by 20% to examine the impact on congestion and bridge damage. While VHT and CO_2 emissions increased to 3.12M veh-hours and 7.05 MTCE, damage to both the Manhattan Bridge and Queens Midtown Tunnel in both directions fell between 45 and 47% even though flow increased between 24 and 25%.

Additionally, this project considered parcel deliveries because the e-commerce industry has experienced significant growth in the past decade, particularly post-COVID. Global e-commerce sales grew by 22.7% from 2020 to 2021 (Statista, 2022), and are projected to increase by more than 90% from 2020 to 2026. E-commerce sales experienced a 50.5% increase from 2019 to 2021 in the US, and more than 14.5% of all retail sales in 2021 came from e-commerce (DOC, 2022). The parcel delivery sector has also experienced fast expansion to accommodate such growth. However, there is a lack of study that properly evaluates its social and environmental impacts at a large scale. A model is proposed to analyze such impacts. A parcel generation process is presented to convert public data into residential parcel volumes and stops. A continuous approximation model is fitted to estimate the length of parcel service tours. The two processes can be used collaboratively to estimate the overall impact of parcel delivery operations.

A case study is conducted in New York City (NYC) using 2021 as the data year. 1.91 million daily residential parcels are estimated using the parcel generation process, which matches the volume presented in Komanoff (2021). The continuous approximation model parameters have R^2 values of 98% or higher. By using the model, 61.4 thousand daily vehicle-miles traveled (VMT) are estimated, which contributed to 0.05% of total daily VMT in NYC corresponding to 14.4 metric tons of carbon equivalent (MTCE) emissions per day. By comparing the results between 2020 and 2021, COVID-19 is estimated to contribute to an increase in parcel deliveries that led to up to 1064.3 MTCE of annual greenhouse gas (GHG) emissions in NYC (which could power 532 standard US households for a year).

When coming to the potential application of cargo bike delivery, the existing bike lane infrastructure can support the substitution of 17% of parcel deliveries by cargo bikes, which would reduce VMT by 11%. For example, adding 1.9 miles of bike lanes to connect Amazon facilities can expand their cargo bike substitution benefit from a 5% VMT reduction up to a 30% reduction. Only 17.4 miles of additional bike lanes would connect all major carrier facilities, allowing for a parcel delivery substitution citywide which could increase from 17% to 34% via cargo bike and save an additional 2.3 MTCE per day. Cargo bike prioritization can be set by decision-makers to reduce GHG emissions for environmental justice neighborhoods including Harlem, Sunset Park, and Bushwick.

Finally, this project set out to build a truck routing app for New York City. Originally pitched as a data dashboard, it evolved into a routing app through conversations with NYC DOT about their data inventory and their needs. This product uniquely combines first party data from NYC DOT about the built environment and packages into an open-source tool. By providing dynamic routing to trucks that encourages them to use designated truck routes, this tool will help meet the goals of increased efficiency and reduced emissions, noise pollution, and bridge strikes (NYC DOT 2021). The app works by connecting a front-end user interface that prompts a driver for information about their destinations and their vehicle to a server which hosts script that performs the calculations via a python script accessing the ArcGIS platform via the provided APIs. That information is returned and visualized with the tool created by the Hackathon. The Hackathon was a one-week virtual competition which began at TransportationCamp NYC 2022 in a hybrid format and concluded in a virtual closing ceremony. At both events, interested members of the community contributed valuable conversations and feedback about potential strengths, weaknesses, challenges, and threats to the project. The winning team produced a 3D visualizer which has successfully been integrated into the main product. The team is leading ongoing efforts to get the product into the hands of interested parties through the NYC trucking community and to continue to invest in this tool because of the potential it could have to improve the ecosystem.

This project has resulted in presentations given at TU Delft and ITS-NY as well as a virtual presentation for the World Conference on Transportation Research. . Four papers were prepared from the synthetic population development. The work has supported several PhD students for portions of their dissertations, NYU Tandon School of Engineering's Undergraduate Summer Research Program, and their Applied Research Innovations in Science and Engineering (ARISE) program. It was used in graduate and undergraduate courses by Professor Chow. It was presented publicly at the NYU Tandon Research Expo, the C2SMART Student Learning Hub, TransportationCamp NYC 2022, and a demonstration for NYC DOT is being planned along with a digestible app summary to be broadly released.

The major limitations for this project center around data and timing. For the freight truck portion, a data year of 2019 was chosen because it was the last year that consistent and reliable data was available. The parcel bike portion was able to use 2021, but in both cases, the rapidly changing freight delivery landscape in New York City has altered some of the realities. For example, new distribution centers have come online in the last two years. Additionally, the freight truck section does overestimate the number of trucks crossing the Manhattan-Brooklyn boundary and Manhattan-Queens boundary. The size of the error is deemed acceptable for work, and future efforts are likely to reduce this error.

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Table of Common Acronyms

Abbreviation	Meaning	Context
FAF	Freight Analysis Framework	A comprehensive picture of freight movement among major states and metropolitan areas by all modes of transportation
FTA	Freight Trips Attracted	The quantity of freight attracted a location, in units of freight trucks
FTG	Freight Trips Generated	The sum of Freight Trips Produced and Freight Trips Attracted for a given location
FTP	Freight Trips Produced	The quantity of freight produced a location, in units of freight trucks
NAICS	North American Industry Classification System	The standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data
NCFRP	National Cooperative Freight Research Program	A coalition of government agencies to study problem areas affecting the freight industry. Their findings are published in numbered reports
NYC DOT	New York City Department of Transportation	Government agency which provides for the safe, efficient, and environmentally responsible movement of people and goods in the City of New York
TAZ	Transportation Analysis Zone	A system of dividing land used to show spatial variation in data

1. Introduction

1.1. Project background

E-commerce sales have grown significantly around the globe, which further gained momentum during the global pandemic since 2020. Global e-commerce sales grew by 22.7% from 2020 to 2021 (Statista, 2022), and are projected to increase by more than 90% from 2020 to 2026. E-commerce sales experienced a 50.5% increase from 2019 to 2021 in the US, and more than 14.5% of all retail sales in 2021 in the US came from e-commerce (US Department of Commerce, 2022). E-commerce sales are projected to keep such momentum in the future, which could occupy more than 23.6% of all retail sales in 2025 in the US (Davidkhanian. 2021).

The need for tools to evaluate urban freight policies is greater than ever before, as communities face a combination of a pandemic fallout on supply chains (Schofer et al., 2022); e-commerce surge (U.S. Department of Commerce, 2022); technological advances in urban deliveries (Davis and Figliozzi, 2013; Ulmer and Thomas, 2018; Giampoldaki et al., 2021); and innovations in urban policies (Campbell et al., 2018; Holguín-Veras et al., 2011a); all in an increasingly congested urban space with competing users. Conventional modeling tools for urban truck flows range from truck trip models to behavioral tour and agent simulation models (e.g. Chow et al., 2010; Hunt and Stefan, 2007; Wisetjindawat et al. 2006; Gatta and Marcucci, 2014; You et al., 2016). On their own, they can evaluate many policies related to urban goods movement.

However, policies that relate to time-of-day traffic dynamics and interactions between commercial vehicle movements and passenger travel require models that are sensitive to these variables. For example, the Off-Hour Deliveries" program (Holguín-Veras et al., 2011a) is being expanded upon by NYC DOT and congestion pricing is being implemented for New York City (NYC) in the near future (He et al., 2021). Other examples include electric charging infrastructure planning that allows both electric trucks, cargo bikes, and passenger vehicles share usage (Wang et al., 2019); allocation of urban consolidation centers that replace other land uses; or regulating the roadways for dedicated truck routes. None of these policies can be properly evaluated using conventional modeling tools that ignore passenger travel conflicts with trucks under dynamic congestion. Multiagent simulations of truck movements alone are not enough; multiagent simulations that capture the shifting of departure times of travelers and trucks in highly congested locations and time periods are needed.

There are several multiagent simulation platforms in the literature that include both passenger and freight simulation. MATSim (Horni et al., 2016) has been used to evaluate truck activities (Joubert et al., 2012; van Heerden and Joubert, 2014) and is capable of modeling multiple classes of vehicles and agents on the road network (Schröder and Liedtke, 2017). Mommens et al. (2018) in fact used MATSim to evaluate off-hour deliveries. POLARIS (Auld et al., 2016) is currently being extended to capture freight movements (Stinson et al., 2020; Stinson and Mohammadian, 2022). MASS-GT simulates the freight shipper and receiver decisions as well as the carriers (de Bok and Tavasszy, 2018). SimMobility (Azevedo et al., 2017) has been used to model both passengers and trucks using real data from Singapore (Sakai et al., 2020). Thoen et al. (2020) constructed tours from at the shipment level in a bottom-up approach. As significant as these latter works are, they simulate individual establishment and carrier decisions like supplier selection and shipment size selection and require such disaggregate data. In general, such data are not available to public policymakers.

An example of this limited data setting is with parcel deliveries. Parcel delivery service is commonly used as the final segment of the logistics operation in e-commerce. Increasing the capacity of parcel delivery services is crucial to properly serve the growing customer base. However, more parcel delivery vehicles entering the service would put more pressure on the already congested road network in densely populated urban areas. The added delivery vehicles would induce more vehicle-miles-traveled (VMT), producing higher levels of emissions with internal combustion engine vehicles. Even though the parcel delivery sector is becoming more critical, the literature on quantifying its impact on a large scale remains limited. Without such quantification, it would prevent us from gaining insight into managerial strategies and policies in this important sector. For example: how much greenhouse gas (GHG) emissions will be produced by the delivery service alone, how much impact do outside factors such as COVID-19 have, and what benefits would the deployment of such service alternatives as cargo bikes bring in terms of social welfare?

Currently, four major companies, the United States Parcel Service (USPS), United Parcel Service (UPS), Federal Express (FedEx), and Amazon Logistics (Amazon), are dominating the parcel delivery industry in the US. The combined parcel volume handled by the four companies occupies nearly 98% of the US parcel shipment in 2021 (Pitney Bowes, 2022). To restrict the impact of added delivery volume on the road network and the environment, pilot programs have been conducted by six companies including Amazon, DHL, UPS, FedEx, Reef Technology, and NPD Logistics (NYC DOT, 2021). However, they are still in their preliminary phases and the full deployment would require years of tests. Without detailed operation data, there is a strong need to develop a model to properly evaluate these new parcel service strategies from a planning perspective on a large scale.

Furthermore, conversations with NYC DOT staff indicated that a major challenge is the lack of digital, dynamic, publicly owned, *truck-specific* routing through the city. Their current practice involves distribution of a pdf updated map roughly every 3-5 years. Free routing services like Google Maps or Waze fail to meet this need because they lack the truck-specific information. Those apps assume a standard passenger vehicle which is not subject to the same height, weight, or route restrictions as trucks are. While private routing platforms are available, they are costly. NYC DOT makes available the truck route data in shapefiles, but to our knowledge, no one has yet built a freely available routing tool on top of them. NYC DOT is examining the feasibility of developing a free, publicly accessible routing tool, to be able to integrate it with their other digital services to maximize benefits to users, and to analyze the data collected to make further improvements to the truck ecosystem in New York City.

As a result of these motivations, we collaborated with NYC DOT to address the problems in several ways. First, we explored routing app designs that can be of use to NYC DOT in informing truck drivers in NYC. This involved developing a prototype app and engaging in a hackathon in Fall 2022 to refine the visualization of the routing data.

Second, we make use of only public data to construct a synthetic population of trucks that can be incorporated into a multiagent simulation that allows for dynamic passenger and commercial vehicle interactions. The proposed methodology integrates two earlier works in the literature: freight trip generation (Holguín-Veras et al., 2017) and an aggregate tour-based truck distribution model using a variant of the tour-based entropy maximization methods in the literature (e.g. Sánchez-Díaz et al., 2015; You and Ritchie, 2019) that can be calibrated to match observed average number of stops and borough-level crossing volumes. The proposed method is applied to NYC, the first of its kind for NYC, resulting in an original public data set for policymakers. The model includes freight truck productions and attractions within NYC and at designated gateways, split by industry and vehicle class and cognizant of make-use relations, and a set of tours that are validated against average annual daily truck trips (AADTT). A scenario involving the supply chain disruption of one industry on truck flows before and after reallocation of fleet resources is evaluated. The synthetic truck population, which includes schedules of trip chains for each individual truck, will be incorporated into MATSim-NYC (He et al., 2021).

Third, we propose a new model for predicting zonal residential parcel delivery volumes and VMT that is applicable to large-scale scenarios and validate such a model using data from New York City (NYC). We use the model to quantify the impacts of increased parcel delivery due to the COVID-19 pandemic on greenhouse gas (GHG) emissions. We identify all viable depots for substituting cargo bike deliveries using NYC's existing bike infrastructure and apply the model to investigate the benefit of such a substitution. This includes estimating the additional bike lane infrastructure needed to give eligible depots access and quantifying the impact of substituting trucks with cargo bikes on VMT and GHG emissions. These analyses are done for four major companies across two seasons' days. While everything considered in this work is a full sized depot, future efforts will consider the addition of microhubs (NYC DOT 2023).

1.2. Research Objectives

The study consisted of three objectives. The first is to develop a prototype truck routing app that makes use of restriction data from NYC DOT to give more useful directions to truck drivers than what they can get with a conventional driving directions app like Google Maps. The second is to develop a citywide dataset of truck network flows, one that relates changes to truck routes to changes in truck tours or to time-of-day congestion pricing policies, for example. This latter objective is achieved using the following framework in Figure 1.1.

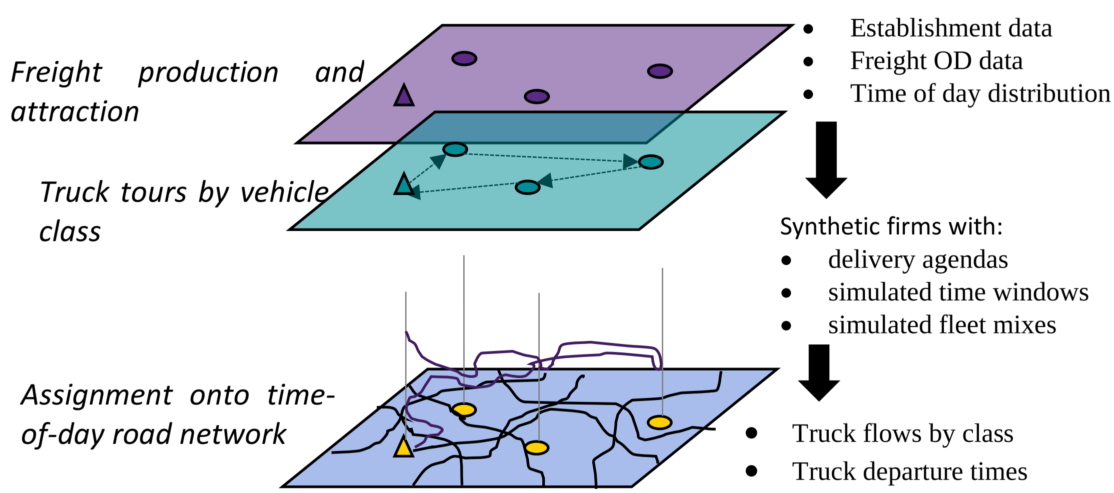


Figure 1.1 Project's data flow framework.

The first arrow is captured using a synthetic population extension which will require a new tour-based freight model. The second arrow is captured with the MATSim simulation platform. The project is an application of MATSim-NYC for NYC DOT that also expands on the literature on urban freight network modeling.

The third objective is the development and calibration of a large-scale analytical model for parcel deliveries for NYC.

1.3. Report organization

The rest of this report is organized as follows. Section 2 describes the process of combining all the sources of open data into the New York City Commodity Flow. Section 3 details how the freight tours were created and loaded with flow, including a case study which examines the impact of altering truck size on VHT, GHG emissions, and average loads on the bridge crossings. Section 4 details the development of the analytical parcel delivery model. Section 5 outlines the creation of the Truck Routing App and what the next steps could be. Section 6 concludes the report with ways in which this work has been disseminated and future plans for its components.

2. Developing Zonal Commodity Flows for NYC

To better understand this model, it will be helpful to examine the transportation planning process. The traditional four step method is commonly described as trip generation, trip assignment, mode choice, and route choices. For each zone of study, the number of trips originating and terminating are calculated. These trip ends are then matched. Then vehicle type is decided, and then finally the specific links to cross the network are selected. Chow et al. (2010) examines the planning process as it applies to freight demand and classifies several types of models based upon their data inputs, methodologies, and ultimate aims. It recommends two advanced types of models, logistic and vehicle-touring, as being the most beneficial to researchers and practitioners. Logistic models capture supply chain interactions by making behavioral distinctions which can apply to many decision makers with the unit of analysis being a commodity or shipment. Vehicle-touring models focus on the vehicle and try to minimize logistic costs to predict more accurate movements. The model we propose synthesizes these two methods with innovative techniques to overcome the data challenges which had previously prevented this approach.

A method is needed to generate a synthetic population of trucks that can feed into a multiagent simulation like MATSim, based on aggregate modeling methods and public data. We propose a method that combines the freight trip generation, distribution via truck tour set generation and entropy maximizing flow synthesis, after which individual truck itineraries can be sampled similarly to a passenger synthetic population. The overall process is shown in Figure 2.1.

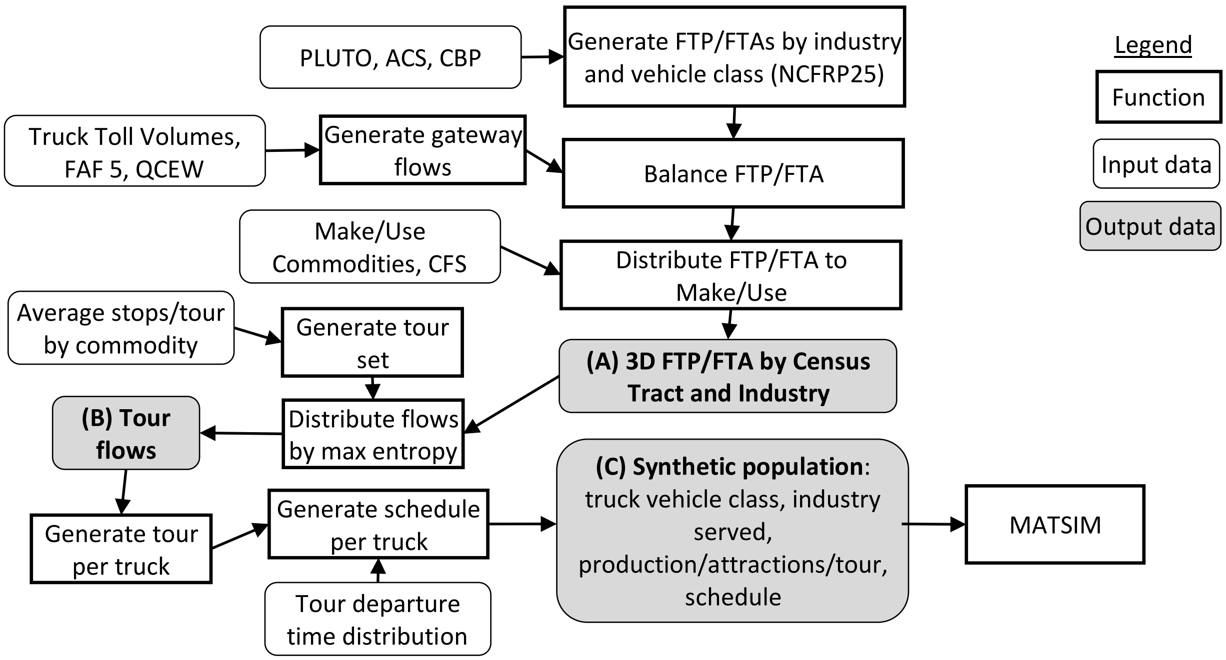


Figure 2.1 Overview of synthetic truck population generation from socioeconomic and aggregate truck flow data.

An initial step generates the trip productions and attractions, divided by internal zones and external gateways. Freight trip productions (FTPs) and attractions (FTAs) are further connected to each other via make/use tables to capture supply chain effects, i.e. scenarios involving the reduction in one industry can result in impacts to other industries (see Ranaiefar et al. 2013, for example supply chain scenarios). A tour set is generated per industrwfy, which is then assigned flows using maximum entropy to fit the FTPs/FTAs. Gateway trips are divided between smaller truck tours versus larger truckload deliveries to warehouses within the city. Truck tours are sampled from a set to generate the tours for the truck population, after which schedules can be synthesized for each truck agent. All forecasted data reflect a base year of 2019, prior to the start of the COVID-19 pandemic.

2.1 Generating Freight Trip Productions/Attractions (FTPs/FTAs)

Freight trips are estimated in three steps. First, freight trips produced and attracted at the establishments level are quantified. Then, inbound/outbound freight trip flows to/from the area of study via gateways are included to have a broader understanding of possible OD movements. Finally, relationships between industries are appended based on supply/production ties to the origin or destination of freight trips. A large number of data sources are used for this effort; a summary of their uses is provided in Table 2.1. For more details about public data sources, see Tok et al. (2011).

FTP/FTA Regression models at the establishment level

FTPs and FTAs (collectively, Freight Trips Generated, i.e. FTGs) are forecasted for each NAICS industry at the 2-digit code and for each zone in NYC. A zone system based on aggregations of census tracts is used based on ensuring consistency with zones used for passenger synthesis (labeled as “optimized census zones” in Table 2.1; see Liu et al., 2023).

In total there are twenty-four 2-digit NAICS codes, divided between “freight-intensive sectors” (FIS) and non-freight intensive sectors (non-FIS), of which we further disaggregated out to a total of 78 industries (some at 3-digit level detail). FIS NAICS codes span from 21 to 49 and 72, while non-FIS codes span from 51 to 81 (except 72). FIS include mining, manufacturing, retail trade, wholesale trade, warehousing, and good services. The non-FIS trips include public administration, offices, health, education, entertainment, and information. We do not have FTA/FTP data by industry at the establishment level to estimate forecast models with. However, NCFRP25 provides estimated parameters for forecast models (see Eqs. (2.1) – (2.4)) drawn from microdata taken across the Commodity Flow Survey, so they are used directly.

Table 2.1 Data inputs and descriptions.

FTP/FTA Estimation	NCFRP-25 Report 37	National Academies of Science, Engineering, and Medicine	2016	Guidebook providing establishment-level models to estimate Freight Trip Generation (FTG), Freight Production (FP), and Service Trip Attraction (STA)	Parameters for linear and non-linear models for FP/FA and FTP/FTA
	Census Tract NTA/PUMA Equivalencies	NYC - Department of City Planning	2010	Relationship between census tracts, Neighborhood Tabulation Areas (NTAs), and Public Use Microdata Areas (PUMAs)	Convert lot level to census tract level
	American Census Survey (ACS)	Census Bureau	2018	Gives the number of employees by 2-digit NAICS industry at the census tract level	Number of employees by 2-digit NAICS industry at the census tract level
	County Business Patterns (CBP)	Census Bureau	2019	Gives the number of employees by 2-digit NAICS industry at the zip code level	Zip code level employment for NYC's landmarks as defined by Jaller et al. (2015)
	Proprietary Zones	C2SMART	2022	Aggregated census tract districts	Zone system used for generating FTPs and FTAs
Gateways & Stimulation	Freight Analysis Framework (V5)	FHWA - Bureau of Transportation Statistics	2019	Complete picture of the flow of freight by all forms of transportation between states and major urban regions (based on the Census Bureau's CFS)	In/Out freight flow by 2-digit NAICS industry to and from NYC Metropolitan Area
	Proposed Payload Factors	FHWA - Bureau of Transportation Statistics	2017	Proposed Freight Analysis Framework payload factors for single unit and combination unit trucks by SCTG commodity type	Splits freight flow to SU and CU to the number of trucks traveling to and from NYC
	Mountain Plains Consortium 13-259	US DOT	2013	2-digit NAICS and 2-digit SCTG cross referenced	Converts SCTG to 2-digit NAICS industry
	American Census Survey	Census Bureau	2018	Gives the number of employees by 2-digit NAICS industry at the county tract level	Subtracts FTP/FTA from counties in the NYC Metropolitan Area to get real freight flow from and to NYC
	Truck Toll Volumes	NYMTC	2007	Movement of truck traffic over toll bridges and crossing between New York City and New Jersey during the years 2006 and 2007	Converts Freight Analysis Framework payload factors to NYC specifics
Synthetic Freight	Movement	Uber	2019	Average speed of Uber in NYC	Determine travel time on each link of the synthetic freight population

To achieve the level of granularity needed, employment is imputed to an establishment level in the study area and assigned characteristics based upon building use or areal information as necessary. Using PLUTO data, it was assumed that one establishment fills an entire lot. Each lot was synthesized with a 2-digit NAICS industry based on the lot's area type, building class, and the Public Use Microdata Areas (PUMA) worker distribution occupation from the American Census Survey (ACS) (US Census Bureau, 2019). Equivalencies between the census tract and PUMA standards were determined using the conversion key provided by the New York City Department of City Planning (NYC Department of City Planning, 2010). Employment data was then aggregated to the PUMA level because the margin of error at the census tract level was too high. Each lot was assigned an industry based on the lot area type and building class (see appendix C of PLUTO). Next, the number of employees was determined by multiplying the area of the lot building type, area of the PUMA total building type, and the PUMA employment distribution by 2-digit NAICS. The employment was corrected using the data from County Business Patterns (CBP) for unique buildings in Manhattan that have a unique zip code (ex. Empire State Building). The list of such landmarks can be found in Jaller et al. (2015). The PLUTO data and employment heatmap for NYC are shown in Figure 2.2. This dataset provides the establishment-level input for applying the models in Eqs. (2.1) – (2.4).

Linear
$$F_i = \alpha + \beta E_i \tag{2.1}$$

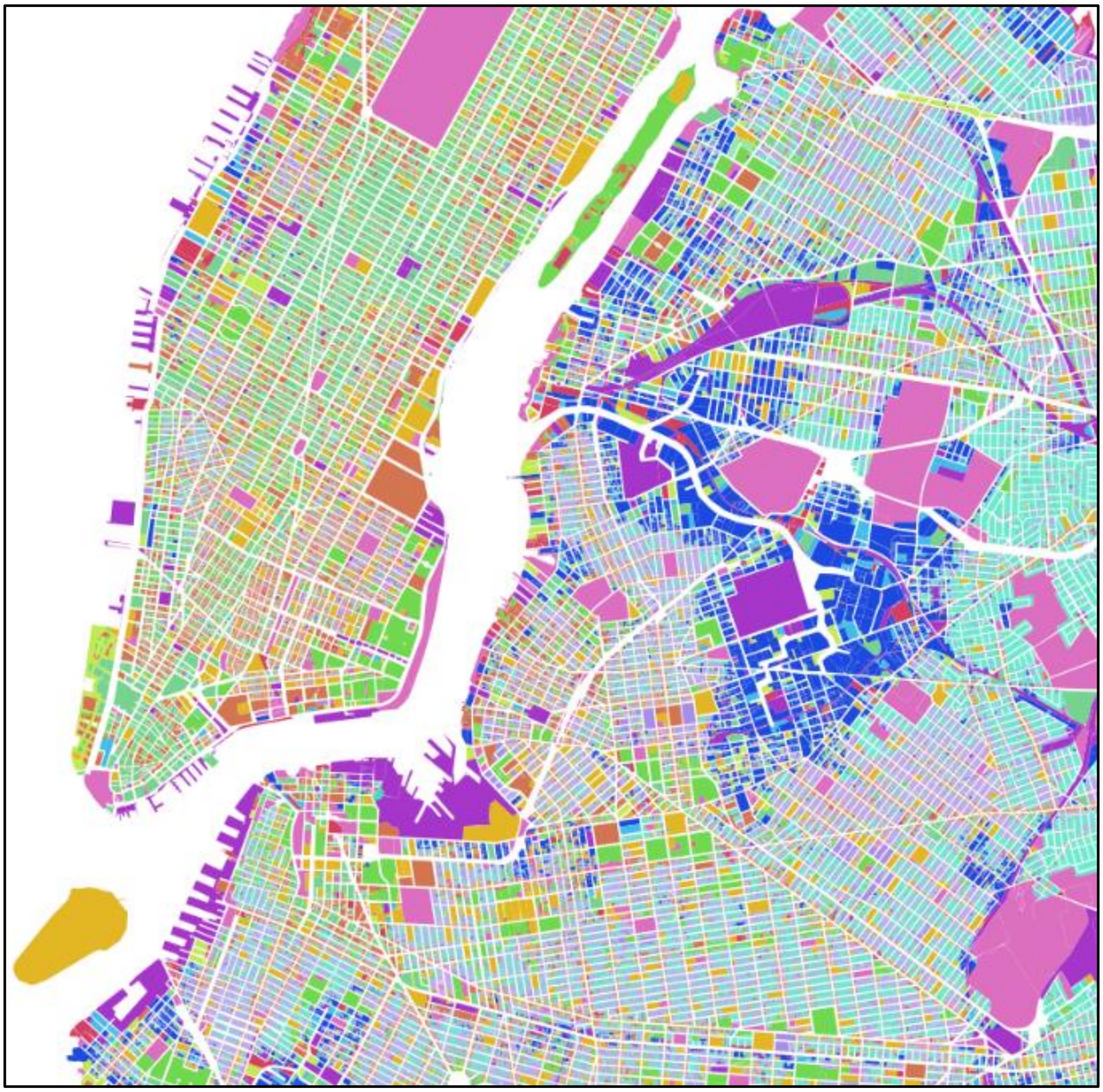
Non-Linear
$$F_i = \varphi E_i^{\gamma} \tag{2.2}$$

Hybrid
$$\begin{aligned} f_i &= \alpha^* E_i^{\beta} \\ F_i &= \alpha^* f_i^{\lambda} \end{aligned} \tag{2.3}$$

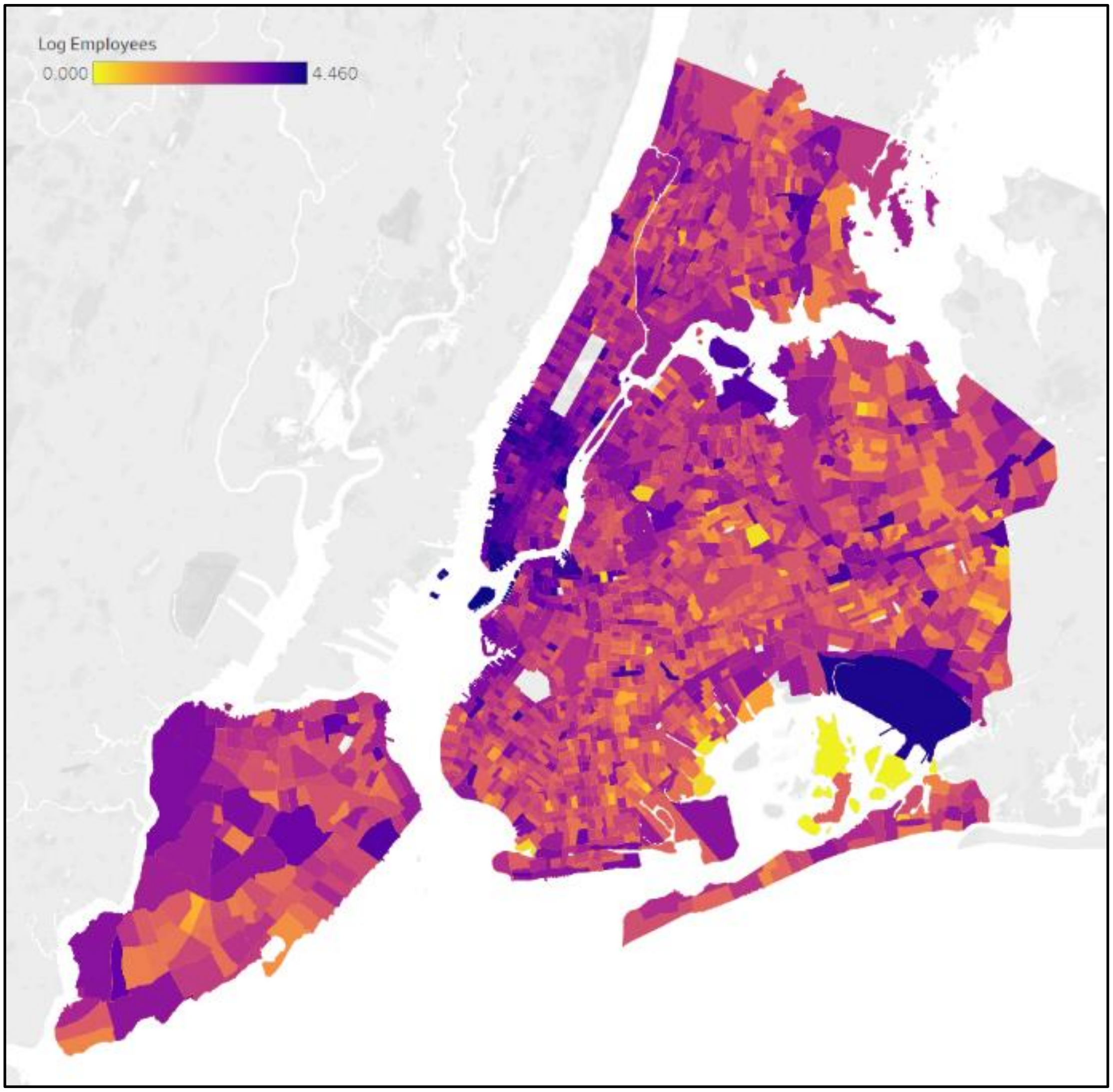
$$F_i = \varphi E_i^{\gamma} \tag{2.4}$$

Where,

F_i is the FTG (FTA or FTP) metric for establishment i;
f_i is the FG (FA or FP) metric for establishment i;
E_i is the employment at establishment i;
$\alpha, \beta, \varphi, \gamma, \lambda$ are parameters.



(a)



(b)

Figure 2.2. (a) PLUTO data in NYC; (b) synthesized employment heatmap.

As dictated by NCFRP25, the linear models Eq. (2.1) was used for non-intensive freight industries, and the non-linear models are utilized for the freight intensive ones. The non-linear models are either a direct function of employment Eq. (2.2) or a function of freight generated, which is a function of employment Eq. (2.3). The hybrid model Eq. (2.3 -2.4) involves using the two above non-linear models, with a threshold for switching between them based on whether the FTA/FTP function of freight generated (FA, FP) is greater than the FTA/FTP function of employment. The hybrid model is preferred due to the underestimation or overestimation of freight for small establishments. From an examination of the model goodness of fit metrics in NCFRP25, the non-

FIS forecast models are not reliable enough and represent less than 5% of the total FTG, so we exclude them. The final set of 49 FIS industries covered and the type of model used for the FTPs and FTAs are summarized in Table 2.2.

Table 2.2 Summary of FTP/FTA model selection by FIS industry

Industry	***Model Type***	***Details***	***Hybrid Threshold***	***NCFRP-25 Ref***
FTA				
23, 31, 33, 45, 72	Non-Linear	FTA(Veh/Day)	N/A	Table 10
21, 22, 32, 42, 44, 48, 49	Hybrid	FTA(Veh/Day) as a Function of FA (Lbs/Day) & FTA (Veh/Day)	FTA_NA_NL ≤ FTA_NL FTA_FA_NL > FTA_NL	Table 17/21 & Table 10
FTP				
21, 31, 32, 33, 42,44, 45	Non-Linear	FTP(Veh/Day)	NA	Table 12
22, 23, 48, 49, 72	Hybrid	FTP(Veh/Day) as a Function of FP (Lbs/Day) & FTP (Veh/Day)	FTP_FP_NL≤FTP_NL FTP_FP_NL>FTP_NL	Table 19/23 & Table 12

Once all the FTPs/FTAs are forecasted by industry and establishment, they are aggregated to zones using Cochran's (1977) sample size formulas in Eq. (2.3) – (2.4) (Holguín-Veras et al., 2017).

$$\bar{f} = \frac{\sum_{i=1}^{n} f_i}{n} \tag{2.5}$$

$$F = N\bar{f} \tag{2.6}$$

where

F is the aggregate generation of FTG
$\bar{f}$ is the average FTG from a sample of size n;
N is the total number of establishments in the study area.

Gateways

To account for the role of external regions on the study area, we need to consider the incoming/outgoing flow of trucks with origins and destinations such as other parts of the United States or the world. First, gateway locations need to be determined to allow for a place to capture those freight movements. Natural choices are freeways, bridges, and tunnels because of their regional funneling effect. Final gateway selections are shown in Figure 2.3 and Figure 2.7b. Freight transmitted to those locations was calculated into the respective zone's FTP/FTA simulating the loading and unloading of the freight onto trucks which would then be assigned normally.

Once gateways are chosen, freight must be assigned to them broken down by commodity type. Using Freight Analysis Framework 5 (FAF5 2017), we determine the quantity of commodity movements in the NYC metropolitan area. The FAF5 data units are converted from Standard Classification of Transported Good (SCTG) and tons to 2-digit NAICS and truck trips using the Mountain-Plains Region Consortium NAICS-SCTG cross reference (Mitra et al., 2013) and the proposed FAF4 (Lindsey et al., 2020) payload factors. Gateways are assigned to each OD pair based on their origin and destination location. Using Google Maps API, we empirically determine which gateway is most accessible to each external region. It is important to note that FAF5 considers meta regions such as urban areas or states. Hence, it is necessary to subtract the difference between the FAF5 studied area and the original zone of interest. To do so in our project, the excess FTA/FTP from the surrounding areas (which includes other portions of New

York state, New Jersey, Connecticut, and Pennsylvania) was estimated at the county level by inputting the Quarterly Census of Employment and Wage data set (US Bureau of Labor Statistics 2021) into the same process used to generate the New York City FTA/FTP.

The freight flows from FAF5 were grouped into four meta-regions that follow gateway attributions: New England, New York State, Long Island, and Other U.S/Foreign. Finally, after assigning the gateways for each OD pair, we subtracted the FTG in metro area that fell outside the city itself. For these counties (Nassau, Suffolk, Westchester, Putnam, Rockland, and Duchess), FTG was computed at the county level using the Quarterly Census of Employment and Wages and the NCFRP25.

As an example, Figure 2.3 depicts the spatial distribution of FTA/FTP for the truck transportation subsector industry (484). We can see that the major production zones within the city include Long Island City, the Brooklyn Naval Yard, and both airports, JFK and LGA. Each of those are major modal change locations so the model captures that as FTP at those locations. The attraction zones are mostly within Manhattan as expected, but there are also hotspots in Downtown Brooklyn, Flushing, and more. These data can be further explored on the C2SMART Mobility Data Dashboard under the "freight" category (C2SMARTER 2022).

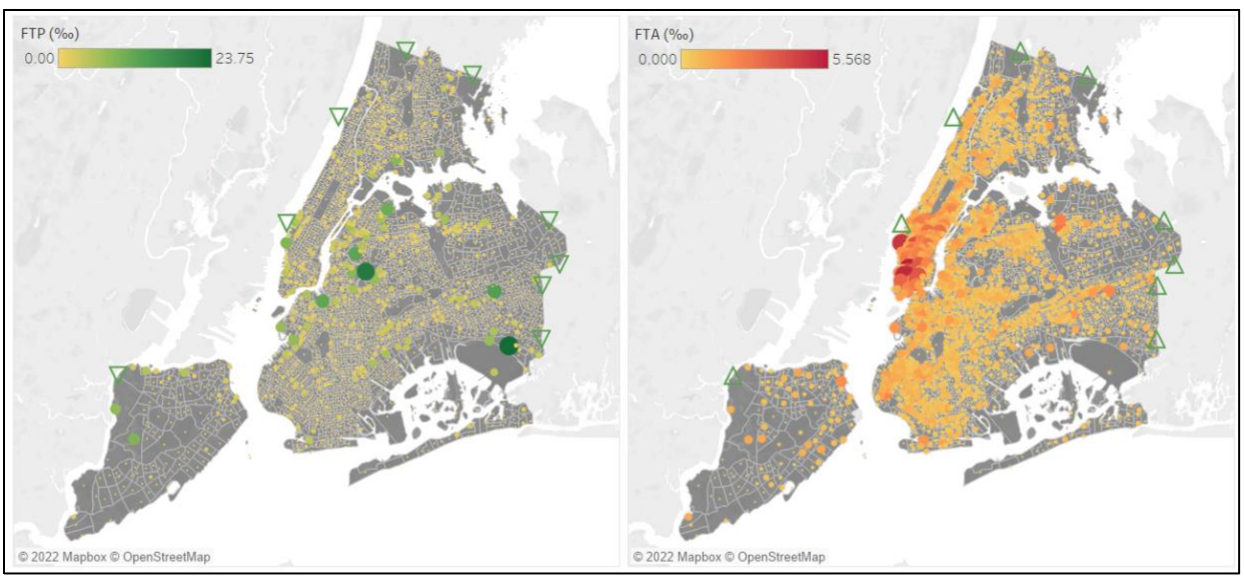


Figure 2.3 Forecasted FTA/FTP zonal distribution with overlaid gateways (triangles) for NAICS 484 industry truck transportation.

Long-haul Trip Redistribution

For a given region, freight trips consist of Internal-to-Internal (I-I), Internal-to-External and vice versa (E-I, I-E), and External-to-External (E-E) trips. Gateways are defined so that E-I and I-E trips are assigned to gateway-based trips. These gateway trips are divided between smaller truck tours making direct deliveries in a region from outside, versus larger truckload deliveries made to warehouses within the region from which LTL trips are then made. The Freight Analysis Framework (FAF) (FHWA, 2022; U.S. BTS, 2017), which is a refined data set from the Census Commodity Flow Survey (CFS) (U.S. BTS, 2012), is used to generate the E-I and I-E trips. E-E trips are ignored unless they clearly cross through the region (such as continental U.S. to Long Island through NYC).

Long haul trips, E-I/I-E, differ from local urban delivery trips, I-I. Whereas the latter behave as long tours visiting multiple stops throughout the day, long haul trips are more likely direct, truckload trips that deposit all the load at a warehouse (Chow and Regan, 2010). For a metropolitan study area, these trips would typically be generated from a gateway to visit a warehouse within the area, and then depart back to the gateway directly.

For the gateways, the unit of tons in FAF5 has been converted using the FAF4 payload factors to trucks corrected with the NYMTC Truck Toll Volumes (Hrabowska et al., 2007) to determine the number of equivalent single units (SU) and combined units (CU) by SCTG, also referred to as medium and heavy trucks, respectively. Medium trucks are vehicles of FWHA class 5, 6, or 7. Heavy trucks are anything class 8 and above. Trips to and from gateways are split between medium trucks assumed to make delivery tours (80%) and heavy trucks making truckload trips direct to warehouses (20%) based on truck tolling data from NYMTC (Hrabowska et al., 2007). These do not include parcel delivery trucks like the sprinter vans used by Amazon, as they are not flagged in the truck counts reported by AADTT sources.

The top 20 zones in terms of NAICS Industry 48 (warehouse and trucking) were designated as “warehouse zones”, and all the long-haul trips were routed directly between a warehouse zone and a gateway. The data year is 2019, so warehouses which have come online since then would not be reflected in this process. To maintain conservation of trips, the FTP/FTA were subtracted from the gateways and added to the warehouse zones on a per industry code basis where they were then normally assigned to tour flows. The warehouse zone locations are shown in Figure 2.4.

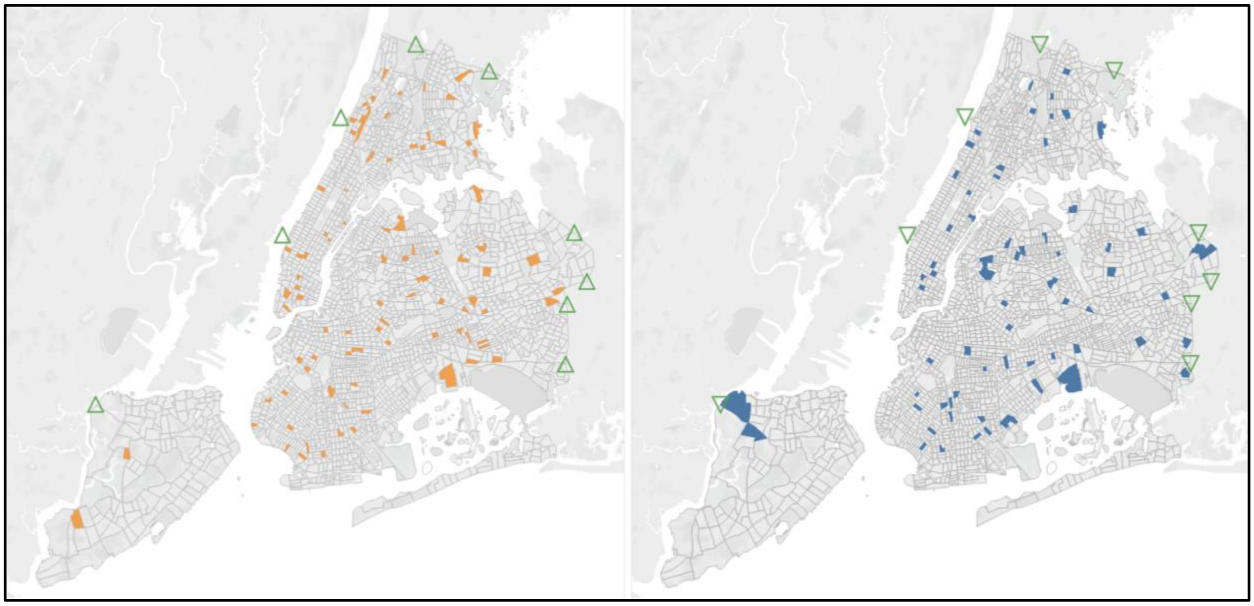
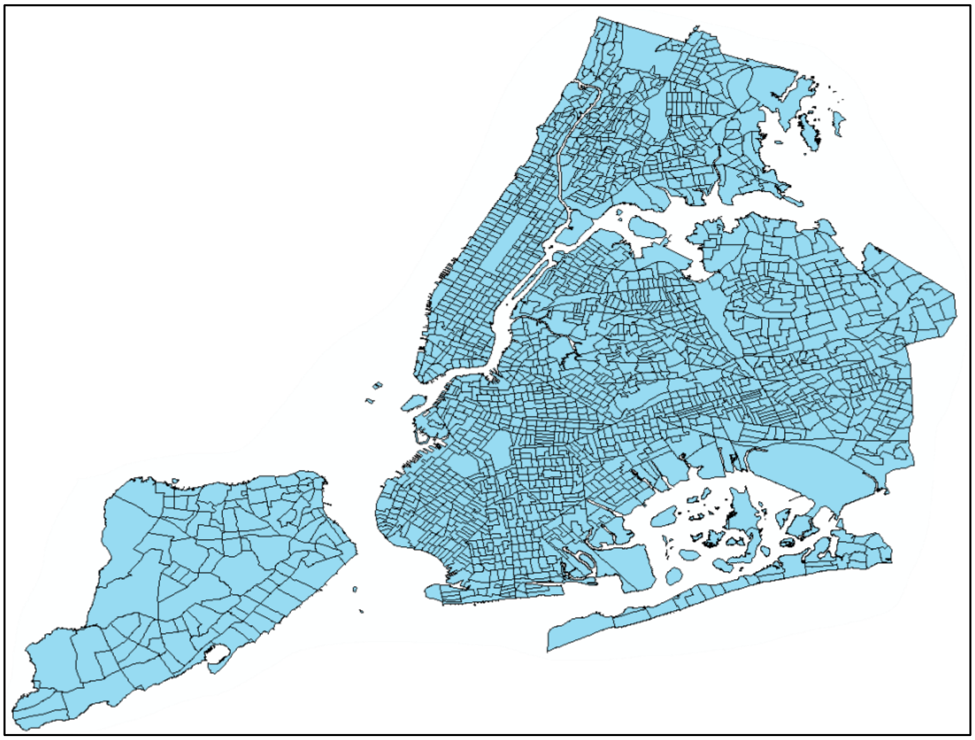


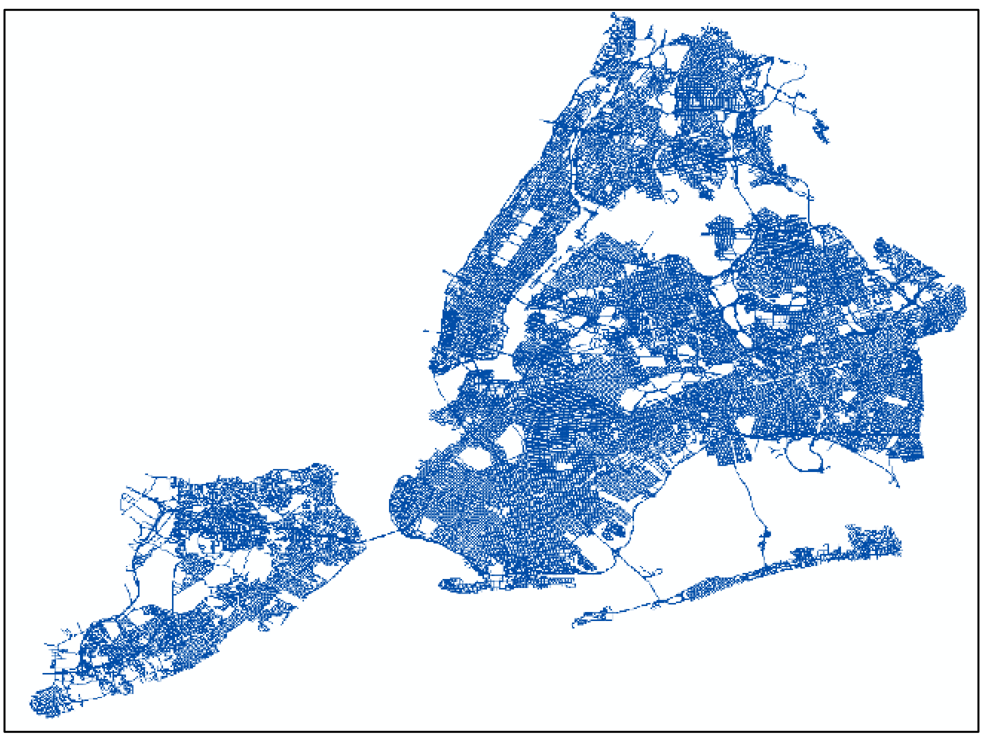
Figure 2.4 Location of zones with Inbound (left) and Outbound (right) FTG warehouses.

2.2 Scenario Data

The project study area encompasses the 5 boroughs of New York City with 9 gateways (gateway locations indicated in Figure 2.3 and Figure 2.7b), 4 between Long Island and NYC, 2 between the Bronx and upstate, 2 between New Jersey and Manhattan, and 1 between New Jersey and Staten Island. For zones, we use proprietary zones (Liu et al., 2023) aggregated from census tracts to be used alongside a synthetic population of passengers designed to more reliably represent different underserved population segments seen in Figure 2.5a.



(a)



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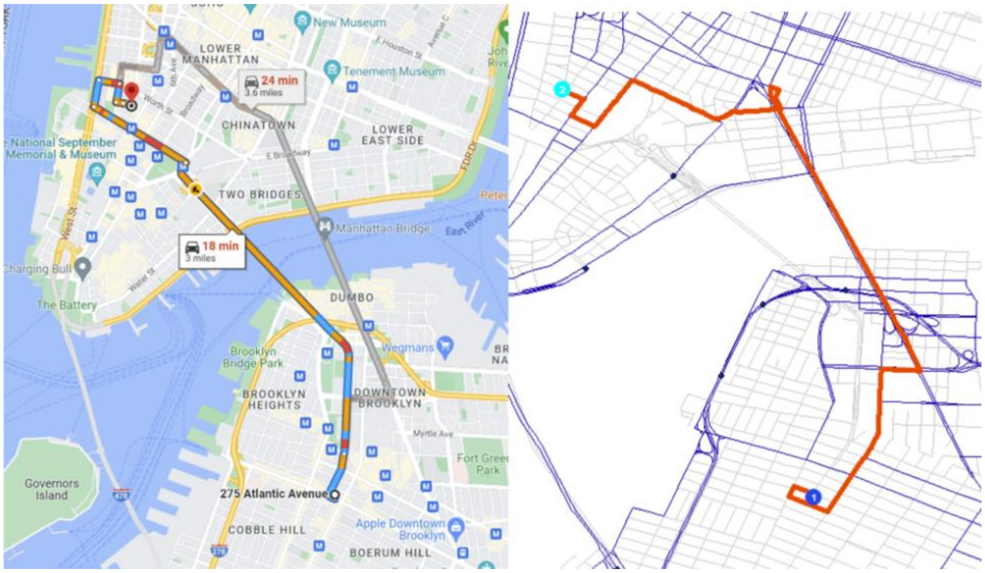

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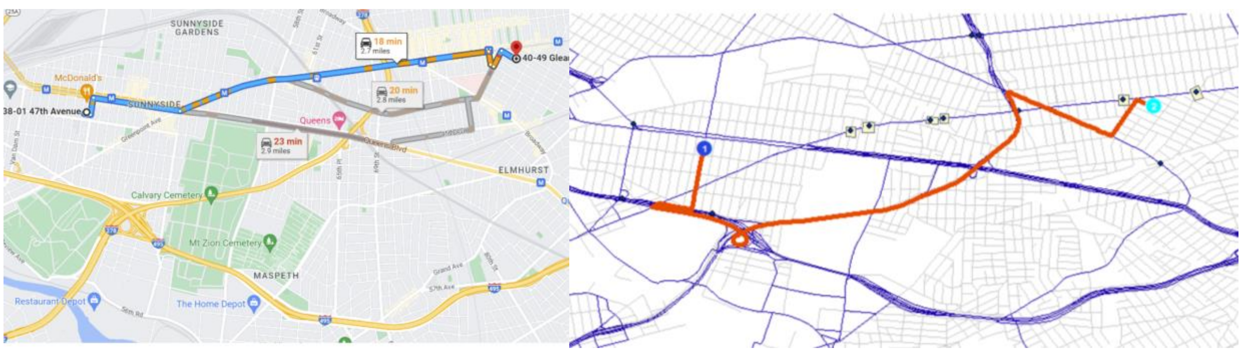


(d)

Figure 2.5 (a) Proprietary transportation analysis zones aggregated from census tracts (Liu et al., 2023); (b) road network from OpenStreetMap with truck routes shared by NYC DOT; (c) and (d) side by side comparisons of naïve shortest paths prescribed by Google Maps (Google, n.d.) vs our pathfinding incorporating the truck network.

For the road network, we use OpenStreetMap supplemented with truck route data shared by NYC DOT (Figure 2.5b). NYC DOT shared information based upon vehicle height restrictions, truck route restrictions, and truck route designations. These were incorporated into the network for finding shortest paths so that the choices generated would mirror real world choices that are available to trucks. Figure 2.5c and 2.5d demonstrate examples of our routing tool providing truck appropriate routes that Google Maps does not. Figure 2.5c shows our tool recommending the

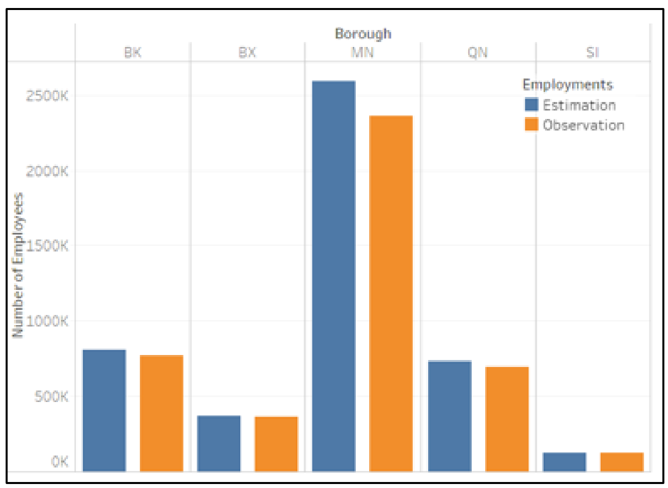
Manhattan Bridge because trucks are not allowed on the Brooklyn Bridge, and Figure 2.5d shows our tool recommending a safer truck route instead of a neighborhood route down Roosevelt Ave that includes elevated subway lines which are flagged as having low clearance in real life.

Link travel times were sourced from the 2019 subset of the Uber Movement dataset. Because the dataset came pre-tagged with OSMIDs, it was very easy to incorporate. We aggregated the travel times into 4 Time of Day blocks: 6:00AM-10:59AM for Morning, 11:00AM-3:59PM for Mid-Day,4:00PM-8:59PM for PM, and then 9:00PM -5:59AM for Night.

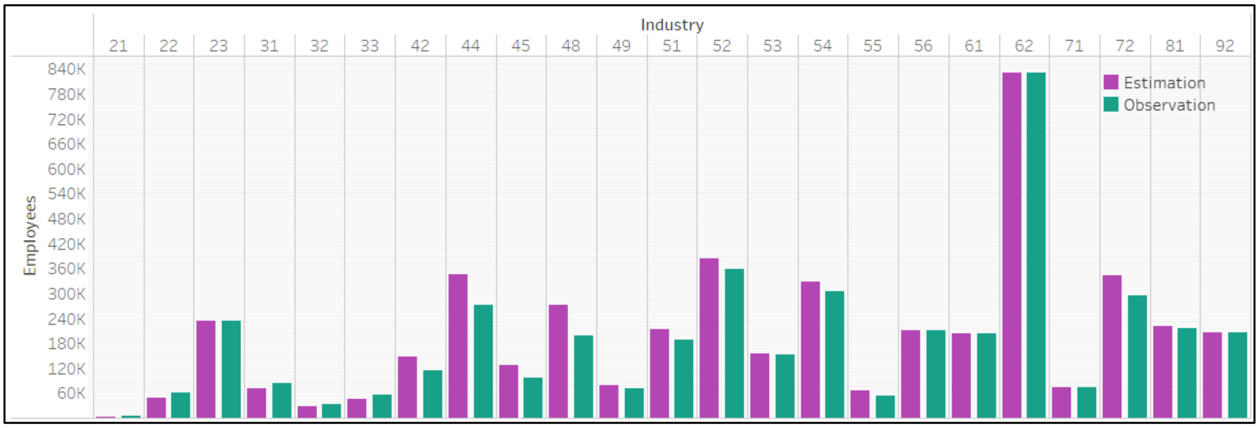
2.3 Validation of Employment by Establishment and FTP/FTA by Industry

Figure 2.6a compares the number of employees measured from real data from the Quarterly Census of Employment and Wages (QCEW) (US Bureau of Labor Statistics, 2021) versus estimated using the model. Manhattan is the largest outlier due to the mismatch between the city land use policy and the economic reality in the field. In each case, our estimates are slightly above the observed data, but are well within an acceptable margin. The estimation of employees by 2-digit NAICS codes is also close to the number measured by the QCEW as seen in Figure 2.6b.

Borough		**Predicted**	**Observed**	**Difference**
Brooklyn	*Total*	806,840	767,475	5.1%
The Bronx	*Total*	369,740	362,546	2.0%
Queens	*Total*	2,593,432	2,357,212	10.0%
Staten Island	*Total*	734,947	696,506	5.5%
	Total	126,766	123,247	2.9%
	Grand Total	4,631,725	4,306,986	7.5%



(a)



(b)

Figure 2.6. US Census Employment data aggregated and compared at the (a) Borough level and (b) 2 Digit NAICS level.

Table 2.3 compares the FTG aggregated to the borough level produced using the microdata available to the authors of NCFRP25 versus numbers predicted using the synthesized establishment employment data that we produced. Four of the five boroughs are within a tight margin, but Manhattan is a meaningful outlier. We believe this difference is because there are differences in defining the zones where our zones are split between internal zones and external zones to account for gateway trips separately. The number of trips that are produced or attracted at the gateways (otherwise understood as Internal/External or External/Internal trips) makes up a meaningful portion of the total number of missing trips, but this project estimates 7.0% fewer total trips generated than NCFRP 25. Given the different methodologies and the inherent uncertainty baked in, these results are seen to largely agree with each other.

Table 2.3. Borough level FTG validation between microdata from NCFRP25 and synthesized establishment employment data

	From microdata		From synthesized establishments		Comparison	
Borough	**Est. FTG**	**% Of Total**	**Est. FTG**	**% Of Total**	**ΔFTG**	**%Δ**
Brooklyn	178,000	24.8%	183,551	27.5%	5,551	+3.1%
Bronx	58,000	8.1%	63,941	9.6%	5,941	+10.2%
Manhattan	300,000	41.8%	159,668	23.9%	-140,332	-46.7%

Queens	153,000	21.3%	148,779	23.3%	-4,221	-2.8%
Staten	29,000	3.8%	24,331	3.6%	-4,669	-16.1%
Gateways	-	-	87,570	13.1%	-	-
Total	**718,000**	**100%**	**667,840**	**100%**	**-50,160**	**-7.0%**

Table 2.4 below compares in detail the distribution of FTA/FTP by industry used. Most of the industries attract and produce a similar amount of freight. However, some in the manufacturing sector (31-33) are heavily unbalanced toward FTP because of the non-linear parameters specified for estimation in the NCFRP report. This leaning is not necessarily problematic as there is no inherent reason that each industry should be equal. In fact, because of industry interactions, we expect manufacturers to attract goods from other sectors, transform them, and produce trips coded as their industry.

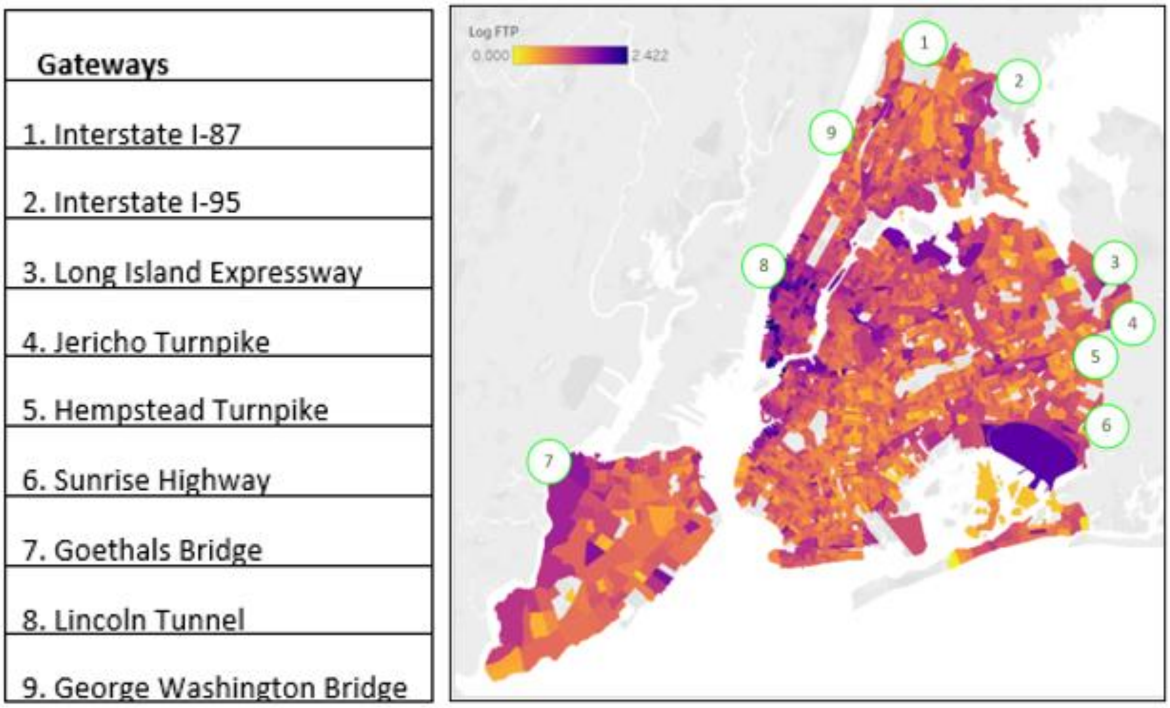
Table 2.4. NAICS breakdown of FTP vs FTA.

Industry	Description	FTP	%FTP	FTA	%FTA
21	Mining	11,691	66.9%	5777	33.1%
22	Utilities	4607	52.1%	4236	47.9%
23	Construction	12164	37.7%	20100	62.3%
31	Manufacturing	5343	65.8%	2781	34.2%
32	Manufacturing	21625	61.5%	13565	38.5%
33	Manufacturing	9239	64.7%	5030	35.3%
42	Wholesale Trade	39712	52.8%	35511	47.2%
44	Retail Trade	145637	55.4%	117268	44.6%
45	Retail Trade	53493	65.7%	27901	34.3%
48	Transportation	27337	35.4%	49890	64.6%
49	Warehousing	7754	41.1%	11103	58.9%
72	Food Services	21166	58.7%	14911	41.3%
Total		359,768	53.9%	308,073	46.1%

The upper heatmap in Figure 2.7a shows the density of FTA within NYC. Most census tracts have small quantities of freight produced or attracted. Hence, a log scale is used to better visualize the differences in density. Ten major zones stand out, listed in no particular order: the airports, industrial zones, harbors, warehouse/wholesale zones, and the heart of Manhattan which has an extremely high density of industry 72 (Food Services). The lower heatmap (Figure 2.7b) shows the density of FTP in NYC with the location of gateways that have been used in the model. As expected, the active locations for FTP and FTA are similar.

Highest Freight Attraction Zones
1. Hunts Points & Port Morris
2. LaGuardia Airport
3. Jamaica Corridor
4. JFK Airport
5. Flatlands Fairfield Corridor
6. Brooklyn Harbor
7. West Shore
8. Navy Yard
9. Lower Manhattan and Midtown
10. North Brooklyn & Maspeth

(a)



(b)

Figure 2.7 Key locations overlaid on FTA (a) and FTP (b) NYC heatmap.

FTP/FTA Balancing

Table 2.5 compares in detail the distribution of FTA/FTP by industry used at an aggregate level. Most of the industries attract and produce a similar amount of freight. However, some in the manufacturing sector (31-33) are heavily unbalanced toward FTP because of the non-linear parameters specified for estimation in the NCFRP report. For distribution purposes, we need to balance the productions and attractions so that total volumes produced end up going somewhere (see McNally, 2007).

Table 2.5. NAICS breakdown of FTP vs FTA

Industry	FTP	FTA	% Split
21	562	423	57/43
22	4424	2837	61/39
23	11485	19894	37/63
31	3746	2353	61/39
32	7153	2680	73/27
33	5796	4545	56/44
42	34911	35255	50/50
44	127715	117099	52/48
45	50189	27836	64/36
48	23105	48753	32/68
49	5986	7830	43/57
72	21106	14587	59/41
Total	296178	284092	51/49

We chose the FTA as the base in which the volumes are not changed because NCFRP25 indicated that the estimation process was more certain of the FTA than FTP. Additionally, because of the certainty regarding the gateway flow estimation due to truck volume data, those FTGs were also held fixed. The FTP in each industry in each internal zone was scaled up or down such that the sum of FTP for all the zones for each industry was set equal to the FTA. However, due to the difference in internal vs gateway FTG, it was not always possible to scale the FTP, so instead for some industries the FTA was scaled, usually up, to match. This process resulted in roughly 8% more FTG bringing the total FTG to 724,994, which is within 1% of the previous estimate of 718,000. Table 2.6 lays out the differences between the FTG estimated in Table 2.3 and the balanced version.

Table 2.6 FTG Comparison Between Initial Estimates and Balanced Model Inputs

	Table 2.3	Balance	Δ FTG	%Δ
Brooklyn	183,551	236,508	52,957	22.4%
The Bronx	63,941	67,826	3885	5.7%
Manhattan	159,886	147,859	-11,809	-8.0%
Queens	148,779	158,721	9942	6.3%
Staten Island	24,331	27,053	2722	10.1%
Gateways	87,570	87,027	-543	-0.6%
Total	668,058	724,994	57,154	7.9%

3 Synthetic Truck Population

3.1 Tour set generation and distribution

Tour set generation

With the FTPs/FTAs generated and balanced, we are now ready to distribute them using tours (except for the long-haul trips, which are direct roundtrips between gateways and warehouse zones as mentioned earlier).

The tour set generation process is composed of three steps. Given a tour set size, the first step establishes the number of stops of each tour. For each specified industry, an average number of stops is found (Holguín-Veras et al., 2013) and then a random number of stops is sampled from a distribution based on that average number. For the choice of distribution, a fatigue-life distribution (Eq. (3.1)) is used as opposed to a simple exponential because its shape sharply increases towards a peak at the average value followed by a long tail. This is argued to be a better representation of possible tour behavior (Figliozzi et al., 2006). The SciPy fatiguelife.rvs() function is used to invert the distribution to draw a random value.

$$f(x,c) = \frac{x+1}{2c\sqrt{2\pi x^3}} e^{-\frac{(x-1)^2}{2xc^2}} \tag{3.1}$$

where

x is the average length
c is an industry specific shape constant derived from calibration

The shape parameter c needs to be calibrated for each of the different industries to keep the desired sharp peak into long tail profile. Each c was calculated by adjusting the value so that mean corresponding to the distribution matched the average number of stops for the industry. Figure 3.1 shows the relationship between industry averages and their respective c values.

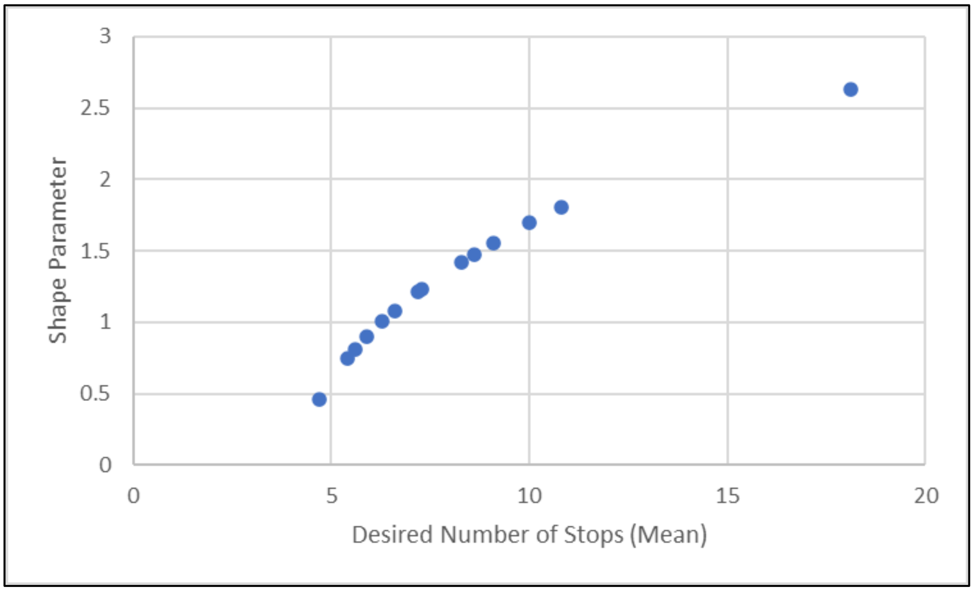


Figure 3.1 Calibration of the c parameter

Each tour is assigned an origin as the FTP location and depot (assumed to be sufficiently close, given lack of data to generate otherwise), and a number of destinations which together equal to the number of stops simulated by Eq. (1). Origins are randomly selected based on FTP volume weighting. For a given origin, the set of chosen destinations can result in very different tours. Purely random destination selections can lead to very large tour lengths traversing throughout a region that does not exhibit any destination clustering in Holguín-Veras et al. (2011). Destinations selected too close to an origin can lead to short tour lengths that do not properly represent observed truck traffic patterns.

As such, the destination selection for each stop is done using iterated weighted random selection from the FTA volumes without replacement. The weight for each zone to be selected as a destination for a given origin is determined by a negative exponential function in Eq. (3.2). The function represents a monotonic distance decay for preference to visit destinations farther away, with a parameter θ that can be calibrated to observed data to ensure output flows closely match observed truck traffic.

$$w_{ij} = e^{-\theta d_{ij}} \quad (3.2)$$

where

w_{ij} is the weight applied to sampling a destination zone j relative to an origin zone i
d_{ij} is a precomputed network distance between origin i and destination j
θ is a calibrated parameter

Finally, a simple insertion heuristic (see Algorithm 2 in Yoon et al., 2022, for an example) is used to sequence the stops into a reasonable tour starting and ending at the FTP zone. The result is visually represented in Figure 3.2. The three tours displayed in the figure represent some of the highest flow tours created by the synthetic population analyzed in section 3.6.

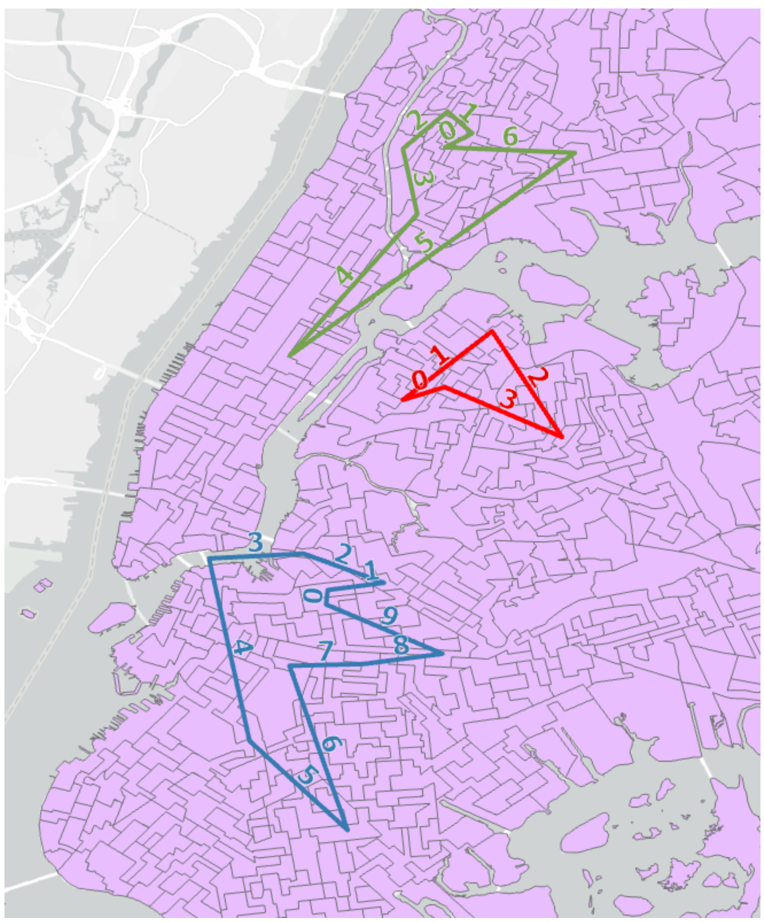


Figure 3.2 Illustration of insertion heuristic used to sequence tour stops.

Tour flow distribution

After the tour sets are generated for each industry, they are loaded with flows based on entropy maximization. Since each truck is assumed to serve only one commodity in a tour, we leave out the industry index in the formulation for simplicity. Two sets of decision variables are desired for each industry: t_m is the number of trucks on tour $m \in M$ while y_{jm} is the weight of freight delivered at zone j on tour m. The variables are shown below.

<u>Decision variables</u>

t_m is the number of trucks on tour $m \in M$

y_{jm} is the weight of freight delivered at zone j on tour m

<u>Parameters</u>

M is the tour set
P is the production zone set
A is the attraction zone set
$\mathrm{O_i}$ is the number of trucks departing from production zone $\mathrm{i} \in \mathrm{P}$
$\mathrm{F_j}$ is the weight of freight delivered at zone $\mathrm{j} \in \mathrm{A}$
$\mathrm{a_{im}}$ is a binary indicator for if zone $\mathrm{i} \in \mathrm{P}$ is on tour $\mathrm{m} \in \mathrm{M}$
$\mathrm{b_{jm}}$ is a binary indicator for if zone $\mathrm{j} \in \mathrm{A}$ is on tour $\mathrm{m} \in \mathrm{M}$
$\mathrm{h^k}$ is the truck capacity for industry code k used to convert between trucks and weight
$\mathrm{s_m}$ is the number of stops on tour $\mathrm{m} \in \mathrm{M}$
C is a predetermined constant representing the desired total truck-stops, which depends on the average number of stops per industry code and the underlying distribution in Eq. (3.1).

The model is shown in Eqs. (3.3) – (3.11). Eq. (3.3) is the entropy maximization objective set for the number of trucks; since the output is truck flow t_m we leave the y_{jm} to be free. Eqs. (3.4) – (3.5) constrain the summation of the number of trucks and the amount of freight assigned to each zone to be equal to the FTP and FTA (converted to weight). Eq. (3.6) ensures that no freight is delivered to zones where it is not assigned. Eq. (3.7) establishes the truckload conversion between a truck and the amount of freight it can hold. Eq. (3.8) is used to calibrate the model to fit the average number of stops per tour. Eqs. (3.9) and (3.10) are non-negativity constraints for the decision variables, and Eq. (3.11) is an integer constraint because only whole numbers of trucks can be assigned.

$$\text{Min } z = \sum_{m \in M} (t_m \ln(t_m + 1) - t_m) \tag{3.3}$$

Subject to

$$\sum_{m \in M} a_{im} t_m = O_i \qquad \forall\, i \in P \tag{3.4}$$

$$\sum_{m \in M} b_{jm} y_{jm} = F_j \qquad \forall\, j \in A \tag{3.5}$$

$$\sum_{m \in M} \sum_{j \in A} (1 - b_{jm}) y_{jm} = 0 \tag{3.6}$$

$$\sum_{j \in A} y_{jm} = t_m h^k \qquad \forall\, m \in M \tag{3.7}$$

$$\sum_{m} s_m t_m = C^k \tag{3.8}$$

$$t_m \geq 0 \qquad \forall\, m \in M \tag{3.9}$$

$$y_{jm} \geq 0 \qquad \forall\, m \in M \tag{3.10}$$

$$t_m \in \mathbb{Z} \qquad \forall\, m \in M \tag{3.11}$$

Note that this model differs from the earlier tour-based entropy models, which are generally provided GPS truck tours and used to fit tour volumes to traffic counts. Here, we are fitting tour volumes to both FTPs and FTAs, while calibrating the parameters to fit the borough crossing traffic counts and constraining the average number of stops to match observed values.

The model is nonlinear (but convex) with linear constraints. Using a nonlinear solver like in Sánchez-Díaz et al. (2015) would end up being very computationally inefficient if we try to fit 10,000 tours to 83583 zones for 48 industries. For example, the python library SciPy took more than eight minutes running in a Google Colab notebook to find a solution to a sample case with only four zones and eight tours. Additionally, the linear matrix needed to represent the constraints was larger than 5,000,000 by 5,000,000 because the model needs to consider every node on every tour. The resulting matrix was too large to be stored in RAM, and SciPy does not provide tools to represent the constraints as a sparse matrix.

To solve the model efficiently, a new iterative balancing algorithm is proposed in Algorithm 3.1. The algorithm is inspired by iterative proportional fitting algorithms for fitting origin-destination (OD) trips in passenger travel (e.g. Fratar, 1954; Wilson, 1969), but expanded upon to account for the structure of the present model.

To seed the initial cost of the tour, the fatigue life function from Eq. (3.1) is used to generate the value of f_m, the seed value for the tour length. The algorithm then proportionally rebalances the assigned tour flows to better match the FTP and then performs the same on the freight assigned to each stop. This process repeats until the change between iterations drops below a predetermined threshold.

Given that this process will naturally result in non-integer flows for each iteration (and hence relaxing the integral constraint 3.12), we enforce the integral constraint after the tolerance check has been met. A rounding step is introduced to heuristically assign fractions to either zero or one. Rounding results in the removal of tours with fractional levels of flow which has the effect of better satisfying the goals of entropy maximization by moving that marginal flow to the tours already deemed most probable. This redistribution is only necessary at a level below one unit of flow because a tour must assign at least one vehicle. Without this step, tours with hundredths of a unit of flow would still receive one truck leading to their outsized influence in the validation phase.

Algorithm 3.1: Iterative balancing algorithm

1- *Initialize*
   a. Calculate f_m using Eq. (3.1) for each tour $m \in M$.
   b. Set $r = 1$
   c. For each j and for each $m \in M_j$, assign $y_{jm}^r = F_j \frac{b_{jm} f_m}{\sum_m b_{jm} f_m}$
   d. For each m, set $t_m^r = \frac{\sum_{j \in A} y_{jm}^r}{h_k}$

2- *Iteratively rebalance*
   a. Rebalance the tour volumes: $t_m^{r+1} = \sum_i O_i \frac{a_{im}\left(\frac{\sum_{j \in A} y_{jm}^r}{h_k}\right)}{\sum_m a_{im}\left(\frac{\sum_{j \in A} y_{jm}^r}{h_k}\right)}$

b. Rebalance the stop volumes: $y_{jm}^{r+1} = F_j \frac{b_{jm}\left(\frac{t_m^{r+1}}{t_m^r}\right)y_{jm}^r}{\sum_m b_{jm}\left(\frac{t_m^{r+1}}{t_m^r}\right)y_{jm}^r}$

3- *Tolerance check*

a. If tolerance condition is not met (e.g. change in t_m^{r+1} vs t_m^r and y_{jm}^{r+1} vs y_{jm}^r) let $r = r + 1$ and repeat step 2, else stop.

4- *Integerization Rounding*

a. Round every tour volume: $t_m = int(t_m)$

b. For every tour where $int(t_m) = 0$, $t_m += 1$ for a corresponding number of tours ranked by highest flow

---

Proposition 1. *Algorithm 1 converges to a unique solution for a given set of f_m.*

Proof. The algorithm belongs to the class of iterative proportional fitting procedures first proposed by Deming and Stephan (1940) and popularized in transportation planning by Fratar (1954). The f_m and the tours simply define the interaction structure. The tours each represents one dimension in which $p_{ij} > 0$ for a production zone i with attraction zone j in its tour, and $p_{ij} = 0$ otherwise. Then a system with 10,000 tours can be modeled as a 10,000-dimensional matrix. With this established, we then refer to Bishop (1967, 1969) who showed that convergence of the IPFP to a unique solution is applicable to any multidimensional table.

Illustrative example

To measure the efficiency improvements, the iterative balancing algorithm was run on the same simple test case that took the SciPy solver 500 seconds. Four interconnected zones [A, B, C, D] were created which attracted 400, 300, 200, and 100 units of freight respectively while producing 40, 10, 20, and 30 trucks respectively. Eight tours were created, each with one pick up and two drop off locations as shown in Table 3.1. SciPy assigned flows (t_m) of [15, 3, 21, 15, 17, 9, 6, 16] which satisfied the constraints perfectly with an objective score of -1282.9. The iterative balancing algorithm assigned flows of [13, 3, 23, 14, 17, 7, 7, 16] was less optimal with an objective score of -1272.9 but took only .05 seconds to solve and was also run in a Google Colab notebook.

Table 3.1 Tours used to illustrate Algorithm 3.1

Tour ID	Pick Up Zone	Drop Off Zone 1	Drop Off Zone 2
1	C	A	B
2	B	D	C
3	A	B	D
4	D	C	A
5	A	C	D
6	B	A	C
7	C	D	B
8	D	B	A

A total of 470,000 tours were generated, divided out to 10,000 tours per each of the 47 industries. The FTPs/FTAs were then distributed among those tours using Algorithm 3.1. The stopping condition specified in Algorithm 1 is set to when as when the average change in freight assigned to each zone $j \in A$ by each tour $m \in M$ and each industry $k \in K$ $\left(\frac{1}{|M|}\sum_{f,m,k}\left(y_{jmk}^{r} - y_{jmk}^{r-1}\right)\right)$ drops below 0.1 tons of freight. The trajectory of the algorithm relative to the stopping criterion for representative industry NAICS 212 is displayed in Figure 3.3.

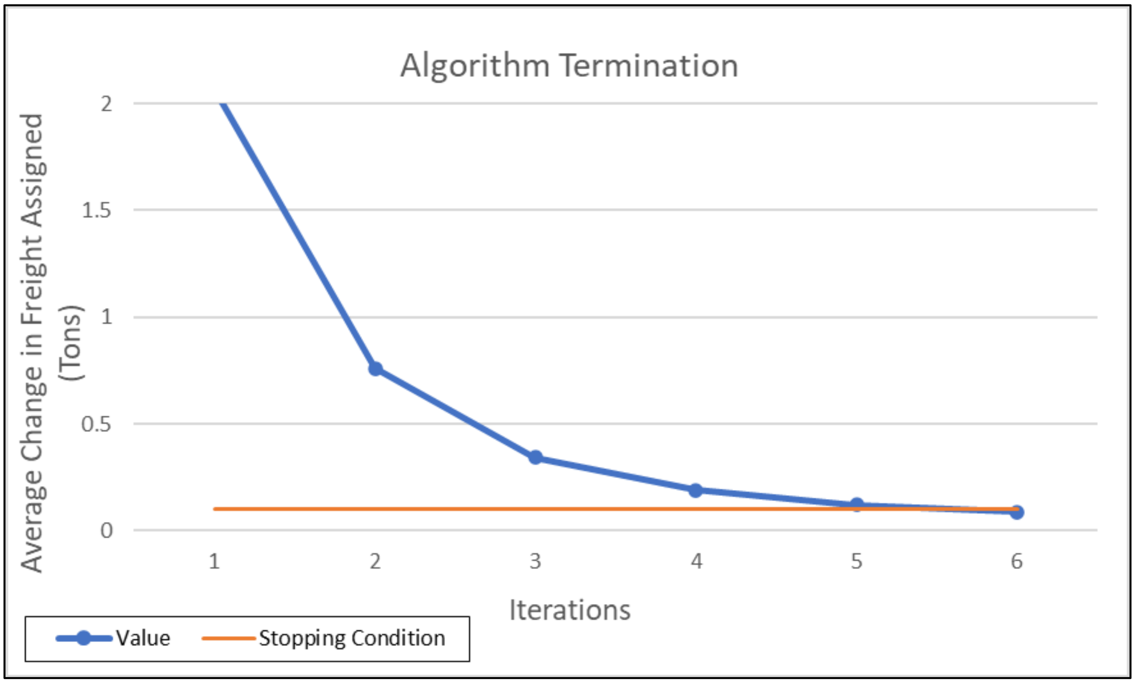


Figure 3.3 Stopping Condition Trajectory

A comparison of the average number of stops per industry in the output freight tours and the desired averages are summarized in Table 3.2.

Table 3.2 Comparison of observed and predicted average number of stops by 3-digit NAICS industry

NAICS	Predicted # of Stops	Calculated # of Stops	NAICS	Predicted # of Stops	Calculated # of Stops
211	4.7	7.6	337	6.6	8.2
212	5.9	7.6	339	10.8	9.5
213	5.9	6.9	423	6.9	8.7
221	4.7	7.9	424	8.7	9.1
311	15.7	10.9	425	9.3	9.3
312	14.3	11.8	441	6.0	8.1
313	6.6	9.1	444	7.5	8.9
314	6.6	8.6	445	15.7	11.4
315	6.6	7.9	446	6.6	8.3
316	6.6	9.4	447	4.7	7.8
321	5.6	8.2	448	6.2	8.3
322	7.4	9.0	452	7.7	8.5
323	7.0	8.1	454	10.0	9.2
324	4.7	8.2	481	5.9	8.0
325	6.6	7.8	482	5.9	8.3
326	5.7	7.8	483	5.9	8.3
327	4.7	7.7	484	9.6	9.3
331	8.3	9.3	485	5.9	7.8
332	9.6	8.7	486	5.9	8.2
333	6.8	8.5	491	9.6	9.5
334	9.0	8.0	492	9.6	9.4
335	9.0	8.7	493	9.6	9.1
336	5.9	8.6	721	9.6	9.0
			722	9.6	9.2

3.2 Gateway tour flow distribution

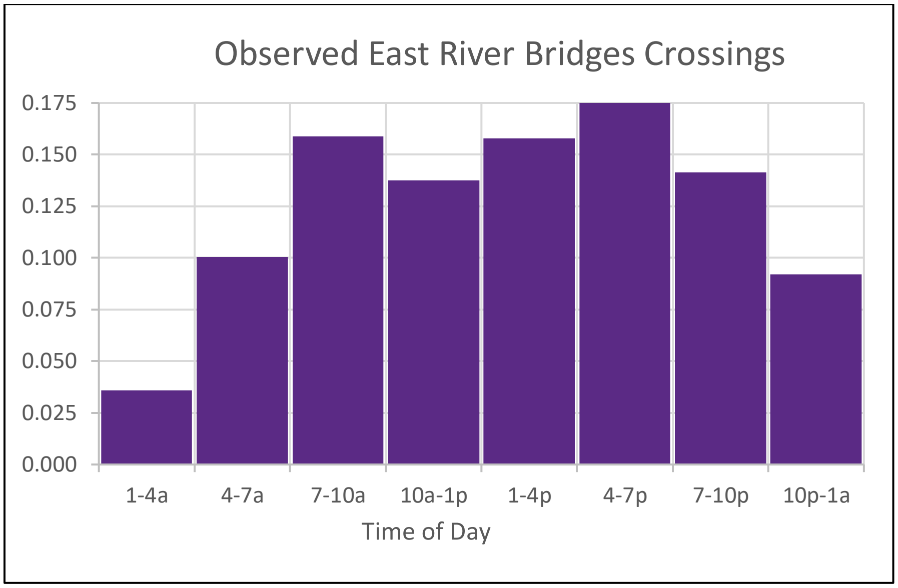
Trips to and from gateways are split into long-haul, truckload trips destined for distribution centers or warehouses within a study area and short-haul less-than-truckload (LTL) trips. AADTT data are used to determine appropriate percentages. The long-haul trips that enter and leave the study area are assumed to be direct round trips while the short-haul trips follow similar tour patterns as the rest of the internal study area. This process results in one-trip tour flows from the gateways to the distribution centers and then creating the otherwise standard tour flows resulting from the new freight trips at the distribution centers. Distribution centers were assumed to be located in the zones which had the highest quantities of FTP/FTA in NAICS code 48 (Transportation and Warehousing).

3.3 Tour assignment and scheduling for synthetic population

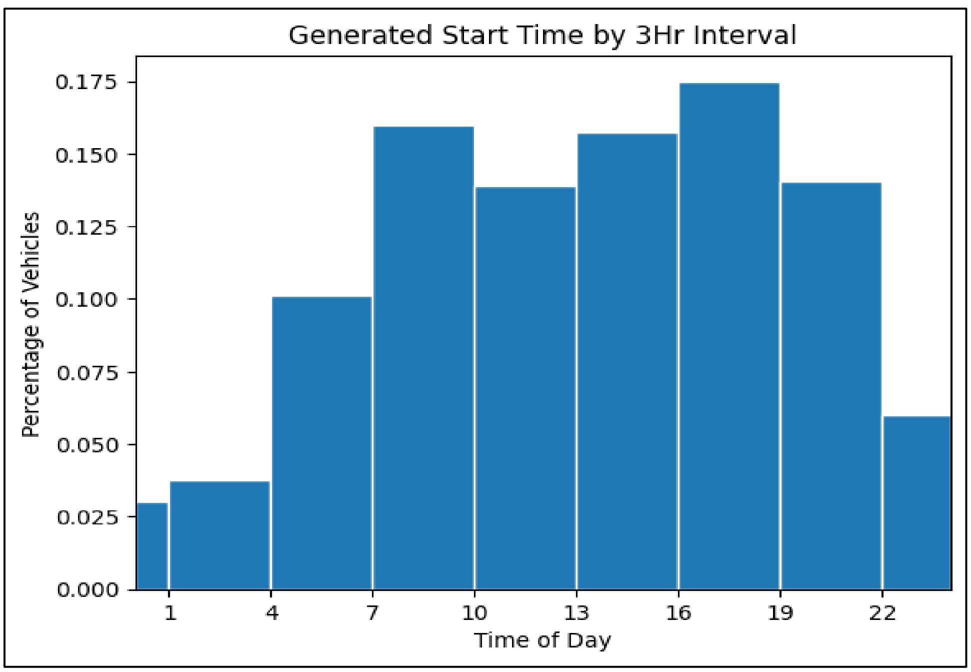
Once the tour flows are determined, the synthetic population is assigned tour details. We know the number of FTPs. Based on those numbers, we randomly sample from the tours using the t_m as weights. Our average tour length for the synthetic population was 6.88 delivery stops per tour which is longer than the 5.5 delivery stops found by Holguín-Veras et al., (2010), but not inconsistent especially given the industries that were examined in that work versus this one.

After assigning tours to the population, we broke them up into vehicle classes according to a distribution (FHWA 2020), the start time of each tour, and service time at each stop. The planned schedule for each truck is then generated. A start time is randomly generated according to a distribution so that the arrival time at the first East River bridge matches measured data from 2015 and 2016 averaged together and binned into 3-hour intervals beginning 1AM-4AM continuing through to 10pm wrapping back to 1AM as in the report 2016 New York City Bridge Traffic Volumes (NYC DOT 2018). The East River bridges (Manhattan, Brooklyn, Williamsburg, Queensboro, and TriBorough) were chosen to be the basis for the time-of-day distribution because of their centrality and data availability. The observed data and the results are displayed in Figure 3.4.

Finally, real world service times can be highly variable and difficult to accurately recreate because they are subject to many external forces (Holguín-Veras et al., 2010, 2016). Holguín-Veras et al., (2010) found that the service time per stop was between 20 and 60 minutes. Holguín-Veras et al., (2016) simulated that, under current conditions, looking for legal curb space added 30 minutes or less more than half the time, and that this number was sensitive to the supply of truck designated curb space available. Given these findings and because this project only attempted to quantify delivery service demand, not supply, a simplifying assumption for total service time per stop was made to use 1 hour per stop in Manhattan and 30 minutes per stop everywhere else. This borough level distinction was drawn to represent the relative lack of curb supply in Manhattan detailed by Holguín-Veras et al. (2016). This curb availability distinction can be seen in policies like double parking being legal in many of the outer boroughs.



(a)



(b)

Figure 3.4 Truck Tour Start. Time -of-day distribution of (a) observed bridge crossings and (b) synthesized truck tour bridge crossings.

3.4 Tour Volume Model Calibration and Validation

The output of the truck tour distribution model is a sequence of OD pairs per tour. For example, a tour visiting nodes [1,2,3,4,5,1] implies ODs [1,2], [2,3], [3,4], [4,5], and [5,1]. To calibrate and validate the model at this step without a further trip assignment model, we compare major corridor and crossing AADTT data to the tour OD pairs using the shortest truck-restricted paths under different times of day. At borough-level crossings, this should be sufficiently accurate (route assignment would determine the ways they cross over).

To calibrate the theta parameter from Eq. (3.2), different values were sampled. Beginning with a theta of 1, then branching to 2 and 0.5, and then trimming back to 0.75. Figure 3.5 shows the process of the calibration. For each value of theta, the percent error comparing our model-produced volumes crossing each borough boundary (both in and out) to the counts from the locations defined in the Delivering New York report (NYC DOT 2021) is displayed. A clear trend can be seen where 0.75 is consistently among the best performers for each borough boundary, including the smallest total error of 6%.

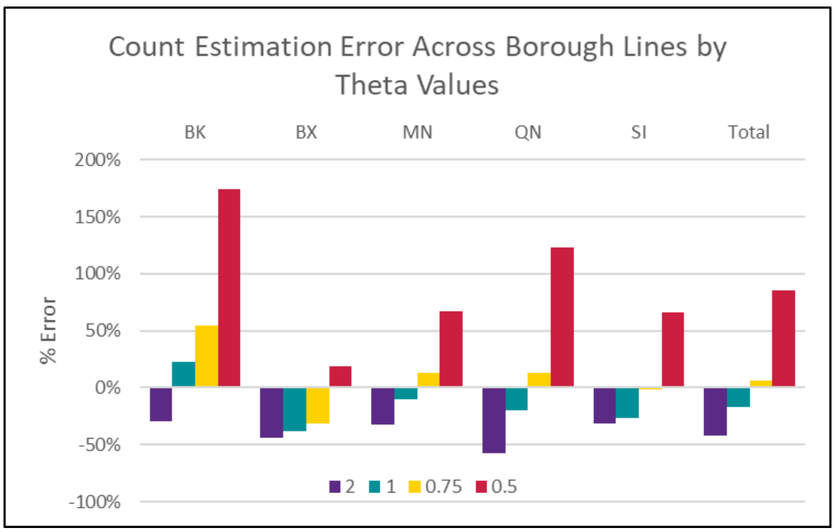


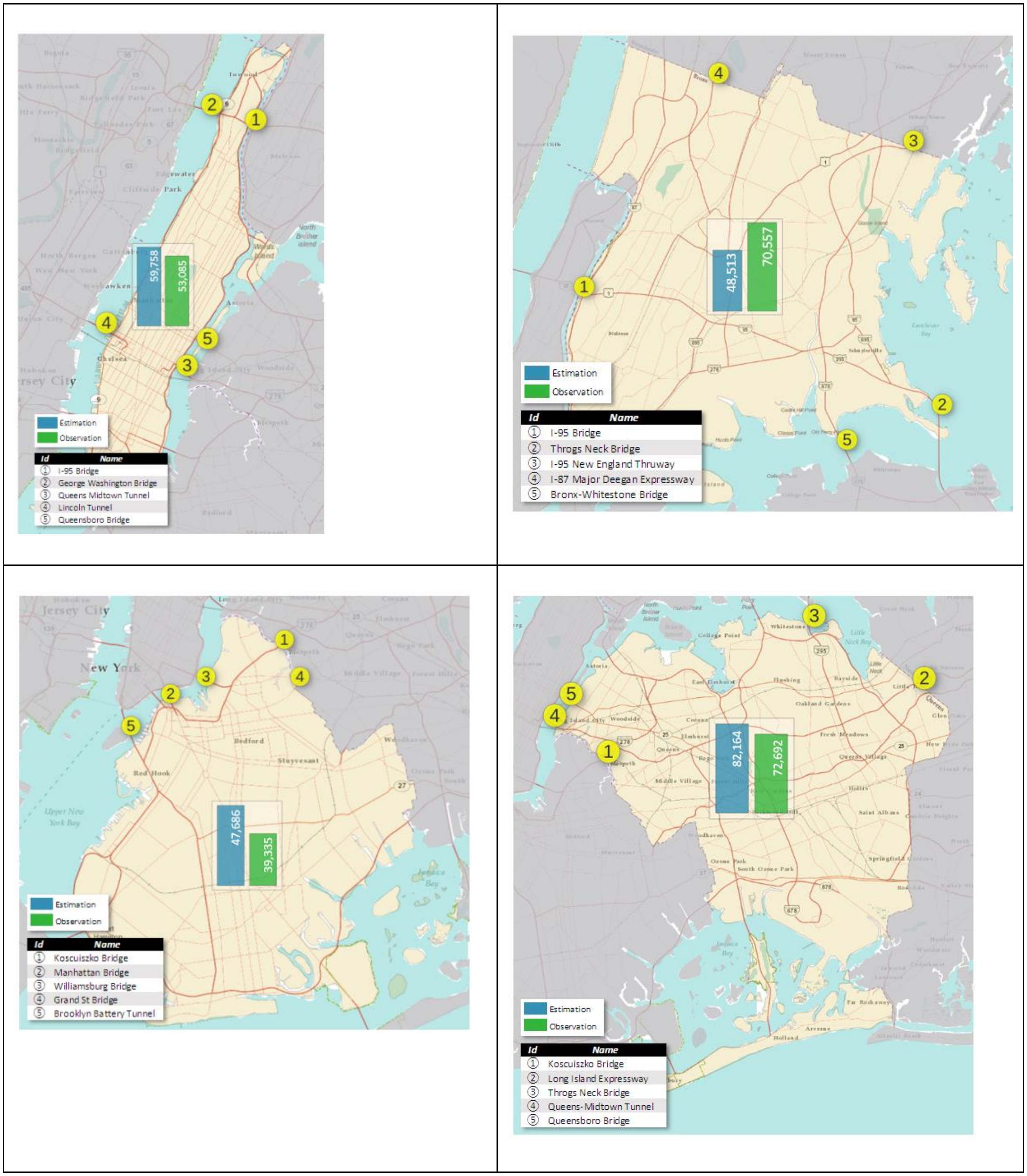
Figure 3.5 Count Estimation Error Across Borough Lines by Theta Values(a)

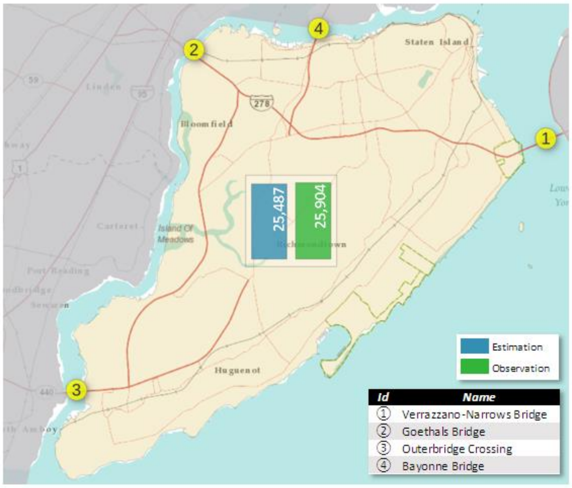
(**b**)

Figure 3.6a shows these locations from the report with the counts from the calibrated model compared to the real-world values. From these, we can begin to understand the nuances of the results. Staten Island is very accurate, Manhattan and Queens are slightly overestimated, and Brooklyn is overestimated by the same absolute value that the Bronx is underestimated which leads to the total values of measured and estimated trucks being acceptably close.

Digging deeper though, we separate out borough boundaries by destination and include measurements at more internal locations (mapped in Figure 3.6b). This analysis suggests that the Bronx is well estimated. Its borders with Manhattan and Queens are both within acceptable limits. Continuing this more in-depth lens reveals that every borough boundary that does not cross the East River, 8 out of the 12, have a combined average error of only 10.9%. Those four remaining borough boundaries (Manhattan to/from Brooklyn, Manhattan to/from Queens) contain the majority of the error. Taking all the borough boundaries together, the average error is 19.8%.

Overestimates across the East River are due to the nature of the tour set being constructed to favor proximal zones. In subsequent research, another parameter might be needed to differentiate impedance of trips crossing the Manhattan-Queens and Manhattan-Brooklyn borders from the other tours in NYC to reduce the crossings, e.g. $w_{ij} = e^{-\theta_1 \theta_{MN} d_{ij}}$, where $\theta_1 = 0.75$ and $\theta_{MN} > 1$ if (i, j) are between Manhattan and Queens or Brooklyn (and vice versa), and 1 otherwise.





(a)

(b)

Figure 3.6. Truck movements mapped across borough boundaries at (a) NYC DOT specified locations and at (b) all major locations.

Overestimates across the East River are due to the nature of the tour set being constructed to favor proximal zones. Since the flow assignment did not account for congestion effects, it is likely that some amount of real-world flow would be diverted off the main routes which is not captured here.

The relative agreement between the projected truck counts and real-world measures lends support to the model results.

3.5 Synthetic Freight Population

Two synthetic freight populations were produced for this project: a base version and one that meets the scenario outlined in Section 3.8. A truncated version of a synthetic truck population can be seen in Table 3.3. The tours have been broken into individual agents. A small amount of randomness was added to the start times for each tour and the coordinates for each destination to reduce overcrowding on the specific values.

Table 3.3 Synthetic Freight Population Structure

Index	*Tour*	*NAICS*	*Light0/ Heavy1*	*Start Time*	*Tot TravTime*	*TotEmiss*	*P*	*A*	*A.1*	*Trip Time*	*Serv Time*	*Trip Emiss*	*Tons/Trk*	*Lat1*	*Long1*
15	1	212	0	22.3691	7.30	13201	189	189	472	0.301829	0.5	1160.083	12.65	-74.0167	40.7055
16	1	212	0	21.39118	7.30	13201	189	189	472	0.301829	0.5	1160.083	12.65	-74.0169	40.70667
17	1	212	0	20.77578	7.30	13201	189	189	472	0.301829	0.5	1160.083	12.65	-74.0439	40.6900
18	1	212	0	21.59336	7.30	13201	189	189	472	0.301829	0.5	1160.083	12.65	-74.0445	40.68917
19	1	212	0	21.41276	7.30	13201	189	189	472	0.301829	0.5	1160.083	12.65	-74.0157	40.70947

One branch of future work will incorporate this synthetic freight population into MATSim-NYC. For more information on the specifics of MATSim synthetic population files, see He et al. (2021).

Component Calculations

Tour travel times were constructed by summing the link travel times based upon the appropriate ToD block. Medium trucks are vehicles FWHA class 5, 6, or 7. Heavy trucks are anything class 8 and above. As described in section 3.2, all heavy trucks were assumed to be long haul trucks destined for warehouses. All other trucks at the gateway and all internal trucks were assumed to be light trucks. These do not include parcel delivery vehicles like the sprinter vans used by Amazon (ex. Figure 3.7) because they are considered commercial vehicles and not flagged in the truck counts reported by AADTT sources.

Figure 3.7 Light Duty freight commercial vehicle

To calculate emissions, these speeds were then fed into the primary equation described by Bigazzi & Figliozzi (2013) (Eq. 3.12) which relates average speed to the emissions of various pollutants for different truck sizes. This work used class 6 and class 8 as the representative trucks for light and heavy vehicles respectively. For simplicity, only CO_2 emissions (measured in terms of metric tons of carbon equivalent) are reported, although an analysis on other harmful pollutants would follow the same process. Analysis showed that trucks traveling during the night had the lowest emissions because their speed was closest to free flow allowing for more efficiency. Having emissions per link also allows for using them as a link cost to calculate a cleanest path. The five values of $a_{i,hd}$ used to compute CO_2 emissions are [9.254, -0.1748, 0.006307, -1.007 x 10^{-4}, 5.74 x 10^{-7}].

$$e_j(v_j) = \exp\left(\sum_{i=0}^{4} a_{i,j} \cdot v_j^i\right) \tag{3.12}$$

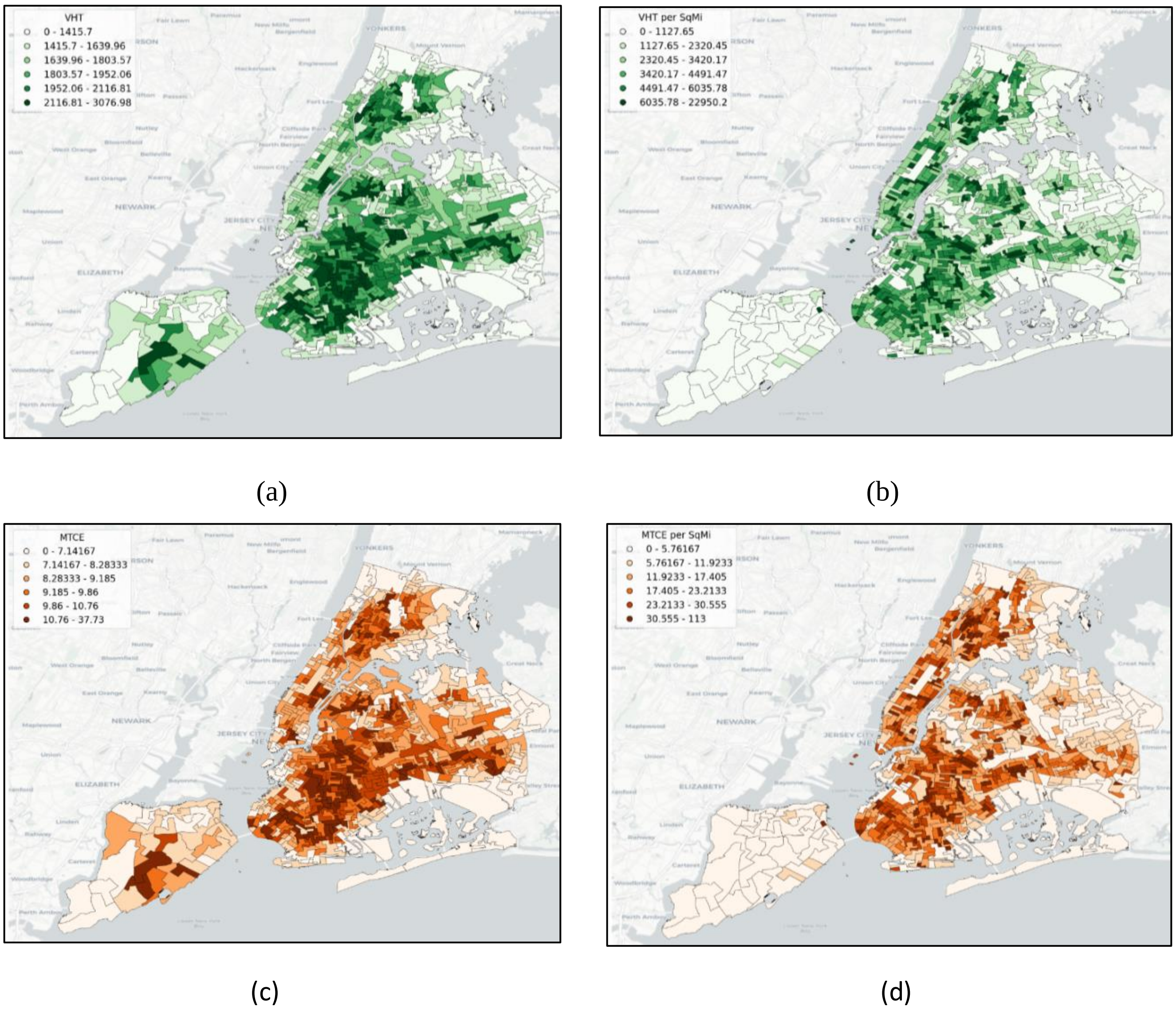
Where:

e_j is vehicle class average spatial emissions rates in grams emitted per vehicle mile
v_j is vehicle class average speed in miles per hour
j is vehicle class

$a_{i,j}$ are fitted parameters

3.6 Base Case Exploration

An analysis of the synthetic population as initially generated produces the following results. In total, 333,843 trucks were assigned, and they produced 2,573,441 trips. Figure 3.8 shows for each custom TAZ the estimated (a) Vehicle Miles Traveled, (b) total emissions in MTCE of CO2, and (c) veh-hours accumulated within each zone. Results are normalized as densities by dividing by area (mi^2). As these results ignore congestion effects, we can assume that the real-world numbers would be larger.

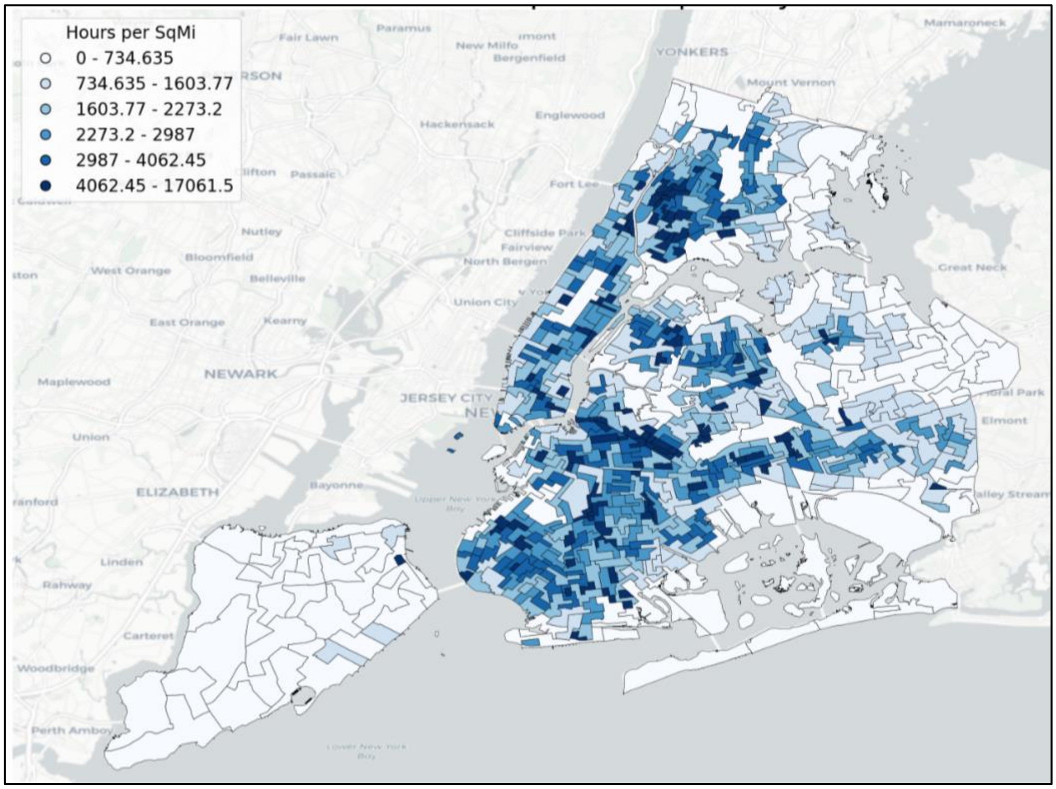


(a) (b)

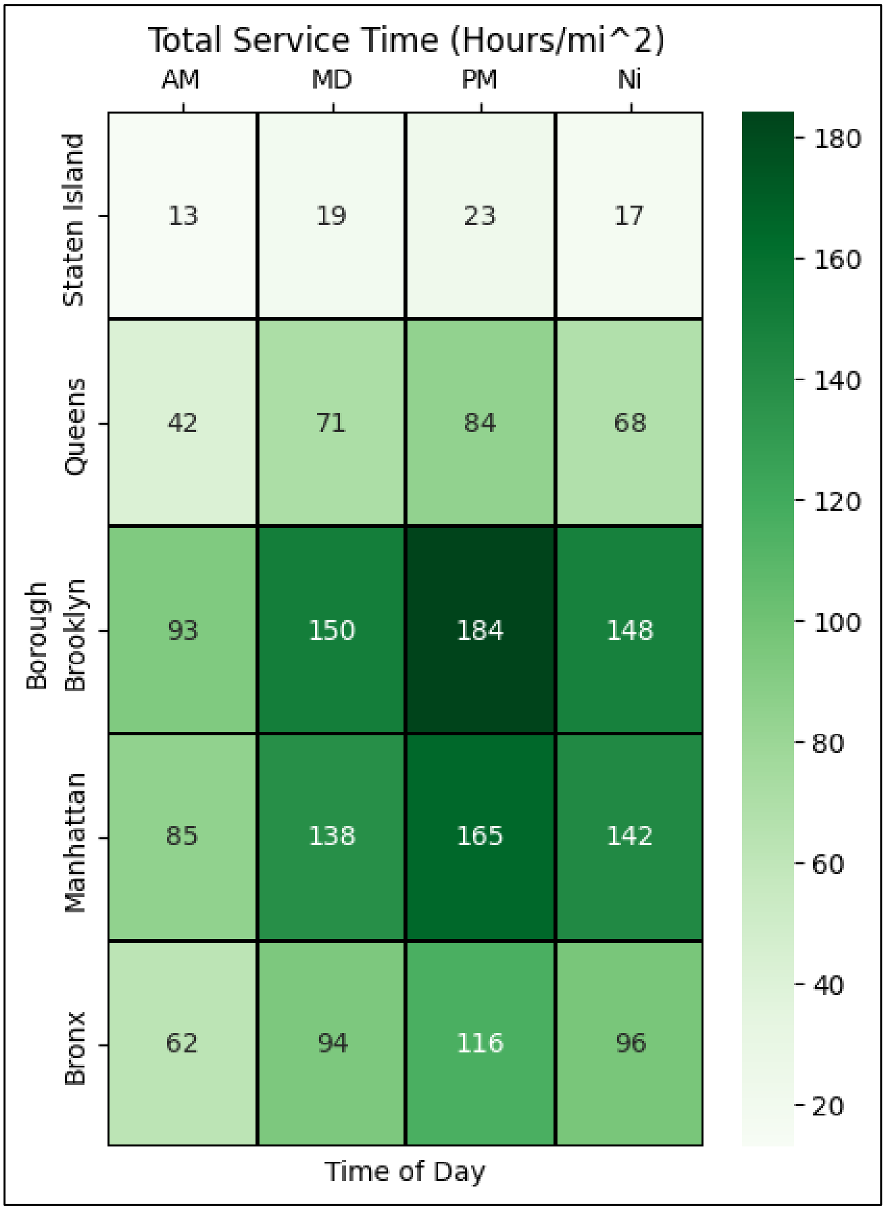
(c) (d)

Figure 3.8 (a) NYC heatmap of estimated VHT; (b) VHT density; (c) CO2 Emissions; and (d) CO2 Emissions density.

Figure 3.9 is designed to show the synthetic population's ability to represent the variation of the data in time and space. Results are normalized by mi^2. Figure 3.9a captures total vehicle service time per day by zone which represents how much time vehicles are waiting at each drop-off location. The shading is broken down into 6 quantiles. Bin 3 having the smallest range indicates that the most zones fall between 1603 and 2273 hours/mi^2 of service time. This metric can be used as a proxy for parking demand especially in the areas where businesses are not going to have private loading and unloading zones, and its importance is discussed in Holguín-Veras et al. (2016). As expected, several of the areas designated as high freight attraction zones in Figure 2.7a standout. Figure 3.9b captures how total service time varies throughout the day. A similar analysis could be performed with the other currently tracked metrics such as emissions.



(a)



(b)

Figure 3.9 (a) Cumulative Service Time per Day per Zone; (b) Service Time per Hour per Time of Day for Each Borough

Table 3.4 shows the top NAICS industries by their total emissions, vehicle hours traveled, and vehicle miles traveled. As expected, we see a strong correlation between these measurements.

Even among the top 5 though, there is a strong drop off in volume across all three statistics showing the unique characteristic of each, and why it is necessary to separate them out when modeling their behaviors. Industries 221 and 722 make up the 4th slot in Table 3.4. NAICS 221 is utilities while 722 is food service. While NAICS 722 takes that slot for VMT, it is not among the top 5 for VHT. This indicates that restaurant deliveries spend a higher percentage of their time on faster roads like freeways and major arterials than utilities. This suggests that utility destinations are more likely to be farther from major freeways or arterials.

Table 3.4. Top 5 NAICS codes by emissions, VHT, and VMT.

Industry (NAICS)	Avg Daily CO_2 Emissions (MTCE$\times 10^6$)	Industry (NAICS)	Avg Daily VMT (mi$\times 1000$)
Building material (444)	24.2	Building material (444)	103.7
Motor vehicles (441)	20.1	Motor vehicles (441)	81.4
Wholesale trade (425)	16.3	Wholesale trade (425)	68.4
Utilities (221)	9.4	Food services (722)	48.1
Non-store retail (454)	7.4	Non-store retail (454)	47.0

3.7 Policy Use Cases

The proposed synthetic truck population model can be used for many different purposes, even without integration with MATSim. Several that take advantage of its unique characteristics are highlighted here.

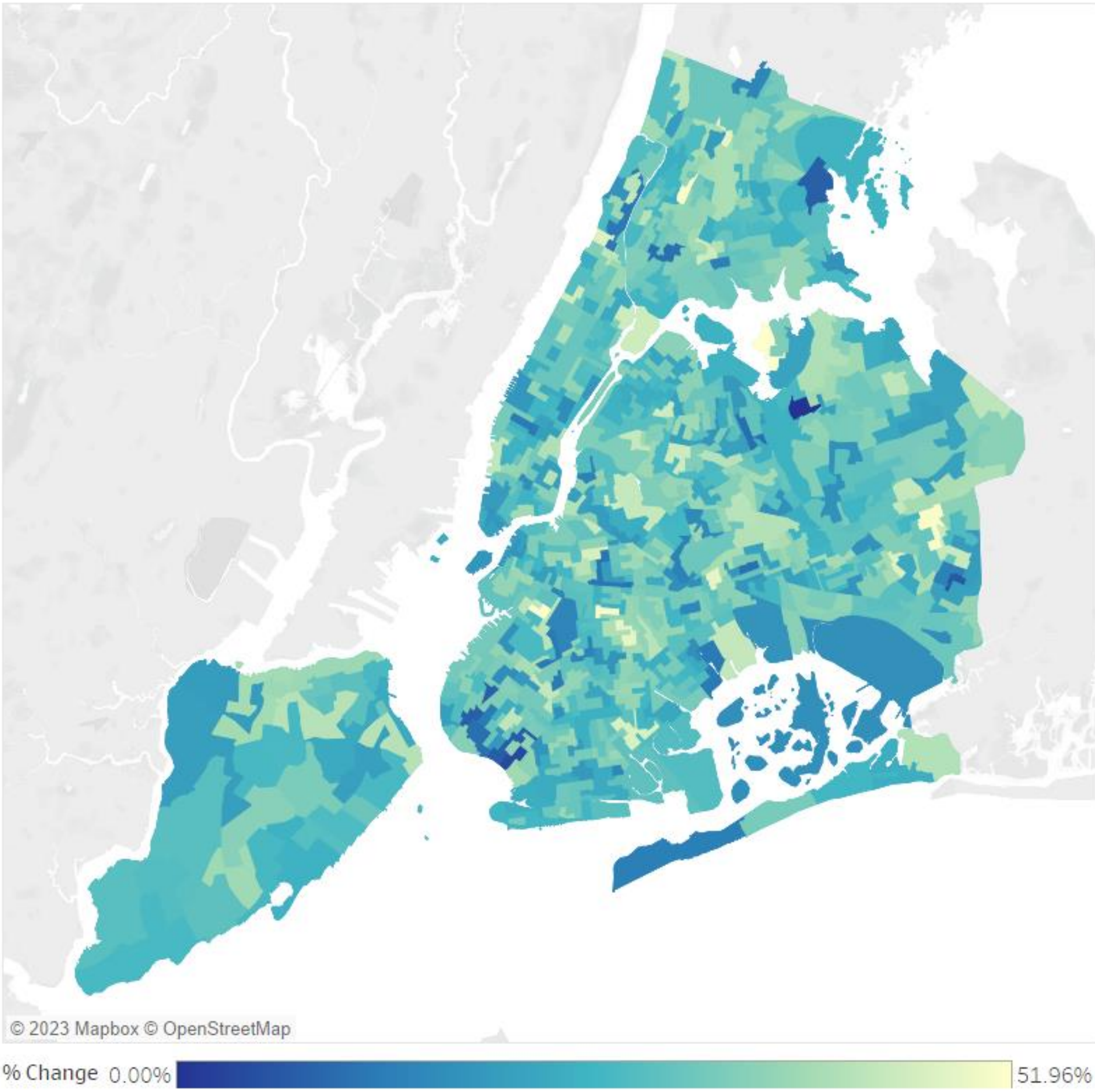
- *High resolution*: The model can be used to forecast an approximate number of truck trips (by OD) and corresponding weight of goods by industry for a given link, based on simple assignment of truck trips via shortest paths. Of course, MATSim would lead to more accurate assignments, but for a rough "daily" figure and evaluation of major corridors/bridges this should suffice.
- *Supply chain impacts*: We can examine a scenario where an industry or a zone suffers a disruption and model the resulting reverberations across other industries and the resulting fallout in truck flows. Truck flows can be non-responsive, i.e. right after a disruption they might be following the same patterns; or responsive, where trucks are re-assigned to new tours based on new flows accounting for these disruptions.
- *Sensitivity of tour patterns from technological changes*: Changes to vehicle capacity can impact tour flows; travel time changes can lead to new tour patterns and changed tours for the truck population.

- *Operating policies*: Changes to average number of stops per tour (e.g. operating hours) can be modeled, as can having a new urban consolidation center lead to shifts in the long-haul trip proportions assigned to a location and redistributed from there.

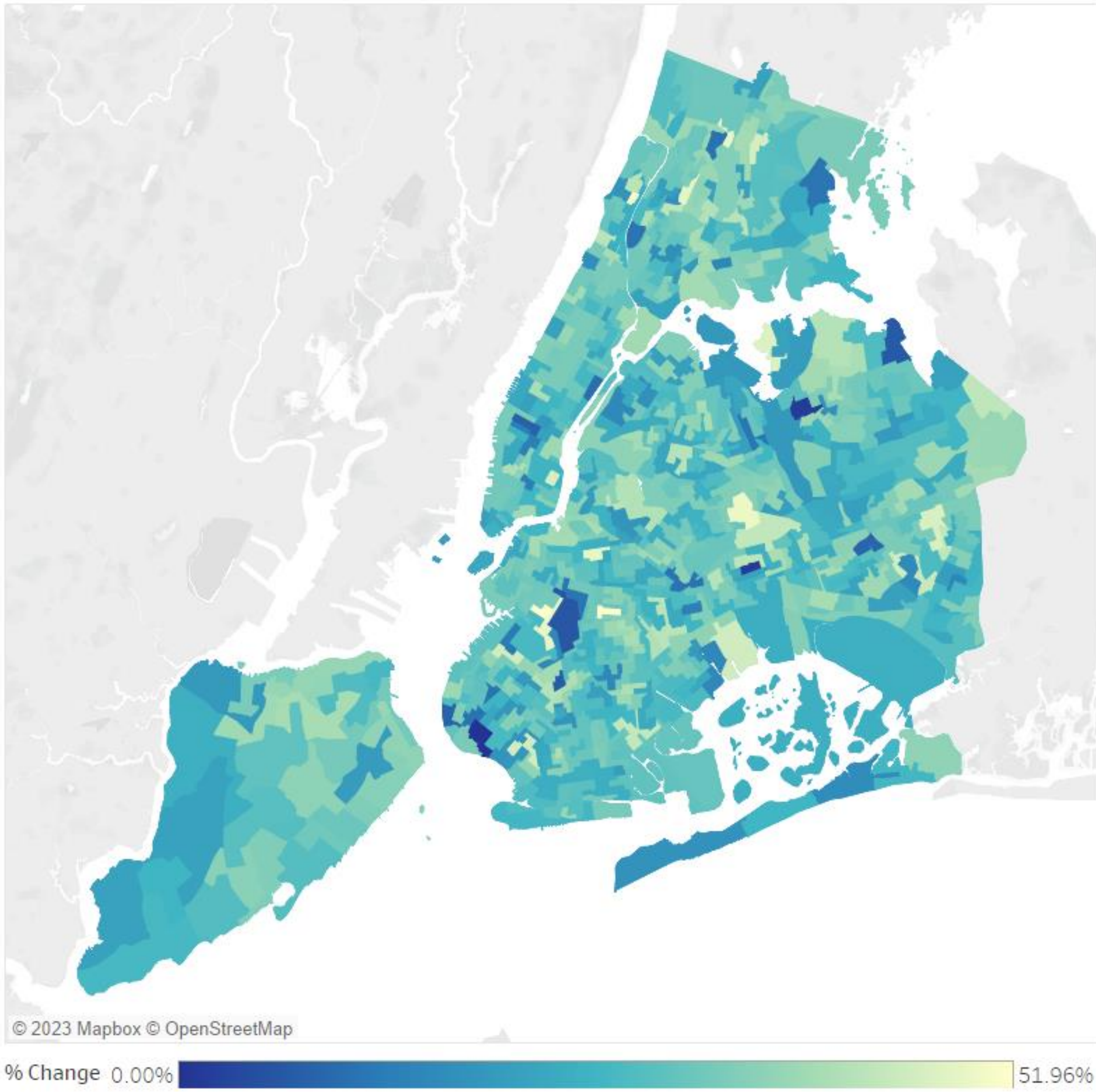
3.8 Truck Size Reduction Scenario Analysis

The purpose of the scenario analysis is to demonstrate the strength of the synthetic freight population model to describe the interdependencies of freight truck travel in New York City by using the multifaceted dimensions of data reported for each tour. This tool will be able to help evaluate policy proposals by quantifying the benefits and drawbacks through the lens of congestion, emissions, and infrastructure.

The specific scenario studied was a 20% reduction in the size of all trucks in New York City. While this scenario is not under consideration by policymakers, it helps to illustrate the trade-offs stated above. Since the total amount of freight is kept constant, a vehicular capacity reduction this leads to an increase of 20% in the number of freight trucks, which manifests negatively in many factors, some of which are captured in Figure 3.10. It shows heatmaps of the percent difference from the base case at the custom TAZ level. Figure 3.10(a) shows the percent difference between the base scenario and the 20% reduction scenario for vehicle miles traveled. Figure 3.10 (b) displays the percent difference in gas emissions in MTCE of CO_2.



(a)



(b)

Figure 3.10 NYC heatmap of Case Study increase over base case in (a) VMT and (b) CO_2 emissions.

Additionally, the extra trucks require extra curb space and dwell times which can manifest in issues around overnight and long term truck parking. The increase is shown geographically in Figure 3.11. Again, the high freight attraction zones can be seen with the greatest increase in service time per area. The shading is broken down into 6 quantiles. Bin 3 having the smallest range indicates that the most zones fall between 7 and 14% added.

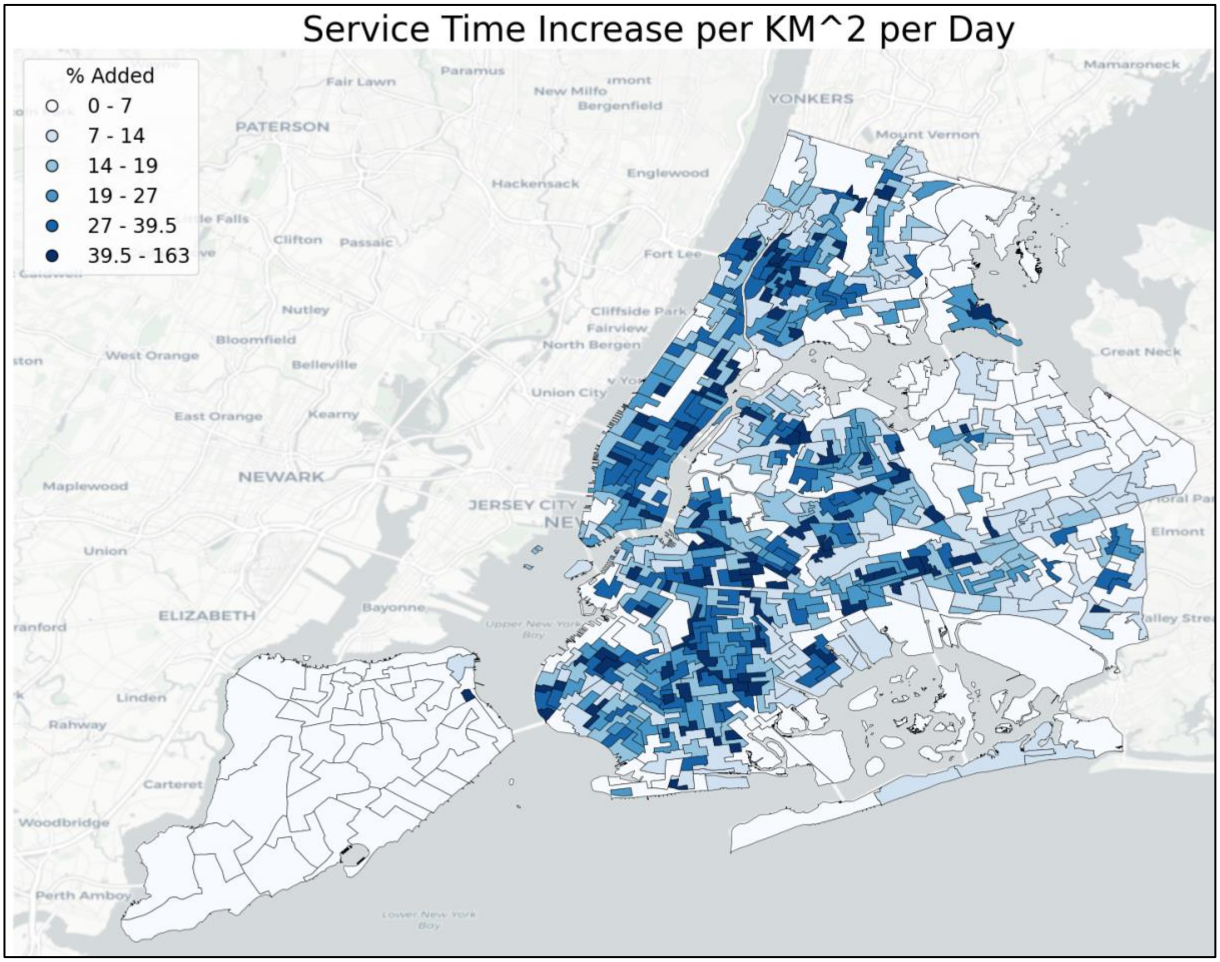


Figure 3.11 NYC heatmap of increase in truck service time hours over base case.

Despite the increase in VMT and CO2, the scenario could reduce the damage to infrastructure. Even with the 20% reduction in weight, the number of daily Equivalent Single Axel Loads (ESALs), calculated by Eq. 3.13 (AASHTO, 1986), almost halves across the Queens Midtown Tunnel with similar results on the Manhattan Bridge as seen in Table 3.5.

$$\text{ESAL} = \left(\frac{Veh\,Weight}{18{,}000lbs}\right)^4 \qquad (3.13)$$

Table 3.5 ESAL loads on select links in base scenario vs base study

	QMT MN Bound		QMT QN Bound		MN Bridge MN Bound		MN Bridge BK Bound	
Qnty	ESALs	Truck Flow	ESALs	Truck Flow	ESALs	Truck Flow	ESALs	Truck Flow
Base	6327	8813	6103	8468	2626	5666	2962	5318
Case Study	3347	10977	3266	10530	1445	7102	1567	6622
Change	-47.1%	24.6%	-46.5%	24.4%	-45%	25.3%	-47.1%	24.5%

Significant reductions such as these in the load borne by the bridges and tunnels in the New York City area could meaningfully increase their lifespans which is a stated goal in the 2016 NYCDOTNYC DOT Bridges and Tunnels Annual Condition Report. Importantly, the reduction occurs even with an increase in truck flows across the same links. Table 3.5 shows a rise of 24-25% for the selected links which correlates with the 20% reduction in truck size.

4 Parcel delivery for NYC

4.1 Literature review

Parcel delivery

The increase in e-commerce and the emergence of new technologies in recent years have inspired a wide variety of parcel delivery-related research, but much of it remains hypothetical. Even as some models have been evaluated with real-world scenarios, the scale of the case studies is rather limited. Morganti et al. (2014a) empirically studied the effectiveness of adding pick-up points and lockers into the delivery network in France and Germany. Perboli and Rosano (2019) discussed the interaction between traditional and novel operation practices in the delivery industry and makes findings based on real-world data from the city of Turin, Italy. Besides operation costs, the environmental impact of parcel delivery service has also been studied. Jaller et al. (2021) evaluated the cost-effectiveness of deploying electric freight vehicles by considering the negative impact of emissions, and the analysis was based on empirical data in California. Villa and Monzón (2021) studied the additional GHG emission generated from increased parcel delivery services in Madrid, Spain, because of COVID-19. All of these are empirical studies without modeling. It is worth mentioning that the majority of these real-world analyses are based on European cities (Ducret (2014) provides a good overview).

The need to evaluate parcel delivery strategies beyond just using empirical data arises from emerging technologies. For example, Kafle et al. (2017) proposed a system enabling crowdsourcing to undertake last-mile delivery service and used a mixed integer nonlinear program to solve the routing assignment. Seghezzi and Mangiaracina (2022) also proposed a crowdsourcing solution and introduced a model combining gravity-based distribution with vehicle routing optimization to assign parcels in Milan. Models related to autonomous delivery vehicles have been proposed (Buchegger et al, 2018; Schlenther et al, 2020), in which the latter study by Schlenther et al. uses multi-agent simulation (MATSim) with a synthetic parcel demand population to assign tours via a customized taxi module. Other alternative strategies include networks of pickup points or lockers (Morganti et al. 2014b), urban consolidation centers (Simoni et al. 2018), collaborative deliveries via blockchain (Hribernik et al, 2020), and drone-based delivery (Kim et al, 2020; Kirschstein, 2020; El-Adle et al, 2021). Nguyen et al. (2019) employed optimal routing models to evaluate delivery strategies that can include both driving and walking, with a small case study in London. Allen et al. (2018) provided insights into the conflict between current delivery service practices and urban infrastructure using a case study in central London. Kummer et al. (2021) studied the impact of parcel delivery service vehicles on the road network in Vienna, Austria. Beckers et al. (2022) used discrete choice models to translate household survey data into parcel delivery trips and the associated local freight impacts in Belgium were incorporated into simulations.

The cargo bike has been one of the most viable options among all parcel service alternatives. Numerous pieces of literature have explored its application in urban delivery networks. Gruber et al. (2014) studied the preferences of couriers in using cargo bikes using a binary logit model. Nocerino et al. (2016) presented the results of several pilot programs of cargo bikes conducted in the city centers of Genoa and Milan, Italy. Anderluh et al. (2017) proposed a system based on synchronizing vans and cargo bikes and optimizing the system using routing models. Niels et al. (2018) studied a cargo bike project in Munich, Germany, and developed a city-wide cargo bike operation strategy based on the project. Nürnberg (2019) conducted field research on cargo bikes in Stargard, Poland. Arnold et al. (2018) and Llorca and Moeckel (2021) implemented custom simulations of deliveries to evaluate the benefits of cargo bikes. Assmann et al. (2020) studied the environmental impact of cargo bike deployment with the implementation of cargo bike transshipment points. Rudolph et al. (2022) proposed a location optimization model for cargo bike micro-consolidation center and applied it to the city center of Stuttgart, Germany.

The literature on parcel deliveries can be divided into either proposed system designs with logistical routing optimization models or evaluations of alternative strategies. Among the latter, researchers interested in predicting parcel delivery volumes employ either routing optimization models or simulations. While routing optimization models work well in answering “how to” operate such systems, they are more lacking as descriptive/forecast models as there is less parameterization for fitting solutions to observed data without resorting to complex techniques like inverse optimization (You et al, 2016; Chen et al, 2021) and requiring detailed tour data. Furthermore, finding the exact solutions to these problems requires high computational power because of their NP-hardness (Lenstra and Kan, 1981). Simulations are similarly computationally expensive, making it hard to apply to a large-scale environment without relying on extensive assumptions. Because of this, we propose using a continuous approximation model to tackle a large-scale model of NYC.

Continuous Approximation

Continuous approximation makes use of geometric probabilities (e.g., Beardwood et al., 1959) to estimate aggregate measures of a routing system's performance while eschewing unnecessary details such as link selections. In giving up the design outputs (how to serve an area), such models gain in the applicability to large-scale policy analysis with low computational cost.

An effective approximation formula was proposed to calculate the optimal length of a capacitated VRP (CVRP) by Daganzo (1984). The formulation consists of the travel length from the depot to the centroid of the service area and the tour length inside the service area. Such a concept has been widely used in other proposed CA methods (Chien, 1992; Langevin et al, 1996; Figliozzi, 2008). Some modifications to the two components in the formula are made in different studies. For example, the geometry feature of the service area can be incorporated into the tour length calculation (Kwon et al, 1995). In addition to the classic capacitated VRP, CA methods regarding more complex VRP with time window constraints (VRPTW) are also developed. Figliozzi (2009) proposed a CA method addressing the VRPTW by adding more terms counting the additional impact of time windows.

A wide variety of transportation studies have been conducted based on continuous approximation methods. Ouyang and Daganzo (2006) designed an algorithm incorporating CA methods to solve location problems. Davis and Figliozzi (2013) used CA models to evaluate the operating cost of electric delivery trucks and their competitiveness when compared with conventional diesel trucks. Banerjee et al. (2022) designed a method to effectively partition a service area to enhance the same-day delivery service by using CA as part of their algorithm. Tipagornwong and Figliozzi (2014) applied CA to evaluate the cost of cargo tricycles, which is most similar to the method used in this study. In that study, the cost function incorporates a CA model, and the cargo tricycle cost is evaluated based on a small user case in Portland involving 80 daily deliveries. Our study is more comprehensive in predicting trip generations and using CA to estimate associated VMT. In addition, our study differs in the scale of the case study to all the residential population in NYC, and the evaluation of alternative cargo bike modes as substitutions for only a subset of feasible depots in a mixed delivery system.

Most studies involving CA methods are based on Euclidean or Manhattan metrics or are tested on hypothetical scenarios. Few studies apply CA to real-world scenarios on a large scale and more real-world validation of CA is still needed.

4.2 Methodology

The proposed model consists of four major components that are described as follows: parcel volume and service stop generation, service area and volume assignment, CA model fit and VMT estimation, and result adjustment with novel delivery alternative implication. The model is summarized in Figure 4.1. This section explains the flow of the first three components in detail. The last component is best demonstrated in the case study.

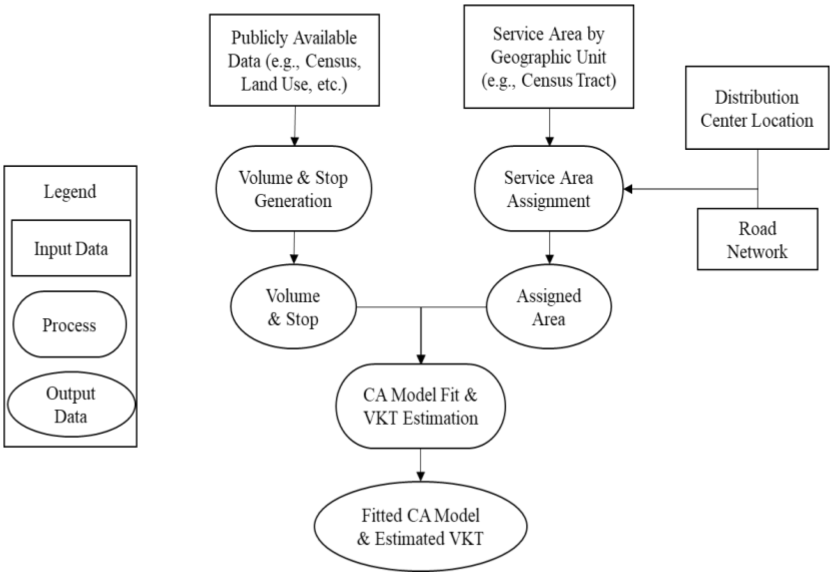


Figure 4.1 Model procedure.

Parcel Volume and Service Stop Generation

We estimate the package volume by using publicly available data and validate our result by comparing the aggregated value to the city-level parcel volume. The algorithm for this component is shown in Figure 4.2. Based on the distribution of residential areas and income level in each census tract, we assign the number of households with a certain income level to each building. In this process, we use the assumption stated as follows.

Assumption 1. *The number of households is proportional to the residential area; all households in one building block have homogenous income levels.*

Validation is needed to ensure that the census tract income level distribution of assigned households is consistent with the provided income level distribution. We generate the parcel volume for delivery and pickup at each building block based on the assigned households by using the "Parcel Generation Factor" provided by USPS (USPS, 2021). These factors are the national average of weekly postal service volumes per household by income. To generate the average daily parcel volume, three more assumptions are made:

Assumption 2. *The number of parcels generated by NYC households is the same as the U.S. national average across income levels*

Assumption 3. *The share of postal service parcels is the same across all households*

Assumption 4*. Each week, 5 days are used to conduct parcel delivery and pickup services*

> Assumption 4 comes from data suggesting that the parcel volume processed during the weekend is much lower than the weekday volume. Since we do not have detailed day-to-day volume distributions, we used a simplistic assumption to estimate the daily volume. Based on these stated assumptions, the average daily volumes of residential parcels can be obtained. Since the "Parcel Generation Factor" is only consumer-based, which excludes business-to-business (B2B) parcels, we only consider the parcel services serving residential locations in this study. The generated volume can be validated by comparing the total number with the city-level residential parcel volume. According to an e-commerce survey conducted in Belgium in 2016, 75% of the respondents stated that they prefer home delivery (Beckers et al, 2022). Since the start of the global pandemic, a growing number of workforces chose to work from home and studies indicate such a trend will be a long-term phenomenon (Barrero et al, 2021). Therefore, a higher percentage of home deliveries can be expected. Therefore, the generated volume and stops would represent the majority of the citywide parcel services.

To generate parcel service stops and the associated volumes, we use the following assumptions.

Assumption 5. *Each building block is a potential parcel service stop by truck. Parcel delivery drivers are assumed to deliver to each residential building on the block by foot, using a cart if necessary.*

Assumption 6. *The market share of parcel service companies represents the delivery volume split at each service stop.*

Assumption 7. *Stops with a volume lower than a certain threshold will not be directly served. Instead, it will be aggregated to the nearest stop having a volume higher than the threshold.*

Based on the assumption, delivery volume at each stop is split by using the market share of the four parcel service companies in the US market. The remaining delivery volume served by other companies is evenly distributed to UPS, FedEx, and Amazon, which are all privately owned. A "Delivery Volume Threshold" for each company is set for stop aggregation. Stops having delivery volumes lower than the threshold are joined to the closest stop whose delivery volumes are higher, and the aggregated delivery volumes are then rounded to integers. The stops joined to others can be treated as service points that do not require dedicated vehicle stops. Instead, they can be served by drivers walking to those points from the nearest vehicle stops, which is a common practice in an urban setting, i.e. "hoteling" (see Allen et al., 2018). Calibration on the thresholds is required to ensure that the delivery volume difference before and after stop aggregation is within a defined tolerance. In terms of pickup service, we assume that all pickup items are collected at the post office for USPS, and Amazon pickup volumes are evenly handled by UPS and FedEx. The same stop aggregation process is applied to pick up stops by setting "Pickup Volume Threshold", and calibration of the threshold is also required.

The e-commerce industry is highly seasonal. Therefore, the estimated average daily volume may not reflect the reality of the parcel service during peak seasons such as the fourth quarter. To capture such fluctuations, peak volume could be calculated by applying peak factors to the average daily volume, which could be obtained using companies' operation data disclosed from their financial reports.

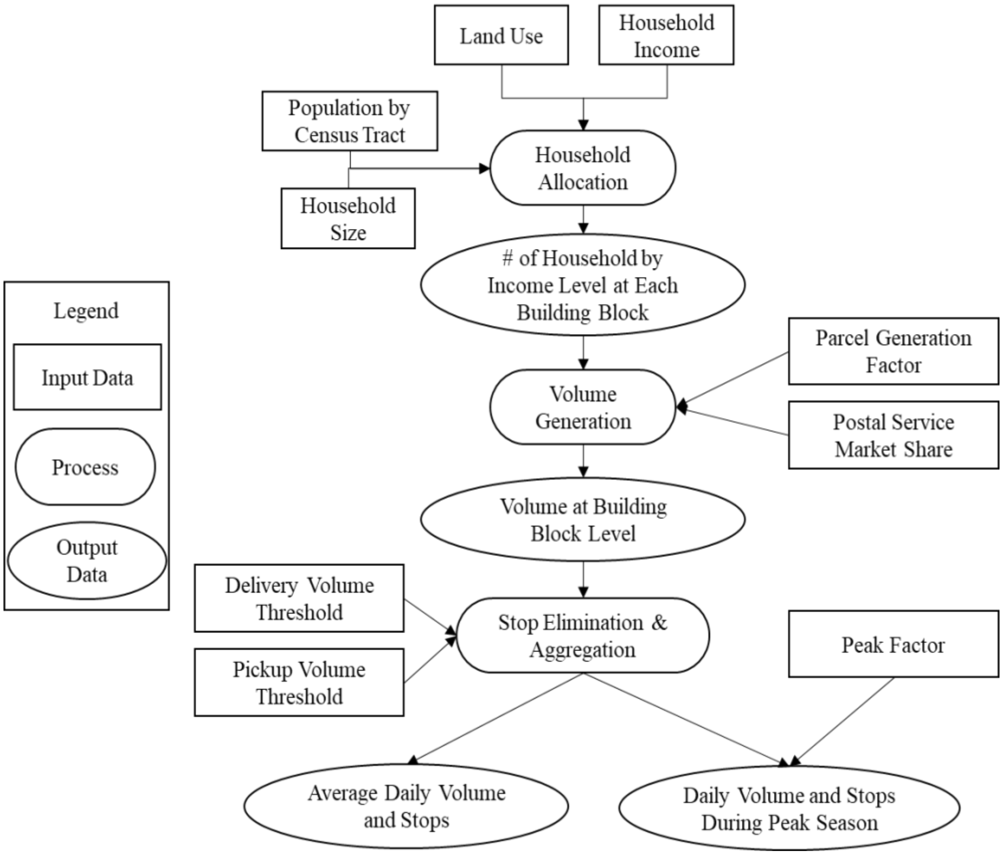


Figure 4.2 Data Processing Procedure for Volume and Stop Generation.

Service Area Assignment

The four major parcel service companies included in this study have their own distribution centers covering different service areas. Since these companies have already publicly listed their facility locations, we only need to determine the service areas covered by each distribution center with the given distribution center information. To estimate the service areas, we use the census tract as the basic unit. The shortest path distances from centers to the centroid of each census tract are calculated based on free flow speed. The service assignment procedure is only from a planning perspective and consists of deliveries made throughout the day, using travel time as a measure of impedance for clustering, not an actual measure of route travel time. As such, the use of real-time travel time throughout the day is not considered. Census tracts are served by the closest distribution center based on distance matrices. As illustrated in Figure 4.3, the shortest path from center B to the centroid of the green census tract is shorter than that from center A. Therefore, the selected census tract is served by center B. We then adjust the assignment result based on boundaries unique to the studied area and the volume balance across the centers.

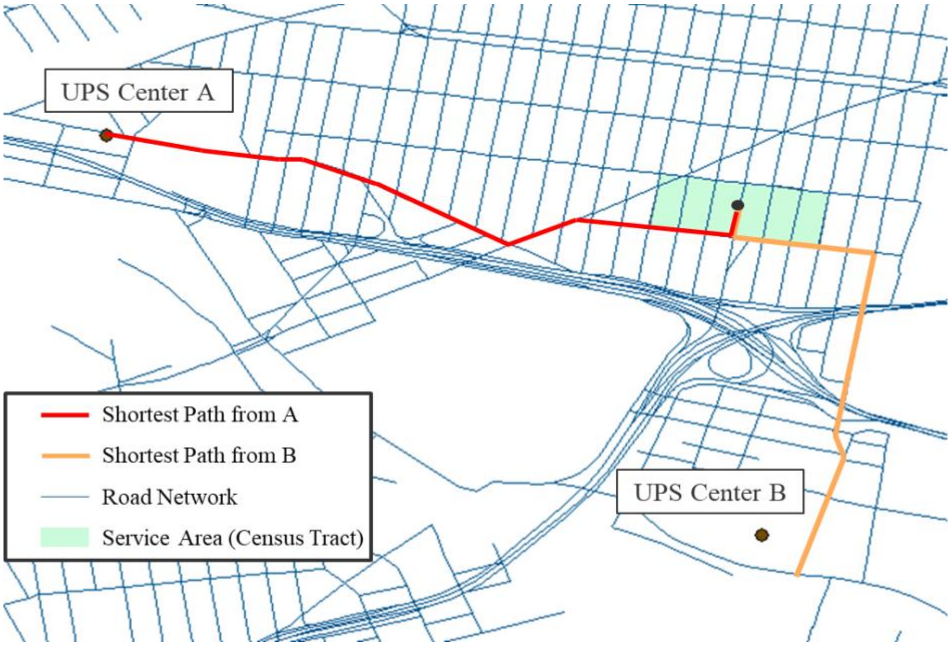


Figure 4.3 Service Area Assignment.

Continuous Approximation Model

The CA model is particularly suitable for this study because of the uncertainty of actual stop locations and the scale of the problem. In our study, a service area is specifically assigned to a unique center for each company. Therefore, the problem becomes a single depot CVRP for each center. A simple yet effective CA formula can be written as Eq. (4.1).

$$V = 2rm + k\sqrt{nA} \quad (4.1)$$

where V is the tour-based VMT, m is the number of trucks, r is the distance between the depot and centroid of the service region, n is the number of service locations, A is the area of the service region, and k is a coefficient for calibration. The original study sets $k = 0.57$ for distances in the area measured using Euclidean distance as opposed to the shortest path distance (Daganzo, 1984). An extra term $(n - m)/n$ is added (Figliozzi et al, 2008) to correct the overestimation of the local tour distance when a service area is served by more trucks, as shown in Eq. (4.2).

$$V = 2rm + k(n - m)\sqrt{A/n} \tag{4.2}$$

We calibrate k_i to reflect real-world road networks by fitting the model to tour samples generated from smaller CVRP problems, where k_i represents the unique value of k fitted to match CVRP tour lengths where distances between nodes are determined using shortest paths on a road network in a specific region i (the regions in the case study are boroughs). The tour lengths vary when solved by different routing algorithms, which reflects different routing strategies adapted by carrier companies. To produce a generalized routing result, we solve the CVRP problem without any additional routing constraint. To make the CVRP tour lengths closer to the actual ones generated by the parcel companies, a more accurate shortest path matrix is required. Uber Movement (2022) is a good resource to generate such a matrix. The speed information gathered from Uber drivers throughout the day accurately reflects various restrictions posed by the city (e.g., bus lane priority, turning restriction, etc.), which could heavily influence the choice of delivery routes. In this study, we only focus on the system-wide traffic and environmental impact generated by on-road activities from delivery trucks. Therefore, the objective function of the CVRP problem is set to be travel time minimization, which excludes the consideration of other operation metrics such as dwelling hour and generated profit. An underlying assumption of using Eq. (4.2) is that there is no time window constraint. Therefore, the generated result would be a lower bound of real-world scenarios where time windows can exist.

In the original study, the formula considered only delivery stops. If deliveries and pickups could be mixed with no capacity constraint, n would be the number of total service points including delivery and pickup (Daganzo and Hall, 1993). We adopt this modification since the pickup volume generated in the case study is significantly less than the delivery volume. To include pickup service, we treat all pickup stops as separate service points even though they are at the same locations as delivery. Separating delivery and pickup points can capture the extra tour length induced by pickup service.

4.3 Case Study

We use NYC as our case study area and 2021 as the base year to apply the parcel service VMT estimation model. Importantly, 2019 is the base year for the truck case study. Each section is consistent within itself though. According to the 2020 census (U.S. Census Bureau, 2022), more than 8.8 million people resided in New York City. There are five big districts inside NYC called boroughs, which are Manhattan (MN), Bronx (BX), Brooklyn (BK), Queens (QN), and Staten Island (SI).

Generating Service Demand

Households are synthesized by combining information from the 2020 census population and household tables, as well as land use data (NYC Planning, 2022). For each building block, we randomly apply the income level drawn from the census tract level household income distribution (U.S. Census Bureau, 2022) to each building block. According to the statistical table, the median Margin of Error (MOE) of the NYC census tract income level is 40%. The rest of the procedures described in the methodology section is applied to generate corresponding stops and volumes for parcels in 2020. Based on the result, we further applied an 11.4% volume increase based on e-commerce sales (US Department of Commerce, 2022) to scale the parcel volume up to 2021. The result is an average daily volume of 1.91 million residential parcels estimated for 2021. For validation, the New York Times (2021) reported 2.4 million average daily parcel volumes in NYC in 2021 of which ~80% are residentially destined, which equals 1.92 million residential parcels. Our result is nearly identical to the reported data. The delivery volume by census tract is shown in Figure 4.4.

For stop aggregation, Delivery Volume Thresholds are calibrated to be 0.8, 0.7, 0.6, and 0.65 for USPS, UPS, FedEx, and Amazon respectively. The Pickup Volume Thresholds are uniformly set to 0.66. Table 4.1 summarizes the final service metrics among the four companies, where the market shares are provided by Pitney Bowes (2022).

Table 4.1 Average service metrics among USPS, UPS, FedEx, and Amazon in 2021

	Market Share	Daily Delivery Volume	Pickup Volume	Delivery Stops	Pickup Stops
USPS	32%	611,208	0	83,881	0
UPS	25%	477,617	97,376	70,100	34,183
FedEx	20%	382,635	85,644	63,557	30,506
Amazon	23%	439,813	0	69,138	0
Sum	100%	1,911,144	153,483	332,558	66,586

The quarterly US domestic parcel volumes disclosed from each company's financial report are used to calculate the peak season factors (USPS, 2022a; UPS, 2022a; FedEx, 2022a). Since Amazon does not disclose its parcel volume, the average value of the other three companies' peak season factors is applied. Table 4.2 shows the peak factors and their corresponding peak volume. This is used to identify two demand scenarios: an Average Daily Volume and a Peak Daily Volume based on the peak season. The total is approximately 10.4% higher at a predicted 2.11M daily residential parcels during the peak season for 2021. It is important to note that these are residential parcel deliveries only, so low volumes for places like airports or other terminals are expected.

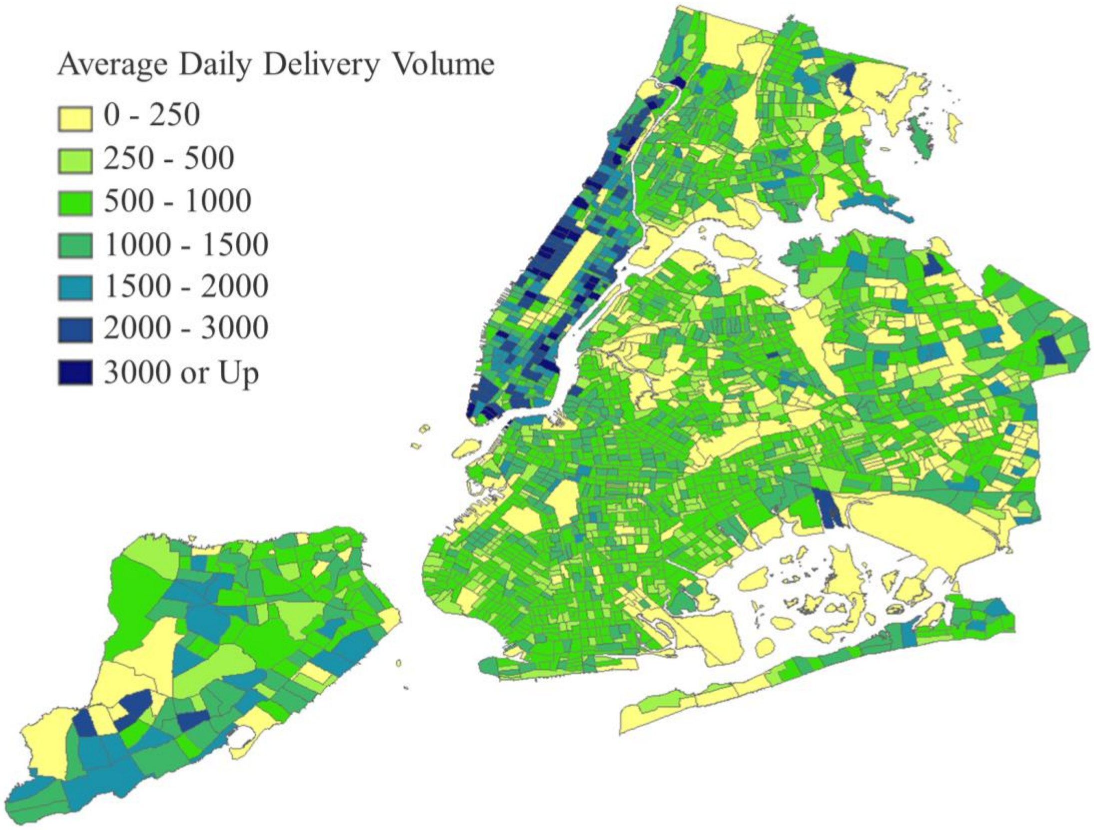


Figure 4.4 Average daily volume by census tract.

Table 4.2 Peak season factor and peak daily volume from financial disclosure reports

	USPS	UPS	FedEx	Amazon	Total
Peak Factor	1.065	1.173	1.057	1.122	1.104
Peak Delivery Volume	651,318	560,443	404,016	493,190	2,108,966

The location information of the distribution centers was collected in July 2022. Any facilities constructed later than that are not captured. In addition, we do not include the facilities run by the 3rd party logistics partners cooperating with Amazon due to limited availability of information. There are 9 UPS centers (UPS, 2022b), 8 FedEx centers (FedEx, 2022b), and 5 Amazon centers

(Wulfraat, 2020) in NYC. For USPS, only the destination delivery units (DDU) are included in this study. In total, there are 304 DDUs in the NYC area (USPS, 2022b). To match the unique characteristics of NYC's road network, we restrict the census tracts in Manhattan to only be served by centers either in Manhattan or Bronx, and census tracts in Brooklyn and Queens cannot be served by those centers because of the operational difficulties of crossing the East River. The NYC road network obtained from OpenStreetMap (OSM) on June 5, 2022, is used to generate the shortest path distances for assigning service areas and for sampling distances for the CVRP solver below. Service areas are assigned to each center accordingly using these distances. Adjustment is made to further match each center's assigned volume and its actual size. Figure 4.5 shows the final assignment result for each company.

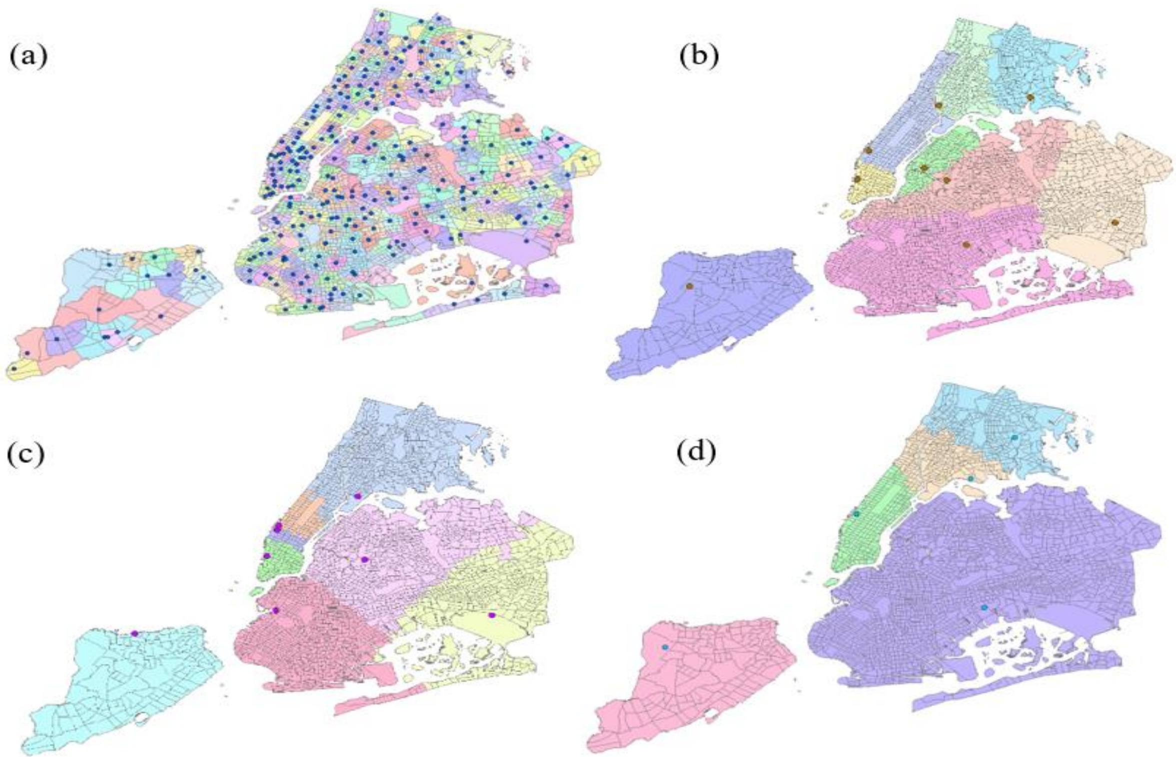


Figure 4.5 Service Area of (a) USPS, (b) UPS, (c) FedEx, and (d) Amazon defined by census tract.

To calibrate k in Eq. (4.2), we first solve CVRP on the census tract level to obtain samples for fitting. Truck capacity is set to be uniformly 300 parcels (Komanoff, 2021). As studies have shown, CA models become more effective with higher stop density (Daganzo, 1984). Therefore, only census tracts with more than 200 delivery parcels are selected to ensure fitting accuracy. Based on such conditions, we randomly select 50 census tracts in Manhattan, 100 census tracts in Brooklyn and Queens, 40 census tracts in Bronx, and 30 census tracts in Staten Island. For all selected census tracts, we combine the stop information, the distance matrices generated from OSM, and the defined truck capacity to formulate CVRPs. The problems are solved using Google OR-Tools (Perron and Furnon, 2022). The Path Cheapest Arc algorithm, which is equivalent to Nearest Neighbor (Johnson and McGeoch, 1997), is selected to generate initial results. The Guided Local Search (GLS) is selected to find final solutions using previously generated results. Studies have found that combined with simple heuristics algorithms, GLS can find optimal or close-to-optimal solutions when solving small to medium size routing problems (Voudouris and Tsang, 1999). Therefore, the previously obtained solutions can be used as reasonable fitting samples to calibrate the CA coefficient. As mentioned in Section 3.3, we obtain the NYC road network speed data from Uber Movement (2022) to generate the shortest path matrix and calculate the sample route lengths. The shortest paths are calculated based on the NYC morning peak travel speed, which is defined by the average speed from 6 am to 10 am during workdays in the week of March 16th, 2019. The selected days reflect typical workday traffic before the pandemic. The traffic restriction in the selected period is the most stringent, which further limits the flexibility of route selections for parcel service companies, making the generated tour closer to real-world operations. For the final CA model, the unit of r is in miles, and the unit of A is in square miles.

Table 4.3 shows the calibration result and the corresponding model accuracy. We calibrate 4 distinct values of k_i to capture the unique network characteristics in each region. The value of k_i corresponds to the network density in each region, with Manhattan having the highest density and Staten Island having the lowest. To put these values in perspective, known theoretical values of k are 0.57 for Euclidean distance (Daganzo, 1984) and 0.97 for Manhattan distance (Jaillet, 1988). To measure the model accuracy, R^2 is calculated using Eq. (4.3).

$$R^2 = 1 - (V' - V)^2/\left(V' - \underline{V}\right)^2 \tag{4.3}$$

where V' is the model distance, V is the sample distance, and $\underline{V}$ is the average sample distance. The selected CA model shows a high level of accuracy in all four regions (BK and QN are combined) with R^2 all being higher than 0.98. The results demonstrate the capability of the CA model to accurately represent tour lengths of CVRP decisions in real-world applications even for complicated road networks.

Table 4.3 Estimated coefficient and model approximation quality

Region	Sample Size	k_i	R-squared
MN	50	0.708	0.995
BX	40	0.894	0.981
BK & QN	100	0.856	0.993
SI	30	0.993	0.983

Census tracts are aggregated to Neighborhood Tabulation Areas (NTA) for VMT estimation. In total, there are 262 NTAs and each NTA has eight to nine census tracts. The geographic and demographic characteristics are relatively uniform within each NTA, which makes the NTA a suitable unit to apply the CA model. Since there are more USPS DDUs than NTA, NTAs are only used for the other three companies. Instead, we aggregate census tracts served to each DDU for USPS, showing a more decentralized network of its operation. To calculate the average daily VMT in each service area, we set r in Eq. (4.2) to be the trip distance between the center and the service area centroid and set m to be the roundup integer of $n/300$.

Table 4.4 shows the estimated daily parcel service VMT. According to Futurism (2017), there were around 2200 trucks owned by UPS. Since we are only considering residential parcels, which is roughly 80% of the total parcel volume, our estimated number of 1683 UPS trucks is very close to the 1760 trucks used for residential delivery by UPS.

Table 4.4 Estimated daily parcel service VMT

Company	Average Day Truck Trips	Average Day VMT	Average VMKT per Truck Trip	Average Day MTCE Emissions	Peak Day Truck Trip	Peak Day VMT	Peak Day VMT per Truck Trip	Peak Day MTCE Emissions
USPS	2,172	4,805	2.21	1.12	2,309	5,151	2.23	1.21
UPS	1,686	18,482	10.96	4.33	2,080	22,790	10.95	5.33
FedEx	1,374	15,881	11.56	3.72	1,389	16,029	11.54	3.75
Amazon	1552	22,268	14.35	5.21	1736	24,865	14.32	5.82
Total	7653	61,436	8.03	14.38	7514	68,836	9.16	16.11

The daily total distance generated by parcel service in NYC is estimated to be 61.4 thousand vehicle-miles (veh-mi) each average day, and the number becomes 68.8 thousand veh-mi during a peak season day, an increase of 12% in VMT corresponding to the 10.4% demand increase.

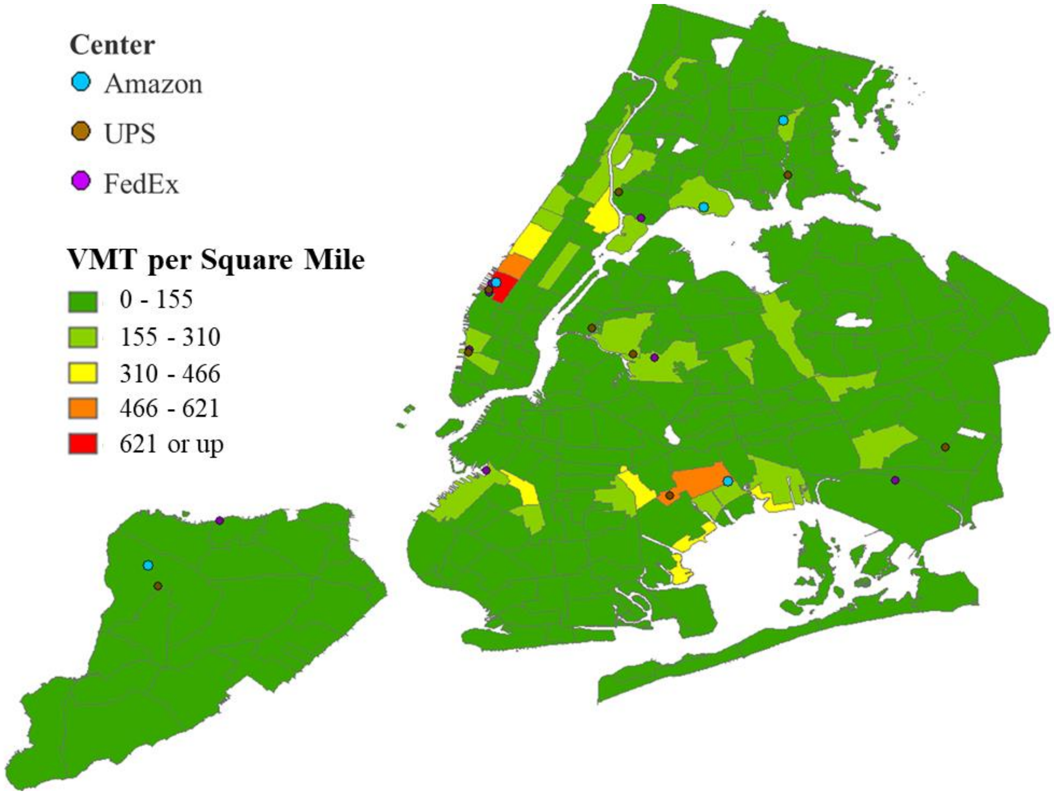


Figure 4.6 Average daily total VMT per square mile by NTA.

NYCDOTNYC DOT regulates that all trucks must turn off their engines while dwelling, which prevents additional emissions. Therefore, only the emission generated from on-road operations needs to be considered. A typical light truck is estimated to produce 234 grams of carbon dioxide per mile (EPA, 2021). By applying the emission factor, 14.38 metric tons of carbon equivalent (MTCE) emissions are estimated to be emitted from average daily parcel service operation, and during peak season it becomes 16.11 metric tons per day, as shown in Table 4.4. Interestingly, while Amazon only represents 23% of the market share in parcel demand and USPS has 32%, the nature of the denser depot design for USPS and routing results in a significantly higher MTCE for Amazon for these local deliveries, almost five times more. Granted, there is also an amount of VMT for transporting the parcels to those USPS facilities that are ignored here.

Figure 4.6 shows the average day VMT density aggregated by NTA. Most NTAs with the highest levels of VMT density are located in areas nearby big distribution centers or areas with high population density. Notably, neighborhoods in west Manhattan and southeast Brooklyn are impacted the most due to the clustering of distribution centers.

Impact of COVID-19 on GHG emissions from parcel deliveries

The COVID-19 pandemic accelerates the growth of e-commerce and delivery services (US Department of Commerce, 2022). To illustrate the environmental impact caused by such service increase, we use the 2019 report released by USPS (USPS, 2020) to estimate the 2019 VMT and associated GHG emissions. Annual GHG emission is estimated by aggregating the results on both average daily operation and peak season operation. The full 4th quarter is considered to be the peak season. Therefore, the peak volume is applied to each day of the 13 weeks of operation while the remaining 39 weeks assume average day volumes. Five workday schedule is used for the whole year. In 2019, the average daily VMT is estimated to be 44.36 vehicle-miles and 50.07 vehicle-miles for peak season.

The annual GHG before and after the pandemic generated by parcel services are 2787 and 3851 MTCE, respectively. The GHG emission produced from parcel services is estimated to increase by 38.2%, or by 1064.33 MTCE, partially due to the COVID-19 pandemic (there are other factors and trends in play as well so we cannot assume all the increase is due to COVID). For context, reducing emissions by 1 MTCE is equivalent to saving enough energy to power an average American home for 6 months (EPA, 2016), so the pandemic's impact on parcel deliveries may attribute up to additional GHG emissions from powering 532 homes for a whole year. Therefore, more measures are needed to mitigate such environmental impacts in the future.

Electric Cargo Bike Substitution for All Bike Lane-Eligible Depots

To mitigate the negative impact of parcel services demonstrated in the previous section, other delivery alternatives have been explored in practice. Among all options, the electric cargo bike is a viable delivery alternative to replace delivery vans in urban areas. Cargo bikes do not produce GHG emissions during operation. They can be used to provide access to the metaphorical "last 50 feet" of deliveries, which are typically operationally costly for parcel delivery trucks in which the driver would have to haul the parcels on foot. Cargo bikes can also take advantage of microhubs which can be placed at intermediate locations to distribute parcels more efficiently at lower costs.

Currently, most cargo bikes are deployed in Asian and European cities. With NYC having more than 1200 miles (1931 km) of bike lanes (NYC DOT, 2020) while having the worst traffic condition in the US (Inrix, 2021), deploying cargo bikes in NYC would be a good example of showing its potential in the US. There are already existing pilots using cargo bikes in NYC (NYC DOT, 2021). In this study, we explore the feasibility of deploying cargo bikes based on current infrastructure and how cargo bikes could reduce parcel service VMT in corresponding areas, using the model to systematically identify the best alternative deployments. Detailed operation options such as adding additional facilities like microhubs dedicated to cargo bikes are not considered. While cargo bikes may have lower impedances in delivering the last 50 ft and through the use of microhubs, the focus of this study is not on a comparison of operational costs between truck and cargo bikes (see Sheth et al., 2019, instead). Instead, it is only looking at the potential of cargo bikes in replacing truck VMT and GHG emissions. As such, the operational savings of cargo bikes in the last 50 ft or via microhubs are not the focus of this analysis. Readers interested in the design of microhubs for cargo bikes can refer to Rudolph et al. (2018), Katsela et al. (2022), and Rudolph et al. (2022) instead.

Figure 4.7 UPS quad-cycle prototype. Source: UPS (2022c).

We use the UPS quad-cycle prototype shown in Figure 4.7 as the primary cargo bike type. According to UPS (2022c), the quad-cycle is 84 centimeters wide which meets the dimensional requirement of legally using bike lanes. The previous tricycle prototype tested by UPS has a capacity of 400 pounds (Electrek, 2018) and can load 40 parcels (Electricbikereport, 2018). With the quad-cycle having a capacity of 462 pounds, roughly 45 parcels can be loaded inside its compartment with the same average package weight as 10 pounds. The quad-cycle has a top speed of 15 miles per hour (Reuters, 2022). According to Dybdalen and Ryeng (2022), the average speed of a cargo bike is 10 miles per hour in real-world operation, which is adopted in our analysis.

We use the total bike lane length divided by the total road length in each service area unit to get the bike lane percentage, and only areas with more than 10% bike lane percentage are considered eligible for cargo bike operation. In this study, cargo bikes are assumed to only provide delivery service and the following analysis is based on average daily operation. According to an e-commerce shopper survey conducted by International Post Corporation (2022), more than 50% of global cross-border parcels are lighter than 2.2 lbs. We expect that the US domestic e-commerce market will have a higher weight per package. Since the average cargo bike delivery package would weigh 10 pounds (4.54 kg), we use a more conservative assumption that up to 50% of all parcels can be handled by electric cargo bikes. Based on this assumption, we divide the delivery stops into three categories. Stops with delivery volumes higher than 45 are excluded from receiving cargo bike service. If a USPS stop receives less than 7 parcels, all parcels are assumed to be delivered by a cargo bike, while half of the delivery volumes are handled by cargo bikes for all other eligible stops. This number becomes 6, 5, and 6 for UPS, FedEx, and Amazon respectively. As such, the aggregated delivery volume that is eligible for cargo bike services is roughly half of each company's total delivery volume.

Studies have found that bike lanes can significantly reduce bicycle crashes (Morrison et al, 2019; Cai et al, 2021), especially along major roadways and at larger intersections. Therefore, the tours from distribution centers to service areas are restricted to only using bike lanes in this study. Such restriction is relaxed when conducting local deliveries because of the reduced risk of bicycle accidents on local roads (Cicchino et al, 2020). In this analysis, we assume that there is no restriction on electric cargo bike usage on bike lanes. If no bike path could be found from a center to a service area, the area is excluded from the cargo bike operation. While technically cargo bikes would be allowed to use any street, we believe this assumption is valid because their exclusive use of bike lanes would likely be safer and more efficient. Figure 4.8 shows the eligible service areas having viable connections to their service centers (represented as dots) through the bike lane network based on current bike infrastructure (NYC DOT, 2022). All Manhattan neighborhoods and eligible Bronx areas could receive cargo bike services provided by UPS. FedEx can provide cargo bike services to all the eligible areas in Bronx and upper Manhattan, and Amazon can use cargo bikes to service most Manhattan neighborhoods. With USPS having its DDUs scattered throughout the city, the accessible areas are confined to a smaller scale. Interestingly, part of Staten Island could receive cargo bike service through USPS, showing the advantage of such a decentralized distribution network.

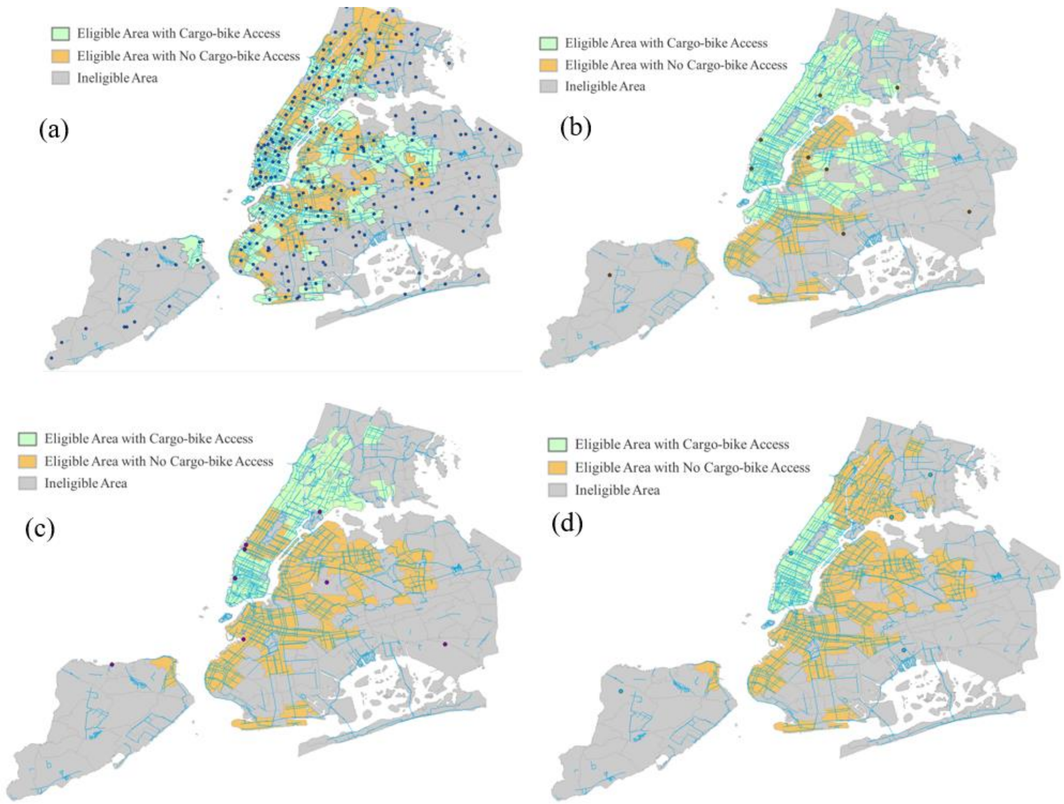


Figure 4.8 Bike-accessible areas of (a) USPS, (b) UPS, (c) FedEx, and (d) Amazon.

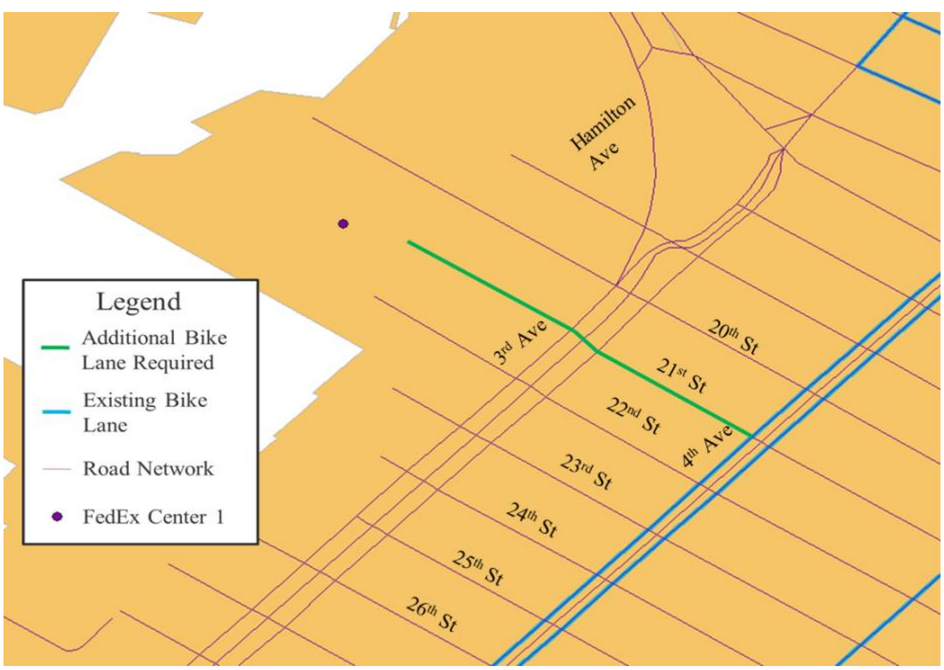


Figure 4.9 Disconnection between FedEx Brooklyn Center and bike lane network.

The cause of the areas being excluded is because of the disconnection between the centers and the bike lane network. Except for centers in Staten Island, other centers could gain direct bike lane access by adding only a few hundred meters of bike lanes. Such a case is illustrated by using the FedEx Brooklyn Center as an example, which is shown in Figure 4.9.

Table 4.5 shows the bike lane length required to connect centers and the average daily impact of adding those bike lanes. The centers in Staten Island are excluded due to the sparse bike lane network in the area. For USPS, the results are aggregated to the borough level. Areas in Manhattan, Brooklyn, and Queens can have significantly more cargo bike access by adding more bike lanes connecting the centers. Connecting FedEx centers to the bike lane network in Brooklyn and Manhattan, as well as connecting the Amazon Brooklyn center are the most cost-effective in adding cargo bike operation.

New VMT is calculated by eliminating the volumes and stops served by cargo bikes and applying the fitted CA model again.

Table 4.6 shows the VMT reduction based on two scenarios, one with cargo bikes being operated only in the currently bike-accessible areas, while the other one has all centers gaining full bike lane access except centers in Staten Island. All results are based on average daily operation. With the current bike infrastructure, 10.69% of daily VMT could be reduced. All eligible centers can be connected to the bike land network by investing in an additional 1.20, 0.85, 1.80, and 13.40 miles of additional bike lanes for depots at FedEx, UPS, Amazon, and USPS, respectively, for a total of 17.2 additional miles, which is 1.4% of the 1200 existing miles of bike lanes in NYC. Doing so would improve the VMT reduction from 10.69% to 26.41%, resulting in a spatial distribution of VMT reduction shown in Figure 4.10. Clearly, shifting deliveries to cargo bikes can reduce local GHG emissions in the western parts of Manhattan along with East Harlem and the neighborhoods stretching between Sunset Park in western Brooklyn to Cypress Hills between Brooklyn and Queens, including Bushwick to Maspeth. Many of these areas outside of Manhattan are lower-income neighborhoods more susceptible to impacts of GHG emissions so cargo bikes targeted for deliveries in these areas are highly favorable for environmental justice. Some parks show VMT reductions because they are traversed by highways and bike lanes meaning that a reduction in vehicles will show a reduction in travel on the links through those areas.

Table 4.5 Required bike lane length and average added bike service

Company	Center	Borough	Added Daily Bike Volume	Bike Lane Required (feet)	Added Daily Bike Volume per Feet
FedEx	1	BK	27,317	1,611.55	182.45
	2	MN	16,151	910.43	190.94
	3	BK & QN	31,340	3,808.40	88.58
UPS	1	BK	29,335	3,383.53	93.31
	2	BK & QN	9,940	1,093.50	97.83
Amazon	1	BK	69,971	4,075.79	184.81
	2	MN & BX	23,688	2,698.16	94.49
	3	BX	8,853	2,673.88	35.63
USPS		MN	36,810	15,899.61	24.93
		BX	18,465	12,772.97	15.55
		BK	37,153	21,143.70	18.90
		QN	14,888	20,908.47	7.68

Table 4.6 Vehicular Parcel Volume and VMT Reduction with Cargo Bike Deployment with and without Added Bike Lanes

	Current Bike-Accessible Area Served		All Eligible Area Served		
Company	Vehicular Parcel Volume Reduction (% reduced)	Daily VMT Reduction (% reduced)	Vehicular Parcel Volume Reduction (% reduced)	Daily VMT Reduction (% reduced)	Added Bike Lanes (miles) (% increase)
USPS	104,460 (17.1%)	660 (13.7%)	211,776 (34.7%)	1,305 (27.2%)	13.40 (1.1%)
UPS	118,860 (24.9%)	3,419 (18.5%)	158,135 (33.1%)	4,831 (26.1%)	0.85 (0.07%)
FedEx	52,054 (13.6%)	1,378 (8.7%)	126,862 (33.2%)	3,316 (20.9%)	1.20 (0.10%)
Amazon	44,903 (10.21%)	1,110 (5.0%)	147,415 (33.5%)	6,777 (30.4%)	1.80 (0.15%)
Total	320,277 (16.76%)	6,566 (10.69%)	644,188 (33.71%)	16,228 (26.41%)	17.23 (1.4%)

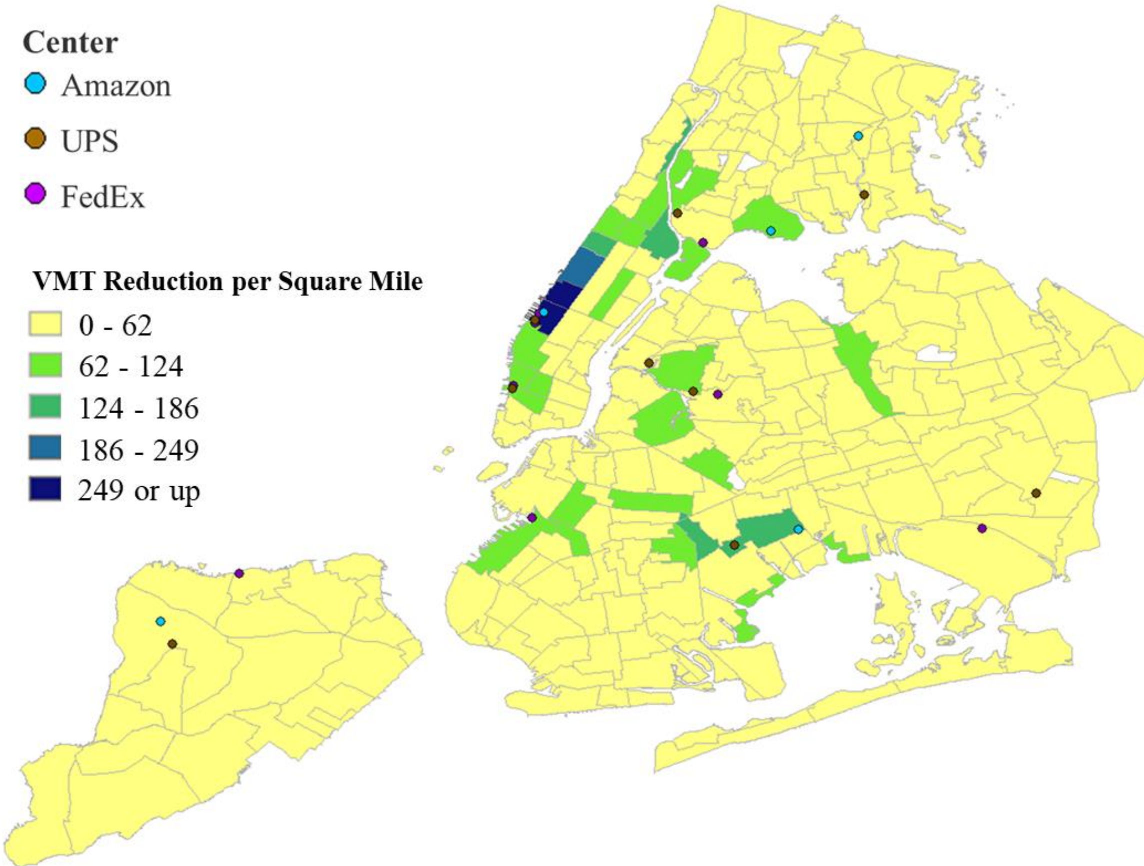


Figure 4.10 Estimated average daily VMT density reduction after cargo bike deployment for all eligible areas.

In terms of GHG emissions, investing in the additional 17.23 miles of bike lanes could unlock additional 9662 VMT savings, which translates to 2.26 MTCE emissions reduction. A breakdown of the savings by the company suggests under the current bike lane infrastructure, having UPS switch to cargo bikes where eligible would benefit the city the most. If the companies have to be prioritized which depots to connect bike lanes first, enabling Amazon's depots with bike lane investments is most urgent as 1.80 miles of added bike lanes can change the daily VMT reduction from 5% up to 30.4% savings.

4.4 Conclusion

Parcel delivery service plays a crucial role in the e-commerce industry. With e-commerce experiencing significant growth in the past decade, parcel delivery operations have expanded significantly to meet the demand. However, little work has been done regarding the quantification of impacts from parcel service at a citywide level. In this study, we build a framework to estimate the impact of residential parcel delivery services based on publicly available data. Residential parcel service demand is initially generated based on census, land use, and postal service information, and proper adjustments are made afterward. By solving CVRP on smaller areas using the generated demand, the coefficients of a CA model are calibrated based on the sampled results. By applying the calibrated model, both neighborhood-level and citywide VMT and associated greenhouse gas emissions can be estimated.

The model is applied to the whole New York City area. A high level of fitting accuracy is demonstrated when fitting the CA model, showing its capability in estimating the tour length when less detailed stop information is available, even if it is based on a complicated road network. Total VMT is estimated using the fitted CA model, and the local impact of parcel services is also investigated based on the result. The model is then applied to evaluate the impact of the COVID-19 pandemic on parcel deliveries and to investigate priorities for electric cargo bike adoption by borough and by company. The following insights are made based on 50% of existing and available parcels switching to cargo bike:

- 61.44 thousand vehicle-miles (14.38 MTCE) is estimated to be generated from daily parcel service during an average day in 2021.
- Peak season VMT increased by 12% to 68.84 thousand per day while demand increased only 10.4%, due to the company distribution of the demand increase.
- VMT density due to residential parcel deliveries is most concentrated in upper west side Manhattan and between Brooklyn and Queens near the JFK airport.
- COVID-19 attributed to up to an additional 1064.33 MTCE in annual GHG emissions due to increased parcel deliveries in NYC, which is equivalent to emissions from powering 532 homes for a year.
- Existing bike lane infrastructure can support a substitution of up to 16.76% of parcel deliveries to be made by cargo bike, which would reduce VMT by 10.69%; most of this decrease would be drawn from UPS (18.5% VMT reduction) and it should be targeted for electric cargo bike switching.

- Investing in 17.23 miles (1.4% of current bike lane infrastructure) of additional bike lanes could increase the potential parcel delivery substitution from 16.76% up to 33.71% (which saves an additional 2.26 MTCE per day), which would increase VMT reductions from 10.69% up to 26.41%. The largest gain in VMT reduction due to these bike lane investments comes from Amazon, which goes from a 5.0% VMT reduction to a 30.4% reduction due to 1.80 miles of bike lane investments.
- Spatial analysis reveals that many lower income neighborhoods stand to gain from cargo bike strategies, including Harlem and areas stretching between Sunset Park to Cypress Hills and from Bushwick to Maspeth.

Our result shows the importance of the infrastructure related to parcel service. More distribution centers are needed to fulfill the growing needs of e-commerce activities while limiting the impact of parcel service operations. A more complete bike lane network is needed to accommodate the future expansion of cargo bike operation, and more effort is required to improve the bike accessibility of distribution centers.

The developed framework can be further improved when more detailed parcel-related information is available, especially delivery information regarding office and commercial addresses. The model can be used to evaluate different service changes including the impact of added distribution centers and other delivery alternatives. The model does not consider the time window limitations, which could underestimate the generated VMT.

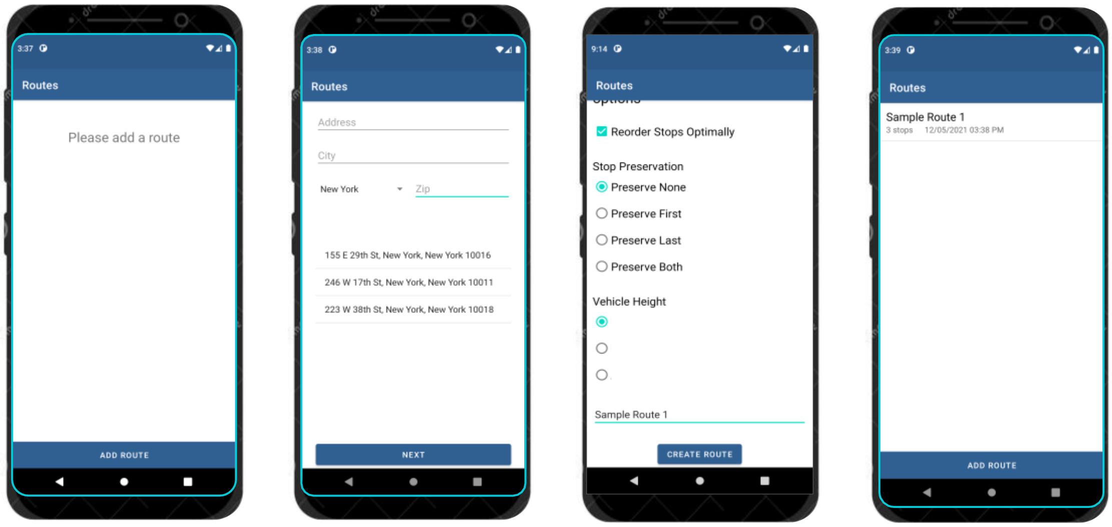
5 Routing App

5.1 Development

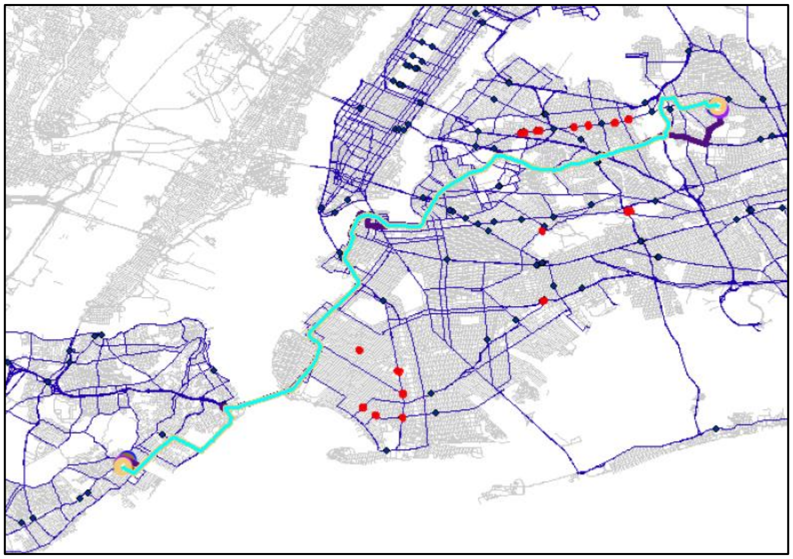
Originally designated as a data dashboard, the idea for a truck routing app grew from conversations with NYC DOT about the nature of their data and their needs. Since the truck data they offered was updated no more than yearly, a dashboard did not seem to be the right conceptual fit because they work best to show the dynamic variance of key performance indicators on a daily, weekly, or monthly basis. However, the staff indicated that a problem they were looking to solve was the lack of digital, dynamic, and publicly available routing for trucks through the city. Their current practice is a mixture of the distribution of a pdf which is updated every 3-5 years and a telephone bank which drivers could call to speak with experts who would direct them turn-by-turn to their destination. Services like Google Maps or Waze fail to meet this need because they lack truck specific information. Those apps assume a standard passenger vehicle which is not subject to the same height, weight, or route restrictions as trucks are. NYC DOT makes available the truck route data in shapefiles, but to our knowledge, no one has yet built a freely available routing tool on top of them. Private services exist which perform this task, but NYC DOT would like to provide the tool for free, to be able to integrate it with their other digital services to maximize benefits to users, and to analyze the data collected to make further improvements to the truck ecosystem in New York City. Therefore, an app-based route navigator with New York City specific information about truck restrictions emerged as a solution. NYC DOT would provide necessary data and design guidance, and the BUILT lab would create the product.

Using open-source tools, a 45km radius around New York City was extracted from OpenStreetMap as a shapefile for manipulation in ArcGIS. The truck route network was added to be able to properly prioritize or ban certain links. Truck turn restrictions were considered, but technical difficulties prevented implementation. Layered on top of that were the locations that NYC DOT identified as height restricted. Using the Python ArcGIS APIs, a script was written which could take any reasonable number of origins and destinations and provide a route to connect them which satisfied the input parameters, such as an ability to reorder the stops optimally, height restrictions, whether the route needs to return to the origin, and others. Refer to Figure 2.5 c and d for an example of how our routing tool outperforms a standard Google maps search.

To make the backend routing accessible, a front end was built in Kotlin which would prompt the user for the input parameters (Figure 5.1a), pass them to the server hosting the routing script, and then receive and display the resulting solution (Figure 5.1b). Figure 5.1b also displays as dots some of the locations with routing restrictions which are due to tunnels, underpasses, elevated subway lines, bridge structures, etc. To best present the solution visually to the user, a hackathon was implemented.



(a)



(b)

Figure 5.1 (a) App front end; (b) a route being displayed to the user.

5.2 Hackathon

Planning for the C2SMART Smart Trucking Virtual Hackathon began in earnest in Spring 2022. By utilizing administrative resources provided by C2SMART, the BUILT lab was able to lay out and develop a plan in conjunction with NYC DOT to host an event which would provide interested participants the opportunity to contribute to this project and demonstrate their skills. Two promotional videos were produced by the C2SMART lab to generate interest in the event. Figure 5.2 is a screenshot from one of the videos.

Figure 5.2 Screenshot from a Hackathon promotional video.

Logistic considerations dictated that the event would be virtual, have a hybrid kickoff during a session on October 15th at TransportationCamp NYC 2022, and run until the following Sunday. The goal was to produce a visualizer that the driver would use while the truck was in motion. The judges (Kaan Ozbay, Seth Contreras, Eric Richard, Joaquim Rabinovitch, Zach Miller, and Maddalena Romano) represented various stakeholder groups in the New York City trucking ecosystem. At the virtual Closing Ceremony, the judges evaluated the submissions with the criteria of ease of use, functionality, features, accessibility, style, additional features, and product differentiation. The winning submission from Team Braveniuniu comprised of Chuhan Yang, Jiayun Sun, and Liang Niu makes use of various python libraries to render a grayscale 3D model of the built environment around the driver providing them with a more realistic depiction of their route as they traverse the city. Their contribution is demonstrated in Figure 5.3. At both TransportationCamp and the Closing Ceremony, valuable discussions provided insight into various stakeholder groups who were interested in the product. These conversations will be used to develop a vision for Phase 2 of the Truck Routing App along with implementation challenges and avenues for collaboration.

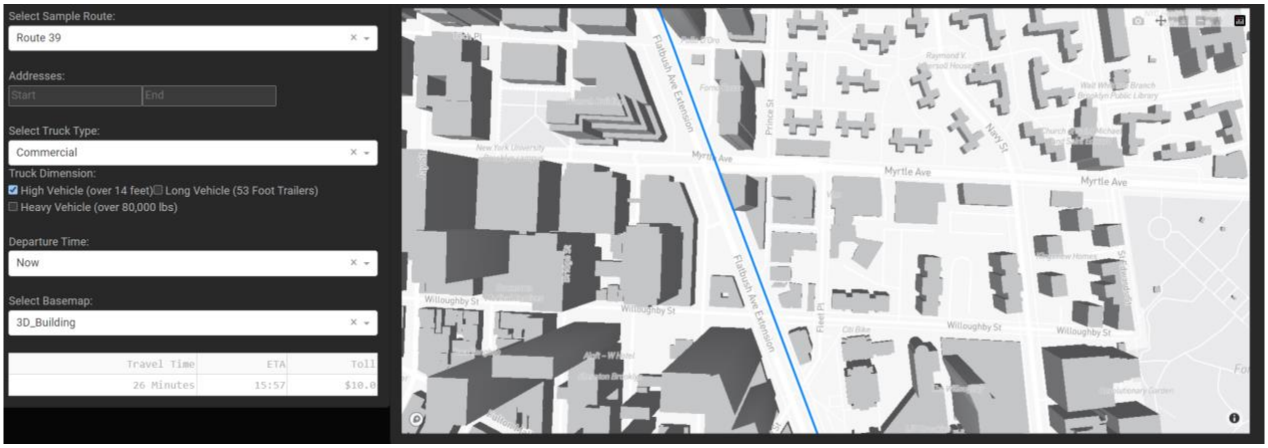


Figure 5.3 Hackathon contribution.

5.3 Implementation

Phase 1 of this project is completed when NYC DOT takes ownership of the app, which includes training. Importantly, it has been designed with them in mind. By using the ESRI ArcGIS platform, they will be able to edit the network without needing knowledge of the code itself. ArcGIS Pro is easy to use and well supported which is why it was chosen over an opensource platform. Network editing needs to have a low barrier to entry because of its frequency and the power resting in the dynamicity. Being able to add temporary restriction layers for a short term such as a parade or a longer event such as construction allows NYC DOT to place more accurate information into the hands of the truck drivers in the city. If the situation called for it, the truck routes themselves or the time-of-day traffic fluctuations could all be altered through the user interface.

Another benefit to the NYC DOT would be that since the data would flow across their servers, they would be able to analyze it to learn about truck patterns. Being a responsible entity, they would practice good data governance by anonymizing and securing the data. Getting origin-destination and route choice data for trucks traveling through New York City would be incredibly valuable. Currently, very little of this type of data exists, so it must be estimated. Even small amounts of collected data here would be very useful in validating the larger scale estimations. This project also works towards accomplishing the goals laid out in the Delivering New York, Smart Truck Management Plan: E6, SR1, SR7, SR9, PK4, and PK5.

Finally, the intention is not that this project is handed off and shelved. Initial conversations with members of several different sectors of the trucking community have shown that there is enthusiasm for this tool. We are planning phase 2 of this project to manifest the potential here, and the continued support of the community will be essential for securing the resources needed to make that happen. Because the app has access to the data which fuels the other half of this project, there is potential to use it in a variety of practical ways. For example, the app can estimate the CO_2 emissions of the truck and prescribe to the driver a cleaner route.

A potential idea is to develop a pilot program where a select number of drivers test the application. NYU would collect data about their routing behavior, which is valuable for future research to build with, the driver would receive the benefit of truck specific routing, and NYC DOT would be able to evaluate how to grow and scale the app for larger implementation.

6 Summary of research outputs and tech transfer

6.1 Summary of Findings and Recommendations

Freight Truck Tours

- 333,843 trucks were assigned on daily basis producing 2,573,441 trips
- The total estimated daily VHT in New York City is 2.49M veh-hours with 0.65M veh-hours of that being service time.
- The total estimated daily emission of CO_2 is 5640 metric tons of carbon equivalent (MTCE).
- At the borough level, peak service time density, and therefore likely truck parking issues, occurs in Brooklyn from 7-10pm. Manhattan and Brooklyn both experience service time densities greater than 130 hours per square mile in the Midday, PM, and Nighttime blocks.
- NAICS Industries 444, 441, and 425 contribute the most average daily CO2 Emissions and VMT
- If vehicle capacity was shrunk by 20%, VHT and CO2 emissions would increase to 3.12M veh-hours and 7.05 MTCE, but damage to both the Manhattan Bridge and Queens Midtown Tunnel from truck weight in both directions would fall between 45 and 47%

Parcel Delivery

- 61.44 thousand vehicle-miles (14.38 MTCE) is estimated to be generated from daily parcel service during an average day in 2021.
- Peak season VMT increased by 12% to 68.84 thousand per day while demand increased only 10.4%, due to the company distribution of the demand increase.
- VMT density due to residential parcel deliveries is most concentrated in Hell's Kitchen in Manhattan extending up the Upper West side and in New Lots in Brooklyn near the Queens boundary.
- COVID-19 attributed to up to an additional 1064.33 MTCE in annual GHG emissions due to increased parcel deliveries in NYC, which is equivalent to emissions from powering 532 homes for a year.

- Existing bike lane infrastructure can support a substitution of up to 16.76% of parcel deliveries to be made by cargo bike, which would reduce VMT by 10.69%; most of this decrease would be drawn from UPS (18.5% VMT reduction) and it should be targeted for electric cargo bike switching.

- Investing in 17.23 miles (1.4% of current bike lane infrastructure) of additional bike lanes could increase the potential parcel delivery substitution from 16.76% up to 33.71% (which saves an additional 2.26 MTCE per day), which would increase VMT reductions from 10.69% up to 26.41%. The largest gain in VMT reduction due to these bike lane investments comes from Amazon, which goes from a 5.0% VMT reduction to a 30.4% reduction due to 1.80 miles of bike lane investments.

- Spatial analysis reveals that many lower income neighborhoods stand to gain from cargo bike strategies, including Harlem and areas stretching between Sunset Park to Cypress Hills and from Bushwick to Maspeth

6.2 Shortcomings

Freight Truck Tours

- Some new, large warehouse locations have come online recently which could affect the location of the designated warehouse zones. Additionally, warehouse zones were selected based upon employment data instead of FTG, so large numbers of smaller warehouses would be selected over fewer large, efficient, and automated warehouses. Given the relatively small number of trucks taking these trips though, this is not believed to meaningfully impact the results.
- The primary weakness of the work is the overestimation of trucks between Manhattan and Brooklyn as well as between Manhattan and Queens. Future efforts could look to improve these crossings by adding an additional parameter to the distribution equation which could increase the penalty for these crossings to better mirror the real-world penalty drivers face from congestion on these bridges.

Parcel Delivery

- A small portion of packages are delivered on weekends, especially near the holiday season. Data from companies about a full week's distribution could increase the accuracy of the conclusions.

- Similar to above, new warehouses such as the Amazon Red Hook facility have recently come online. Future efforts will update the active locations.

- Future efforts could consider the impacts of the NYC DOT Microhubs Pilot Program (NYC DOT 2023).

6.3 Research outputs

As an outcome of this research project, several research outputs were produced along with dissemination. This section summarizes those results.

Table 6.1 Summary of research outputs

Output type	Description	Link/source
Paper	Yang, H., Landes, H., Chow, J.Y.J., 2023. A large-scale analytical residential parcel delivery model with cargo bike substitution in New York City. Proc. 102nd Annual Meeting of the TRB, Washington, DC.	https://annualmeeting.mytrb.org/OnlineProgramArchive/Browse?ConferenceID=999
Paper	Yang, H., Chow, J.Y.J., 2023. A large-scale analytical residential parcel delivery model with cargo bike substitution. 12th Intl Conference on City Logistics, Bordeaux, France.	
Paper	Yang, H., Landes, H., Chow, J.Y.J., A large-scale analytical residential parcel delivery model with cargo bike substitution. IJTST, in press.	https://www.sciencedirect.com/science/article/pii/S2046043023000692
Paper	Davis, H., Landes, H., Namdarpour, F., Yang, H., Chow, J.Y.J., Tour-Based Entropy Maximization Algorithm for Constructing a Truck Synthetic Population from Public Data. In preparation.	https://zenodo.org/record/5517983#.YUozC7hKg2w
Data	Estimation of Freight Trips Produced and Attracted in NYC	https://c2smart.engineering.nyu.edu/c2smart-data-dashboard/#daily-freight-trip-in-new-york-city

Data	NYC truck tour flows	https://zenodo.org/record/7926986
Data	Parcel VKT	https://zenodo.org/record/7927126
Code	Truck tour distribution algorithm	https://github.com/BUILTNYU/Iterative-Balancing-for-Entropy-Maximization
Code	Truck routing app	https://github.com/BUILTNYU/Frieght-Truck-Routing-App
Hackathon	C2SMART Virtual Hackathon	https://c2smart.engineering.nyu.edu/smart-trucking-hackathon/ https://www.youtube.com/watch?v=MB8sHWRWpY0
Presentation	"NYC FREIGHT: DATA ANALYSIS TO BUILD A SYNTHETIC POPULATION", ITS-NY Yearly Meeting, Saratoga, NY, June 16, 2022	https://www.abstractsonline.com/pp8/?__hstc=194041586.9ad974a5999e3a9e202e99f21eba80a4.1598648681888.1630698234610.1630762393840.57&__hssc=194041586.1.1630762393840&__hsfp=2759698710&hsCtaTracking=76a3f7ff-51d5-4ec3-9afc-6681cc8dc243%7C1799fe6c-2007-47fc-9053-bd9abe03f130#!/10390/presentation/6213
Presentation	"NYC FREIGHT: DATA ANALYSIS TO BUILD A SYNTHETIC POPULATION", WCTR Virtual Meeting 2022 - Freight Modelling Session, Virutal, July 29, 2022	
Presentation	"Inverse optimization applications in data-constrained freight systems", TU Delft Freight	

	Lab (under Lori Tavasszy), Delft, The Netherlands, Apr 11, 2023	
Presentation	"Parcel and truck delivery modeling research for NYC", workshop at NYCDOT, NYC, May 2, 2023	
Presentation	"Building a Synthetic Freight Population from Open Data in NYC", ITS-NY Yearly Meeting, Saratoga, NY, June 15, 2023	
Presentation	"Building a Synthetic Freight Population from Open Data in NYC", webinar from C2SMART, June 13, 2023	https://www.youtube.com/watch?v=-IIHnO2En-s

Broader Impacts

In addition to the direct dissemination and technology transfer, this research has led to a number of broader impacts.

Student Training and involvement:

Through the Summer Undergraduate Research Program, Jack Gazard was trained. In addition to the main research team, we participated in the ARISE program to expose K-12 STEM students to this research and projects from our lab. Materials from this project have been included in Dr. Chow's undergraduate course, for example, the use of the NYC shapefile for routing in ArcGIS as part of a lecture on routing algorithms.

Public Engagement:

The team presented our work on the Truck Routing App and Commodity Flow data at the 2022 Tandon Research Expo (April 2022), which exposes our project to the local community as well as to other students at NYU Tandon. The topic was "NYC Freight: Routing App and Data Analysis".

Hector Landes led a seminar entitled "Diving into open data - What is available and how to use them for transportation research" which was based around his work on the Commodity Flow product. Those slides and presentation are available on the C2SMART Student Learning Hub.

Haggai Davis, III led a discussion about the Truck Routing App and what would need to be included in it at the unconference TransportationCamp NYC 2022.

As part of recruitment for the Hackathon, the Center produced videos and a website.

https://www.youtube.com/watch?v=MB8sHWRWpY0

https://c2smart.engineering.nyu.edu/smart-trucking-hackathon/

Industry Engagement:

The team has presented the research to industry through the dissemination efforts mentioned above. In addition, the judges from the Hackathon comprised members of various public and private agencies related to trucking in NYC. Their interest has attracted attention from other related agencies leading to the decision to produce an additional, digestible document focusing on the Truck Routing App.

This project has resulted in developing data-driven and modeling insights to support NYC DOT's efforts to manage the growing freight demand in NYC. It paves the way toward a future setup for an "Urban Freight Lab: East Coast" analog to the lab at University of Washington under Prof. Anne Goodchild.

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